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Electric Vehicle Markov-Based Adequacy Modeling for Electric Microgrids

MOHAMMAD AL-MUHAINI, (Senior Member, IEEE)
Electrical Engineering Department, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
e-mail: muhaini@kfupm.edu.sa

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ABSTRACT Microgrids (MGs) offer a new paradigm for the operation of electricity networks, allowing end users to significantly improve the power quality and, more importantly, reliability of their power supply systems. While it is clear that MGs offer a significant advantage by providing electricity to customers who would otherwise be disconnected during outages, there are numerous issues with the safe, secure, and efficient operation of MGs, the most basic being integrated management and coordinated control of all resources in grid-connected and off-grid modes. A valuable component that can provide new opportunities for increased reliability of the system and reduced vulnerability to faults is the electric vehicle (EV). One of the major benefits of utilizing EV energy storage is the mobility feature of EVs, which can add great value to the restoration of the power distribution system. The main aim of this work is to understand and model how EV batteries can be used as an intelligent energy reservoir, utilizing both controllable loads (home-to-vehicle and grid-to-vehicle) and controllable energy storage (vehicle-to-home and vehicle-to-grid). This requires modeling the stochastic behavior of EV driving and charging/discharging as well as quantifying the impact of utilizing EV energy storage to restore service to customers. This paper proposes an EV Markov adequacy model that evaluates the reliability of an MG distribution system utilizing EVs and investigates EV mobility and available capacity modeling and EV system adequacy analysis, including the effects on the system reliability of the EV capacity, driving behavior, recharging mode, and EV penetration.

INDEX TERMS Electric vehicles, Markov models, reliability.

NOMENCLATURE

α	Percentage/Penetration
α_D	Percentage of de-rated level
α_R	Percentage of reserved level
α_{HO}	Percentage of home-only electric vehicles (EVs)
α_{HW}	Percentage of home–work EVs
α_{HWP}	Percentage of home–work–park EVs
D_c	Charging duration
E	EV total available energy
f	Frequency of failures
λ	System failure rate
μ	System repair rate
μ_n	Mean of the normal distribution
N_C	Number of customers
N_R	Number of customers restored
N_{EV}	Total number of EVs
$P(t)$	Time-dependent probability
P_c	Charging power
P_d	Discharging power
π	Steady-state probability
π_{HF}	Steady-state probability for state H_F
π_{HD}	Steady-state probability for state H_D
π_{PF}	Steady-state probability for state P_F
π_{PD}	Steady-state probability for state P_D
σ_{ij}	Transition rate from state i to j
σ	Transition rate during normal operating mode
σ'	Transition rate during emergency operation mode – in-area EV
σ''	Transition rate during emergency operating mode – out-of-area EV
$SOCi$	State-of-charge during period i
SOC_{max}	Maximum state-of-charge
SOC_{min}	Minimum state-of-charge
SOC_D	De-rated state-of-charge
SOC_R	Reserved state-of-charge

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σ_n^2 Variance of the normal distribution
u Number of regions/feeders in the system

I. INTRODUCTION

Increasing requirements to decarbonize and improve the efficiency of the energy supply will impact future electricity networks (i.e., smart grids), leading to significant increases in renewable energy generation; larger numbers of electric vehicles (EVs); radical transformation of transmission and distribution networks; and the introduction of intelligent and automated control, monitoring, and communication infrastructures [1]. This is necessary in order to reduce dependency on fossil fuels and related CO_2 emissions while maintaining the highest possible levels of security, sustainability, and affordability of the electricity supply. It is widely recognized, however, that supply-side solutions alone will not be sufficient to tackle these challenging tasks. Additional support and contributions are needed from the demand side, with the demand for electricity being actively controlled and coordinated. This will increase opportunities for more direct and proactive system support and result in profound changes in the levels and nature of system–user interactions, shifting actual system operating and loading conditions well outside the traditionally assumed ranges, limits, and physical boundaries. One example of such changes are microgrids (MGs), which offer a genuinely new and previously unseen approach to the operation of electricity networks by allowing end users to significantly improve the power quality and, more importantly, reliability of their power supply systems. Essentially, MGs allow end users to install, operate, and balance their own generation, storage, and controllable load resources, providing continuity of supply when the main grid supply is interrupted (for example, due to a system fault). Evaluating the reliability of MGs is a challenging task due to the expected networked connections and the stochastic behavior of EV-based and renewable-based resources.

Electrification of the transportation sector is another challenge for the operation of future distribution systems. EVs, which can be hybrid or fully electric, are viewed as a new, promising technology that can be utilized by customers or aggregators of MGs to boost MG reliability [2]–[5]. EVs provide a range of new functionalities, as they can be utilized as a controllable load (home-to-vehicle [H2V] and grid-to-vehicle [G2V]) as well as distributed energy storage (vehicle-to-home [V2H] and vehicle-to-grid [V2G]), which could significantly enhance the reliability and utilization of the grid's power. However, the availability of EVs ultimately depends on the ability and willingness of EV owners to share their stored energy as well as the availability of the infrastructure to charge and control EVs. Another main challenge in integrating these energy storage devices is determining accurate modeling of the charging and discharging rates based on different operating modes. In [6], a mobility-aware control algorithm (MACA) for V2G was proposed that takes into consideration the mobility of EVs and the estimated/actual demands of microgrids. The work in [7] proposed an intelligent optimization approach based on multimodal approximate dynamic programming (MM-ADP) for the optimal charging/discharging vehicle schedule of a grid-connected charging station, while incorporating price variations in electricity and available solar energy.

EVs can be an adequate energy storage resource that can boost the reliability of the system during outages. Several studies have explored the positive impact of EVs on service restoration and proposed different V2G strategies [8]–[10]. In [11], an interruptible full EV charging load model was used to evaluate the reliability of an urban distribution system in China. The reliability of the distribution power system was also assessed in [12] with consideration of the V2H and V2G charging schemes, while the battery exchange mode was considered in [13] to model the full EV charging load. In [14], the impact of EV penetration level on the reliability of a distribution system was evaluated for scheduled and unscheduled V2G discharging modes. The work in [11]–[15] focused on the evaluation of EV charging load in a distribution system. Moreover, the focus was on assessing power system facilities' provision of 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. This additional load will affect power systems' reliability at both the transmission and generation levels.

EVs can also negatively affect power systems' reliability because of the energy demand to charge EV batteries, which creates a heavy burden on the electrical grid and is already being discussed by system operators [16]. 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 heavier impact on the reliability of power systems. Moreover, increased charging loads may lead to under-voltages, higher losses, phase unbalances, load peaking, and 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 this impact and alleviate various power system problems [17]. For example, many researchers have investigated the integration of EVs into distribution power systems with respect to the dynamic behavior of a power system [18]–[19], economic and financial analyses [20], short- and long-term planning issues [21], [22], and market policies and opportunities [22], [23].

In order to analyze the extent of the expected changes and to assess new conditions on the demand side, new modeling tools and methodologies for planning power supply systems must be developed and implemented to ensure the highest possible levels of reliability, continuity, and quality of supply. However, the reliability assessment of a power system integrating EVs has yet to be given much attention. Because EVs mainly affect local distribution systems, previous studies have mostly tried to determine how different distribution system characteristics will be affected by EVs. Analyzing the reliability of distribution systems incorporating EVs is a challenging issue, especially considering the increased utilization of EVs. Few studies have investigated the impact of EVs on distribution system reliability. Another main challenge in integrating these energy storage devices is determining accurate modeling of the charging and discharging rates based on different operