Risk of Supply Insecurity with Weather Condition Based Operation of PHEVs

D. Jayaweera and S. Islam

Abstract**—**Plug in Hybrid Electric Vehicles (PHEVs) can be a strategic source to mitigate risk of supply insecurity in an active distribution network. This paper proposes a new methodology to quantify the risk of supply insecurity with weather condition based operation of PHEVs in an active distribution network. The approach divides operating characteristics of PHEVs into charging, discharging, and null. Operation of PHEVs with change in weather conditions, intermittent characteristics of distributed generation, sector customer demand characteristics, and random outages of components are modelled on Markov-Chain Monte Carlo simulation. A set of case studies are performed considering distributed operation of PHEVs as oppose to central operation of conventional units. Results suggest that distributed operation of PHEVs can potentially mitigate risk of supply insecurity of moderately stressed networks. Highly stressed networks, which are operated with PHEVs, need supplementary supports from conventional units to mitigate risk of supply insecurity.

1. Introduction

Operation of an active distribution network can be challenged by increased uncertainties, random outages, and intermittent effects of distributed generation (DG). The networks with increased presence of intermittent DG may require standing reserve units to share some loads at intermittent cycles of DG. Standing reserve can be supplied by using fossil fuelled power generation. The philosophy of supplying the standing reserve using fossil fueled power generation can be challenged by PHEVs (Plug in Hybrid Electric vehicles) through their strategic operation. PHEVs have the mobility advantage and they can be integrated into an active distribution network dynamically as per the need.

Operating characteristics of PHEVs are stochastic and detailed characterization of them is challenging. PHEVs can have different charging and discharging modes including normal/ quick charging, partial charging/discharging, network constrained charging/ discharging, inability to charge/ discharge due to charging station and network component failures.

With the advances in smart grid technologies, the operation of future distribution networks can be seen through scenarios that are high penetrated with intermittent DG and PHEVs. In those scenarios, the challenging task would be to capture individual merits of resources for the beneficial operation of PHEV stations to reduce insecurity of power supply to electricity consumers.

The published literature explores a wider aspect of PHEVs in the context of planning and operation of modern power systems. An approach to quantify voltage violations in the presence of battery electric vehicles is proposed in [1]. Indices are proposed in [2] for the performance assessment of micro grids. An approach is proposed in [3] for the optimal scheduling of electric vehicles. In [4], impacts of PHEV behavior on the electric grid is analyzed by taking into account daily driving cycles. In [5], impacts of PHEV charging patterns are analyzed with stochastic unit commitment models. Reference [6] proposes an approach to model PHEV home charging patterns, taking into account the stochastic nature of individual loads. In [7], a distributed framework for demand response and user adaptation is proposed for smart grids. There is a limited published literature that addresses direct impacts of PHEVs on security of supply in an active distribution network. Some literatures address adequacy and security (inverse of risk) with weather conditions. In [8], a three-state weather model is proposed for the adequacy assessment of power systems. In [9], a technique is presented to reduce the errors in the short-term load forecasting with weather conditions. Reference [10] addresses extreme weather conditions and argues that the number of transmission line outages is not necessarily proportional to the physical length of lines. Reference [11] presents a probabilistic method to model wind farm characteristics. In [12], the value of security is assessed with inter-regional transmission lines. Security impacts with the large scale integration of wind power are explored in [13]. In [14], a multi-objective probabilistic risk index is proposed to capture the likelihood and consequences of events. Reference [15] explores splitting techniques to determine the probability distribution of a blackout size. Fuzzy and Monte Carlo simulation based hybrid technique is proposed in [16] for the assessment of power system security. Multi-objective optimization based algorithm is presented in [17] for active distribution network planning. In [18], a probabilistic indicator is proposed to quantify the power system stress. Reference [19] explores the power system restoration schemes. A mathematical model is proposed in [20] for the assessment of impacts of DG in a power distribution network.

This paper proposes a new methodology to assess the risk of supply insecurity in an active distribution network. The approach

Paper received 3rd February 2014 and revised 26 May 2014.
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takes into account weather condition based operation of PHEVs with stochastic processes of individual and combinatorial events. The complex PHEV operating characteristics and their fractional power injections are modeled in the approach by clustering their operating conditions into charging, discharging, and null operating modes and applying mode-based impact factors. The main engine of the approach is the Markov Chain Monte Carlo simulation which integrates multi-dimensional uncertainties of change in weather conditions, random outages, sector customer demand variations, and intermittent cycles of distributed power generation with PHEV operating characteristics and then estimates the risk of power supply insecurity by capturing impacts of disturbances and their durations. Expected energy not served (EENS) is used as the proxy of risk of power supply insecurity because it can capture magnitudes of impacts and their durations in probabilistic terms. The paper also investigates the strategic operation of distributed PHEVs as oppose to central operation of conventional units as standing reserve support units for mitigating risk of supply insecurity.

The remaining parts of the paper are organized as follows. Section 2 presents the proposed methodology in detail. It also presents the probabilistic models of PHEV operating modes, PHEV operational characteristics, and change in weather patterns. Section 3 presents the case study and critically analyses the results. Section 4 presents conclusions of the findings.

2. The Methodology

The operating conditions of PHEVs in an active distribution network can be classified as charging, discharging, and null modes. The null mode refers to a state which results a slack mode of PHEVs. The maximum power into PHEVs (charging) or into the grid (discharging) via branches connected to a node of a power distribution network can be respectively considered as the feasible charging and discharging capacity of connecting feeders to the node. The difference between the feasible charging and discharging levels is considered as the feasible capacity of the null mode of operation of PHEVs. PHEVs can have different levels of depth of discharge (DOD) and state of charge (SOC) and their influences are also captured within the null mode of operation.

2.1. Modeling charging and discharging of PHEVs

Modeling charging and discharging characteristics of PHEVs involves weather condition modeling, PHEV mode modeling (I.e., charging, discharging, and null), and PHEV dispatch level modeling (i.e., level of power injections in a PHEV mode). PHEV mode modeling is used to determine if the status of a PHEV is at charging, discharging, or null mode. PHEV dispatch level modeling is used to determine the level of charge, discharge, or null operation of PHEVs at a sample of Monte Carlo simulation. Fig. 1 shows the basic steps that determine charging levels of PHEVs in Markov-Chain Monte Carlo simulation. As Fig. 1 is for a generic case, the number of charging levels goes up to n and it also depends on the conditions of PHEV stations. In Fig. 1, the charging level 1 gives the minimum charging and the charging level n gives the maximum charging level. Case study uses the minimum, the intermediate, and the maximum levels of charging and discharging.

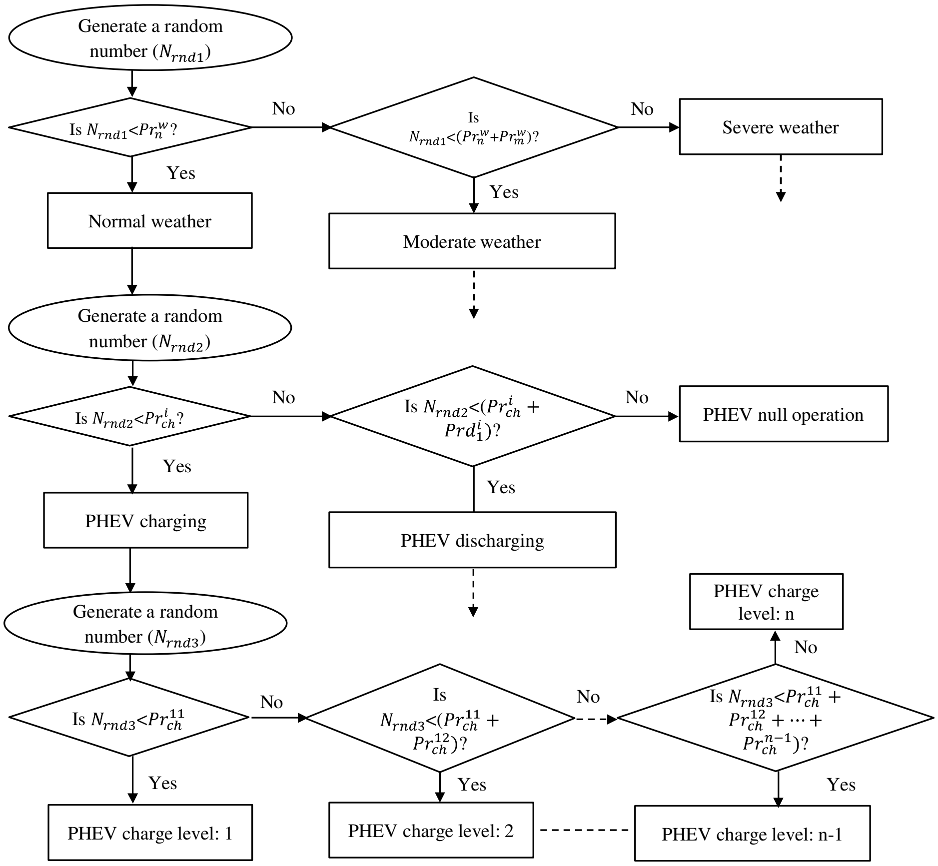

Fig. 1: Process of determining the PHEV charging levels in Markov-Chain Monte Carlo sampling

2.1.1. Weather condition modeling

The Markov-chain Monte Carlo sampling is incorporated to model the change in weather conditions. In that, a random number is generated between 0 and 1.0 for each sample trial and compared it with the probability of experiencing a weather state for the network. A power system can undergo several different weather modes. They can be classed into normal, moderate, and severe. For example, if the probabilities of experiencing a normal, moderate, and severe weather conditions are respectively $\Pr_n^w, \Pr_m^w, \Pr_s^w$ and if the generated random number N_{rnd1} for a sample trial of the simulation is within $0 \leq N_{rnd1} < \Pr_n^w$, then the weather condition for the sample is set as normal. If $\Pr_n^w \leq N_{rnd1} < (\Pr_n^w + \Pr_m^w)$ then the weather condition is set as moderate. If $(\Pr_n^w + \Pr_m^w) \leq N_{rnd1} < (\Pr_n^w + \Pr_m^w + \Pr_s^w)$ then the weather condition is set as severe. When the Markov Chain Monte Carlo simulation converges following a Gaussian distribution, the probability of number of samples that occupy normal, moderate, and severe weather conditions respectively equate to $\Pr_n^w$, $\Pr_m^w$, $\Pr_s^w$.

In the normal weather mode, values of failure rates of equipment, power outputs of DG, and PHEV characteristics of operating modes are same as the base-case values. Section 3.1 and Set A scenarios in Section 3.2 give the base case details of the case study. However, if the weather condition is transited to moderate and severe weather conditions, those values are affected and they are implemented by introducing an impact factor. The impact factors associated with each of those functions are not necessarily constant because impact factors can be varied depend on the type of weather and geographical location of the power network. Thus, to define impact factors, a heuristic knowledge of events are incorporated. Smart technology based monitoring techniques can also be incorporated to gather sufficient information for calculating impact factors corresponding to weather conditions.

2.1.2. Modeling of PHEV modes of operation

Markov-Chain Monte Carlo sampling used in 2.1.1 is expanded further to model PHEV modes of operation, where PHEV modes also undergo the Markov-Chain Monte Carlo process. Consider a node of a network that is connected with PHEV charging and discharging stations. When the PHEVs are charging, the network sees them as a positive load for the duration of the sample-trial. When the PHEVs are discharging the network sees them as a negative load for the sample-trial of Monte Carlo simulation. Charging and discharging rates and state of charge levels are not necessarily constant in all PHEVs and they depend on individual specifications, age, frequencies of charging and discharging functions, and ambient conditions.

PHEVs can have different modes of charging, including quick and normal charging. Some vehicles can be in the quick charging mode whereas others can be in the normal charging mode. Quick charging can have less than an hour to get the battery to be fully charged where as normal charging can have several hours, depending on the type and make of a battery, to be fully charged. However, when there are a large number of vehicles that are in different states of charge and in different modes of operation (charging, discharging, and null), then a probabilistic approach is needed to capture their operation.

If the probability of PHEV charging, discharging, and null modes are defined as $\Pr^i_{ch}$, $\Pr^i_{dis}$, and $\Pr^i_{null}$ respectively, then, a random numbers (N_{rnd2}) between 0 and 1.0 can be generated for each node and the generated random numbers can be compared with probabilities of PHEV modes of nodes. If the generated random number for a node i is within $0 \le N_{rnd2} < \Pr^i_{ch}$ then the PHEV mode of operation of the node for the sample trial is set as charging. If $P^i_{ch} \le N_{rnd2} < (\Pr^i_{ch} + \Pr^i_{dis})$ then the PHEV mode of operation for the node is set as discharging. If it doesn't satisfy either then the mode is set as null. Probability of charging, discharging, and null operation of PHEVs can be calculated using (1) to (3).

$$\Pr^i_{ch} = \frac{N_c}{N_c + N_{dis} + N_{null}} \tag{1}$$

$$\Pr^i_{dis} = \frac{N_{dis}}{N_c + N_{dis} + N_{null}} \tag{2}$$

$$\Pr^i_{Nnull} = \frac{N_{null}}{N_c + N_{dis} + N_{null}} \tag{3}$$

Where, N_c, N_{dis} and N_{null} give the number of vehicles at charging, discharging, and null operation respectively. As the null mode of operation is ineffective for the operation of an active distribution network, operating characteristic of the null mode is not required to be modeled within Markov-Chain Monte Carlo simulation to assess the risk of supply insecurity. In addition, probability distribution for PHEV charging operation can further be refined by using smart grid technologies and monitoring the charging characteristics online.

2.1.3. Modeling of PHEV level of charging and discharging

Markov-Chain Monte Carlo sampling used in 2.1.2 is also expanded further to model PHEV level of charging and discharging, where PHEV charging and discharging levels also undergo the Markov-Chain Monte Carlo process.

Consider PHEVs with different levels of charging and discharging at a node in a network. If the maximum and the minimum allowable charging levels at a node of the network are $P^{\max}_{ch}$ and $P^{\min}_{ch}$ respectively, then the maximum charging level of PHEVs at the node i is given by (4),

$$\begin{aligned} P^{\max}_{ch} &= \alpha_{\max} \times \left| \sum_{s=1}^{n_1} P_{line,s} - \left\| \sum_{j=1}^{n_2} P_{DG,j} + \sum_{l=1}^{n_3} P_{Conv,l} - \sum_{k=1}^{n_4} P_{Load,k} \right\| \right| ; \\ P^{\min}_{ch} &= \alpha_{\min} \times \left| \sum_{s=1}^{n_1} P_{line,s} - \left\| \sum_{j=1}^{n_2} P_{DG,j} + \sum_{l=1}^{n_3} P_{Conv,l} - \sum_{k=1}^{n_4} P_{Load,k} \right\| \right| ; \\ \alpha_{\max} &\le 1.0 \,, 0 \le \alpha_{\min} \,,\; \alpha_{\min} \le \alpha \le \alpha_{\max} \end{aligned} \tag{4}$$

Where, $\alpha, \alpha_{\max}, \alpha_{\min}, P_{line,s}, P_{DG,j}, P_{conv,l}, P_{Load,k}, n_1, n_2, n_3, n_4$ give charging factor, maximum charging factor, minimum charging factor, active power flow rating of s^{th} line, active power injection from j^{th} DG unit, active power injection from l^{th} conventional generating unit, demand level of k^{th} sector customer, number of lines connected at i^{th} node, number of DG connected at i^{th} node, number of conventional units connected at i^{th} node, number of sector customers connected at i^{th} in a sample-trial of Monte Carlo simulation respectively. Distribution network operators are responsible for the security of power supply in a distribution network and they also have the ability to determine the charging factors. Therefore, charging factors are to be determined by the distribution network operators by taking into account their operating strategies. It is to be noted that because (4) gives the formulations for charging, the sign convention of charging is not required and magnitudes of quantities are used.

Then, the level given by ($P^{\max}_{ch} - P^{\min}_{ch}$) is divided into set of PHEV charging levels. If the limit of PHEV charging operation at node i is divided into $\delta\,\%$ steps, at a sample trial, the actual level of PHEV charging at the node can be calculated using $P^{\min,i}_{ch} + \lambda_n \times \delta\% \times (P^{\max,i}_{ch} - P^{\min,i}_{ch})$, where λ_n gives the number of the PHEV charging level of the limit given by (4). Next, a random number between 0 and 1.0 is generated for the node and it is compared with the probability of the occurrence of a PHEV charging level $P^{\min,i}_{ch} + \lambda_n \times \delta\% \times (P^{\max,i}_{ch} - P^{\min,i}_{ch})$. If the probability of occurrence of PHEV charging level $P^{\min,i}_{ch} + \lambda_1 \times \delta\% \times (P^{\max,i}_{ch} - P^{\min,i}_{ch})$ is defined as $\Pr^{11}_{ch}$ and if the generated random number N_{rnd3} is within $0 \le N_{rnd3} < \Pr^{11}_{ch}$, then the PHEV charging level of the node i is set as $P_{ch}^{\min,i} + \lambda_1 \times \delta\% \times (P_{ch}^{\max,i} - P_{ch}^{\min,i})$. If $\Pr_{ch}^{11} \le N_{rnd3} < (\Pr_{ch}^{11} + \Pr_{ch}^{12})$ then the PHEV charging level at node i is set as $P_{ch}^{\min,i} + \lambda_2 \times \delta\% \times (P_{ch}^{\max,i} - P_{ch}^{\min,i})$, where, $\Pr_{ch}^{12}$ is the probability of the occurrence of the next level of PHEV charging. The process continues to cover entire spectrum of charging levels. In this way, random numbers are generated for each of the PHEV node of the network and then the PHEV charging levels are calculated. Same steps are applied to calculate the discharging levels of PHEVs. Mathematical formulation to calculate the maximum and the minimum discharging levels are given by (5).

$$
\begin{aligned}
P_{dis}^{\max} &= \beta_{\max} \times \left| \sum_{s=1}^{n_1} P_{line,s} - \left\| \sum_{j=1}^{n_2} P_{DG,j} + \sum_{l=1}^{n_3} P_{Conv,l} - \sum_{k=1}^{n_4} P_{Load,k} \right\| \right| ; \\
P_{dis}^{\min} &= \beta_{\min} \times \left| \sum_{s=1}^{n_1} P_{line,s} - \left\| \sum_{j=1}^{n_2} P_{DG,j} + \sum_{l=1}^{n_3} P_{Conv,l} - \sum_{k=1}^{n_4} P_{Load,k} \right\| \right| ; \\
&\beta_{\max} \le 1.0\,,\ 0 \le \beta_{\min}\,,\ \beta_{\min} \le \beta \le \beta_{\max}
\end{aligned} \tag{5}
$$

Where, $\beta, \beta_{\max}, \beta_{\min}$, give discharging factor, the maximum discharging factor, the minimum discharging factor in a sample trial of Monte Carlo simulation respectively. As in the charging case, the discharging factors can also be determined by the distribution network operators taking into account their operating strategies. It is to be noted that because (5) gives the formulations for discharging, the sign convention of discharging is not required and magnitudes of quantities are used.

The probability of experiencing a particular PHEV charging step is not necessarily linear. However, the probabilistic model of the PHEV charging level proposed in this paper can also be adopted for non-linear probabilities because it is a matter of ordering the probabilities corresponding to the cluster of the PHEV charging mode. In addition, probability distribution PHEV discharging operation can further be refined by using smart grid technologies and monitoring the discharging characteristics online.

2.2. Modeling intermittent characteristics

Intermittent characteristics of DG can be modeled by applying two techniques. The first technique uses time series profiles of intermittent power outputs of DG and they are sequentially applied in sample trials of Monte Carlo simulation. The method synthesizes time series profile to match the sample duration of Monte Carlo simulation and then they are sequentially applied as the sample trials are progressed.

The second technique clusters the outputs of the intermittent generators to form the state duration curve of the intermittent power generation output and output levels are applied randomly. The operating state is determined by generating random numbers between 0 and 1.0 and then comparing them with the probabilities of occurrences of the DG outputs. Then, the level of the DG output corresponding to the sample is used to model the DG output.

Both techniques achieve similar outcome when Monte Carlo simulation converges.

2.3. Modeling demand fluctuations

As in intermittent power output modeling, the load level variations can also be modeled by applying two techniques. The first technique incorporates load duration curve and then generate random numbers and compare them with the probability of experiencing a level of load to determine the magnitude of the load for the sample trial of Monte Carlo simulation.

The second technique incorporates time-series of loads and their sector customers and extracted samples from time-series are applied sequentially. For example, connected sector customers at a node can be industrial, commercial, agricultural, and residential. All of these customers contribute to form the load demand at a node. The proposed approach weights sector customers at a node of the network from the total connected load of the node and then interpret weights in terms of percentages of total connected loads. The nodes in a distribution network can have an urban, a rural, a semi-rural, or a semi- urban type. Based on the type of the node, the percentage customers connected at a node varies. In this way, the annual load profiles are synthesized sequentially to match the sample duration of Monte Carlo simulation.

2.4. The proposed approach

At first the base case operating condition is modeled and solved with Newton Raphson power flow algorithm to determine convergence and then constraint violations (thermal and voltage limit) in the base-case. The base-case generally has converging operating conditions, however if it diverges then the loads are shedded from the worst mismatch bus to achieve the convergence of the solution. Existence of constraint violations are corrected by applying flexible generation re-dispatch, on load tap changing, shunt compensation, and using network re-configuration options as they are available. Load shedding is also applied as the last resort for the cases which experience a significant level of constrain violations and if all the other options are failed. The approach considers the first half of a sample-trial time duration as the period that would experience outages and the remaining half begins with the restoration of shed loads (if any).

Then, the base-network is integrated with intermittent DG at resource locations. The variations in sector customer load demands are modeled as per the details given in Section 2.2. The network weather-mode for a sample trial is determined by using the method proposed in Section 2.1.1. In addition, weather conditions other than normal weather can increase the total consumption level at a node by α %, reduce the output of intermittent DG by β %, increase failure rates of equipment by $\varphi\%$, and reduce PHEV charging and discharging levels respectively by γ_1% and γ_2%. The electricity consumption of different sector customers can have different levels. They can be defined as $\alpha_1\%, \alpha_2\%, ..., \alpha_{n-1}\%, \alpha_n\%$ for n number of sector customers. These percentages are applied to the base-case operating condition to determine the varied characteristics of weather conditions. Thus, multipliers of consumptions at the n^{th} customer sector, intermittent power output of DG, failure rate of equipment, and PHEV charging and discharging at a sample trial in Monte Carlo simulation are expressed as $(1+\alpha_n\%)$, $(1-\beta\%)$, $(1+\varphi\%)$, $(1-\gamma_1\%)$ and $(1-\gamma_2\%)$ respectively.

The operating statuses of equipment are determined by generating random numbers and then comparing them with probabilities of the outage of equipment. If the generated random numbers are less than the probabilities of outages of equipment then the relevant components are set as out of service components. As the weather-state model is operational at this stage, depending on the weather state, the probability of the outage of the equipment is re-calculated by applying the weather mode related impact factors.

Then, the system power balance is determined by the application of Newton Raphson power flow algorithm. If the load flow solution diverges then the load shedding is applied from the worst mismatch bus. If any constraint violations exist then they are eliminated by applying corrective actions, as suggested before.

If the load flow is diverged then load shedding begins from the worst mismatch bus until eliminating the divergence condition. At first the flexible loads are shedded. If the solution couldn't reach the convergence, the nonflexible loads of the largest mismatch bus are also shedded in lowest levels. If the resulting solution is converged and free from constraint violations, ENS (energy not supplied) for the sample-trial is calculated by considering the amount of shed-load and time to restore the shed-load. Alternatively, the minimum loads can be shedded for a sample of Monte Carlo simulation by formulating costs of outage and constraints and then minimizing the cost of outage while minimizing the level of load shedding at effective buses. One can use both methods of load shedding and determines the most effective method for a network.

At this stage, the operating condition is restored to the operating condition prior to applying the Newton Raphson power flow algorithm and then the system operating condition is modified by connecting PHEVs to potential nodes of the network. The aim of PHEV connections is to provide standing reserve supports for intermittent cycles of DG, as oppose to supports from conventional units that are connected centrally. In this way, the standing reserve thresholds with PHEVs can be calculated and the risk of supply insecurity with PHEVs can be estimated. In this part, the ENS of the sample is calculated by using the amount of shed-load with PHEV connections and time to restore the shed-load.

Next, the difference between ENS with and without PHEVs is calculated, and the process continues until meeting the stopping criteria of Monte Carlo simulation. The approach sets conditions of the stopping criteria as satisfying 95% degree of confidence of the estimation within a 5% confidence interval and processing the minimum number of sample trials. Converging Monte Carlo simulation leads to calculate the expected energy not served (EENS) due to the penetration of PHEVs by taking the difference of without and with PHEVs. The resulting EENS value can be either positive or negative. If the value is negative then PHEV increases the risk of power supply insecurity. If EENS value is positive then PHEV reduces the risk of supply insecurity of the network. Fig. 2 shows the basic steps of Monte Carlo simulation with PHEV operating modes, charging levels, and weather conditions to estimate ENS.

In the next stage, conventional units are applied with PHEVs to assess the risk of supply insecurity with hybrid supports. Risk of supply insecurity is calculated by following the same procedures and then estimating EENS.

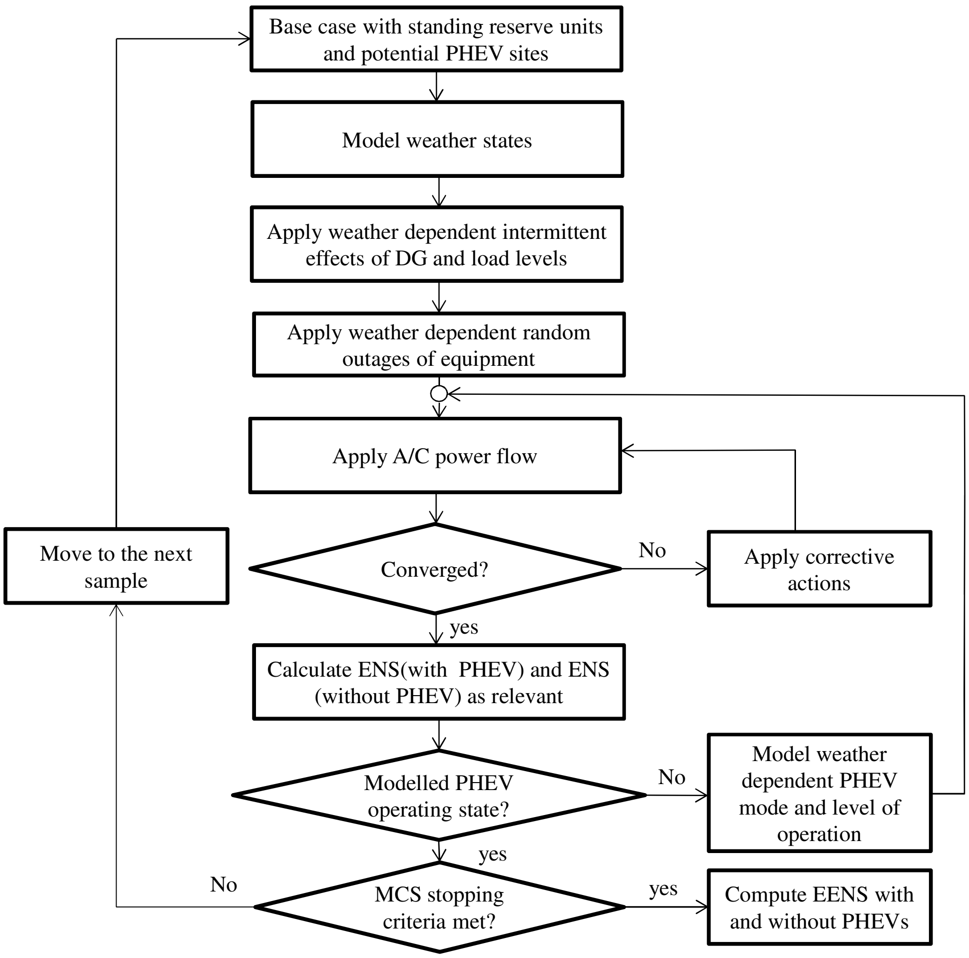

Fig. 2: Basic steps of Monte Carlo simulation of the proposed approach. Note that the next sample refers to the next sample trial of Monte Carlo simulation.

3. Case Studies

Case studies are designed to assess the performance of the proposed approach and its models. Fig. 3 shows a realistic network model that is used for the studies. Case studies uses 12 states in the Markov-Chain. They are: normal weather state, moderate weather state, severe weather state, charging state, discharging state, null operation state, maximum charging state, intermediate chagrining state, minimum charging state, maximum discharging state, intermediate discharging state, and minimum discharging state. In addition, the case study considered that each PHEV station carries 200 vehicles delivering 2MW capacity. All the scenarios use linear probabilities for the occurrences of charging and discharging steps. Intermittent characteristics of wind and PV are modelled with the first technique given in Section 2.2 and the demand fluctuations are modelled with the second technique given in Section 2.3. Load shedding scheme used for the case studies is the first technique proposed in Section 2.4.

3.1. The Network

The network has 24 buses, 4 Wind and PV (photo voltaic) power generating stations, three wind-only power generating stations, five load centers, and 13 transformers. The transformers at HV (high voltage) grid (132/33kV) and Load-1 (33/11kV) are voltage regulating transformers. Total peak active and reactive power loads of the network are 20.4W and 3.6MVAr respectively. This is defined as 100% loading of the network in the case study. The network is capable of absorbing 200% of the base-case load (100%), beyond which the system collapses.

Capacity factors of outputs of wind turbine generators are ranging from 0.28 to 0.30. Each load center has a mix of residential (contracted), residential (non-contracted), industrial and commercial customers. The contracted loads are the first loads to curtail in the event of emergencies. The network operating voltages are 0.6kV, 11kV, 33kV, and 132kV. Total installed capacity of wind and PV are 6MW and 1.2MW respectively. Diesel plant carries 8MVA capacity using 2.5MVA, 2.5MVA, and 3MVA units. The total PHEVs to be connected in the system are 8MW and they are connected to the network via four PHEV stations, which is also shown in Fig. 3.

Markov Chain Monte Carlo simulation was performed on Intel Core2Quad 2.66Hz 4GB RAM machine. The maximum and the minimum number of sample trials of the simulation were set as 17520 to 100000 respectively because the wind plants' output profiles were synthesized in half-hourly intervals and it takes 17520 samples to capture at least a yearlong profile of wind plants' power outputs.

3.2. Scenarios

Three sets of scenarios (Set-A to C) were designed to assess the risk of power supply insecurity with weather constrained operation of PHEVs. Scenarios are also aimed at investigating the potential ability of PHEVs to stay connected in the system as strategic standing-reserve units to mitigate risk of supply insecurity.

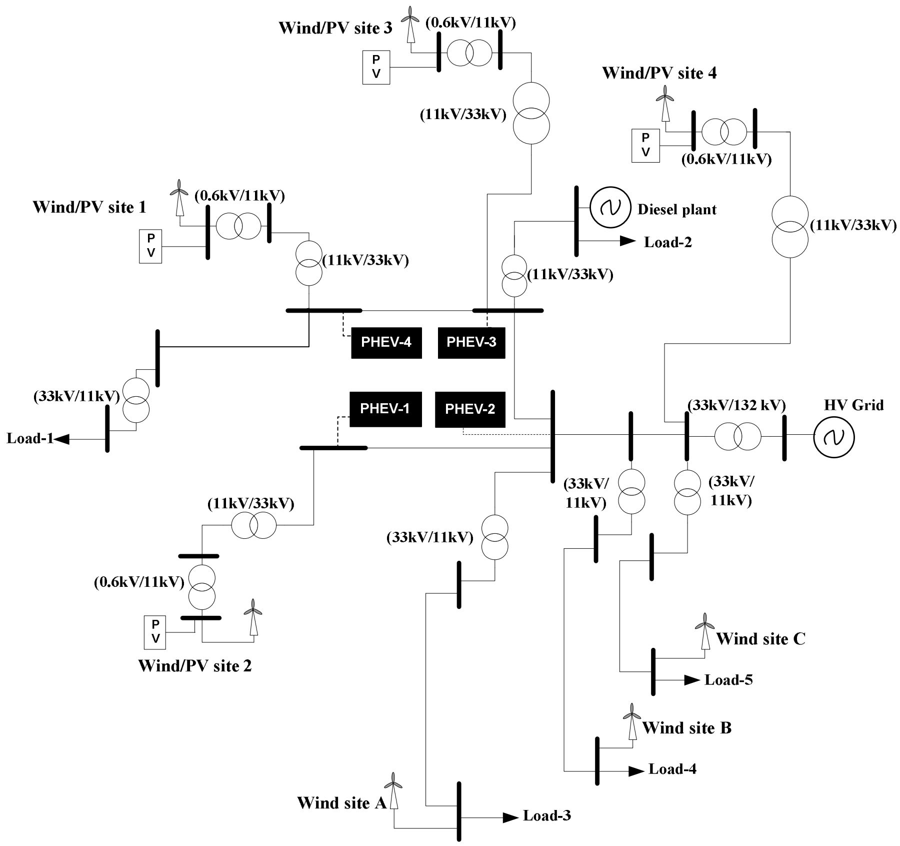

Fig. 3. Active distribution network model

Scenario Set-A: The Set-A scenario consists of three sub scenarios, based on the level of the load of the network. The first scenario in set-A represents the base-case operating condition with change in weather patterns. Standing reserve supports for intermittent cycles of wind and PV are supplied by diesel units. The diesel units, which are shown in Fig. 3, are centrally connected. There are no PHEVs connected in the network in the first scenario. The second and third scenarios in Set-A respectively carry 150% and 200% of the base-case load (100%) while maintaining all other conditions same as in the first scenario. Scenarios in Set-A also act as reference scenarios for the comparison of performances of other scenarios.

Scenario Set-B: Same as scenario Set–A, but the first to third scenarios in Set B carry distributed PHEV connections instead of the central diesel power generation. Thus, these scenarios can also support the standing reserve needs of intermittent cycles of wind and PV. PHEVs are operated same as base-load plants, although they change their operating modes and their output characteristics due to external influences, including weather conditions. The distributed connection of PHEV stations are also shown in Fig. 3. Each PHEV station (PHEV1 to PHEV4) carries 2MW of capacity and all stations facilitate connecting a total capacity of 8MW to the system. The entire scenarios in Set–B are further sub grouped into groups B_1 and B_2, based on the probabilities of charging, discharging, and null operation. Each PHEV station carries different levels of probabilities of charging, discharging, and null operating modes. Table 1(a) shows the probabilities of charging, discharging and null operation together with the factors that determine the level of the power injection from the modes of operation of PHEVs (i.e., charging, discharging, or null operation). Table 1(b) shows the scenario groups corresponding to probabilistic models in Table 1(a). Tables 1(c) and 1(d) show the corresponding probabilities and impact factors of severe, moderate, and normal weather modes respectively. Table 1(e) shows the impact factors of weather conditions corresponding to PHEV operation, intermittent DG operation, and load demand levels. These impact factors are the multipliers that represent weather state effects on the operation of PHEVs, operation of intermittent DG, and the level of load demand.

Scenario Set-C: Same as scenario Set-B, but additionally integrates central diesel generation capacities of 2.5MVA, 5MVA, and 8MVA as standing reserve units. The first, second, and third scenarios respectively carry 2.5MVA, 5MVA, and 8MVA. Thus, diesel capacities act as an additional generation for the needy operating conditions.

Table 1(a): Probabilistic characteristics of PHEVs and factors that determine the level of power injections. Note that the probability of discharging equal to 0 indicates that the PHEV station is out of service.

PHEV operation model	Probability of charging	Probability of discharging	Probability of null operation	Charging factor	discharging factor	Null operation factor
1	1.00	0.00	0.00	-1.00	0.00	0.00
2	0.80	0.10	0.10	-0.80	0.10	0.00
3	0.80	0.00	0.20	-0.80	0.00	0.00
4	0.60	0.30	0.10	-0.60	0.30	0.00
5	0.60	0.20	0.20	-0.60	0.20	0.00
6	0.60	0.10	0.30	-0.60	0.10	0.00
7	0.60	0.00	0.40	-0.60	0.00	0.00

Table 1(b): Scenario groups in Set B scenarios

Scenarios	Operation model of Table-I corresponding to			
	PHEV-1	PHEV-2	PHEV-3	PHEV-4
B1	2	1	4	5
B2	7	6	3	1

Table 1(c): Weather mode probability

Weather state probability		
Normal	*Moderate*	*Severe*
0.7	0.1	0.2

Table 1(d): Impact factors

Impact factors of weather state failure rates		
Normal	*Moderate*	*Severe*
1	2	5

Table 1(e): Impact factors of operating functions

Operating function	Impact factor		
	Normal	*Moderate*	*Severe*
PHEV at weather conditions	1	0.5	0.1
Intermittent DG at weather conditions	1	0.95	0.8
loads at weather conditions	1	1.05	1.2

3.3. Results

All the scenarios were converged within 17520 to 35586 sample trials, with a 95% of degree of confidence, and with a 5% of confidence interval. The time-frame required to converge Monte Carlo simulation for all the cases was ranged from 50 minutes to 2 hours. Although the case studies used naïve Monte Carlo simulation, the processing time could be reduced further if Monte Carlo simulation was performed with a variance reduction technique [18]. The number sample trials that result constraint violations was varied with the scenario. In any case, the number of sample trials that experience constraint violations and leading to shed loads were reported as less than 5% of the total number of sample trials that resulted load shedding due to all causes.

Fig. 4(a) shows the levels of load shedding (of an estimated sample trial of Monte Carlo Simulation) correspond to severe, moderate, and normal weather conditions of Set–A scenarios. When the network is loaded with the base-case load (100% in Fig. 4(a)), the impacts of severe weather condition compared to other weather conditions are not very significant although it is the weather condition that makes large impacts. The results also suggest that loading levels of the network is exponentially proportional to impacts of weather conditions.

Fig. 4(b) shows the level of load shedding (of an estimated sample trial of Monte Carlo simulation) against weather conditions, system loads, and PHEV operating modes of Set–B scenarios. The impacts on the connected load at the base-load operating condition remain steady and same as in Set–A scenarios, under varying characteristics of PHEVs and their operating modes. However, the impacts on security are significantly increased with the increase in system load, in the presence of PHEVs as oppose to central diesel generation. Severe and moderate weather conditions dominate the impacts on electricity consumers against increase in system load. The results further depict that PHEVs have a limited capability to inject standing reserve at intermittent cycles and their highest value is at the normal loading (100%), even under change in weather conditions. Thus, the value of PHEVs can be considerably high for moderately loaded (100%) power networks than the stressed networks (200%).

Fig. 4(c) shows the shed-load of an estimated sample trial of Monte Carlo simulation against increase in system load, change in weather conditions, and additional reserve supports from central diesel units in group B_2 of Set C scenarios. Results argue that the hybrid application of PHEVs and diesel generation can be the most beneficial deployment for this particular network if the network loading is likely to increase considerably. Addition of 2.5MVA of central diesel generation reduces the impact on electricity consumers considerably compared to the parallel case in Set B scenarios. Results also suggest that lower impacts with moderate weather compared to normal weather due to the operating conditions of the network and the likelihood of experiencing the weather mode. For example, if the network is stressed at sample trials of normal weather condition, then resulting outage of component and combinatorial events can increase the impact on security of supply than moderate weather case. On the other hand, if the network is less stressed at sample trials of moderate weather condition and experiencing outages with combinatorial events may not necessarily results significant impacts compared to normal weather case. In addition, the likelihood of experiencing the moderate weather mode is considerably lower than the normal weather mode.

Fig. 5 shows the annual EENS of Set-A scenarios. The EENS values are the accumulated EENS components of severe, moderate, and normal weather conditions. Results suggest that the linear increase in system load can increase the impacts on electricity consumers nonlinearly, following an exponential growth of impacts. Figs. 6 and 7 show the annual accumulated impacts corresponding to Set-B and Set-C scenarios. Results re-affirm that the merits of distributed operation of PHEVs as oppose to central operation of diesels at the base loading condition (100%). Results also depict that PHEV operating modes and their characteristics make a minor variation of impacts for the increased loading conditions. PHEV operating characteristics in group B_1 scenarios help reducing EENS of 20MWh at 150% loading whereas PHEV operating characteristics in group B_2 scenarios help reducing EENS of 33MWh at 200% loading.

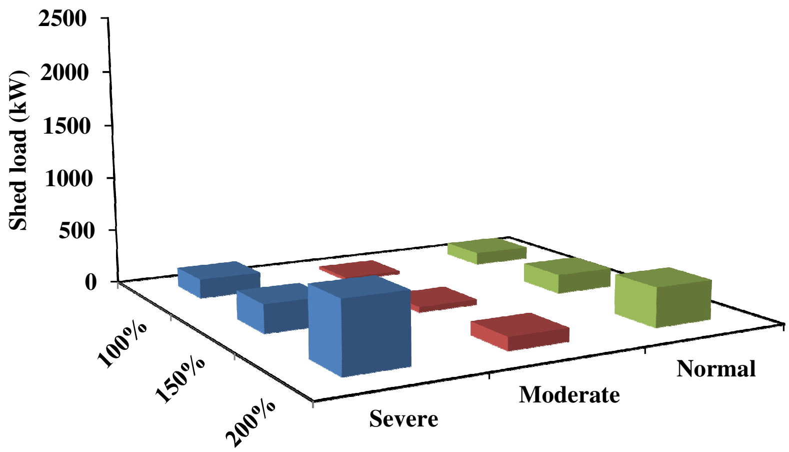

Fig. 4(a): Scenario Set–A with level of load shedding of an estimated sample corresponds to weather conditions and system load levels: Diesel generation provides standing reserve supports.

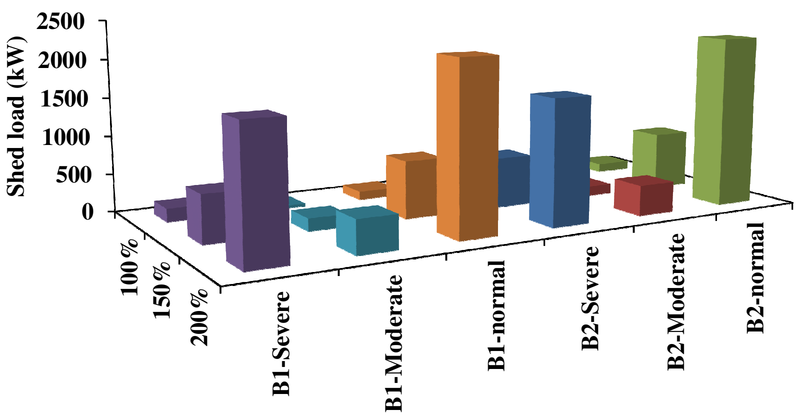

Fig. 4(b): Scenario Set-B with level of shed-load of an estimated sample corresponds to weather conditions, and system load levels: Operation of diesel generation is replaced by distributed operation of PHEVs.

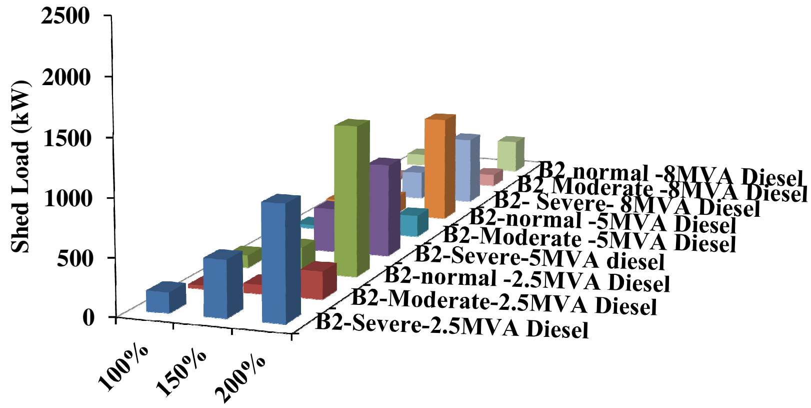

Fig. 4(c): Scenario Set–C with shed-load of an estimated sample corresponds to weather conditions, and system load levels. The network operating conditions in Fig. 4(c) have additional supports from diesel units compared to Fig. 4(b).

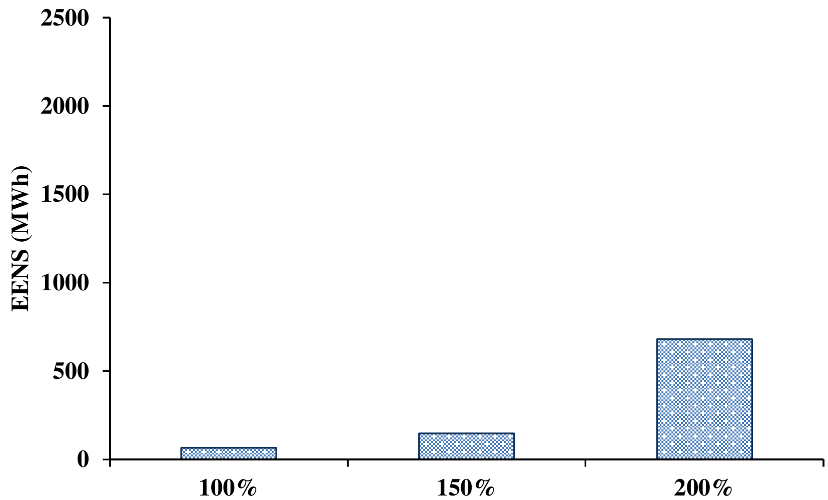

Fig. 5: Annual EENS excluding PHEVs but incorporating diesel units as standing reserve units in Set-A scenarios. Results are for the accumulated EENS components of normal, moderate, and severe weather conditions.

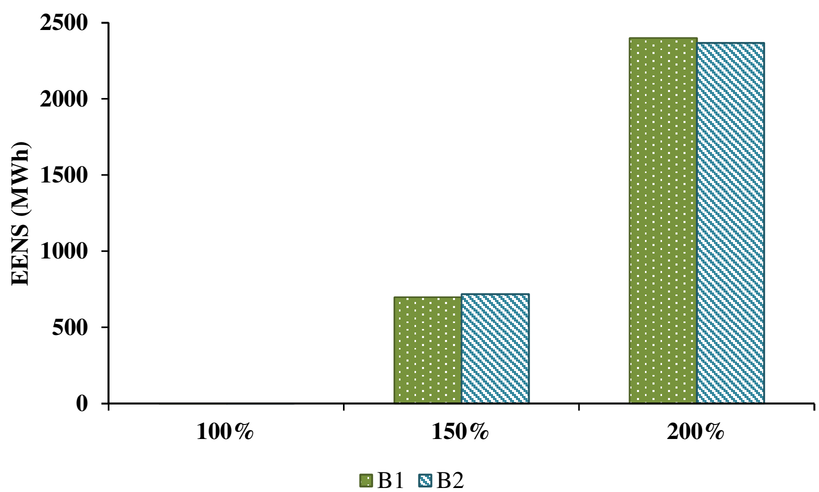

Fig. 6: Increase in annual EENS in Set-B scenarios with PHEVs. Results are for the accumulated EENS components of normal, moderate, and severe weather conditions.

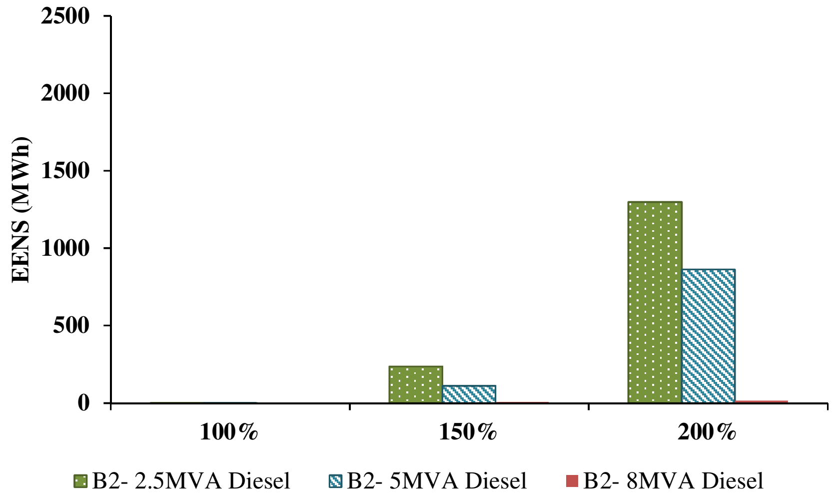

Fig. 7: Increase in annual EENS in Set C scenarios with PHEVs. Results are for the accumulated EENS components of normal, moderate, and severe weather conditions.

The case studies also suggest that the value of PHEVs exists at the 100% level of loading (or 50% of the maximum absorption capacity of the network) for the considered network and its value can stand even with the change in weather conditions. Should the change in weather conditions demand an increased level of load then the presence of diesel generation is vital for limiting the risk of power supply insecurity. Thus, hybrid application of diesels and PHEVs can be the most beneficial option for a network that is highly stressed. Such a deployment also provides additional benefits of reduced need of fossil fuel powered generation and their investments.

4. Conclusions

The paper proposes an approach to assess the risk of power supply insecurity with weather constrained operation of PHEVs. The approach is aimed at active distribution network operating conditions and captures combinatorial interactions of network internal and external uncertainties through the use of Markov-Chain Monte Carlo simulation.

Case studies suggest that the distributed operation of PHEVs potentially mitigate risk of supply insecurity of moderately loaded networks. Highly stressed networks require the hybrid supports from PHEVs and conventional units to mitigate risks and to provide hybrid benefits. PHEV operating modes and their output characteristics can also influence the risk of supply insecurity in an active distribution network.

With the networks advancing towards smart grid operation, the presence of PHEVs can be significantly high and they are to be strategically integrated for global benefits using smart monitoring and control schemes. In that context, the proposed approach provides a platform to benchmark PHEV operating nodes in an active distribution network based on their ability to reduce the risk of supply insecurity. The outcome of the assessment also facilitates identifying potential deferrals of investment thresholds and systematic operation of PHEV stations in an active distribution network.

5. References

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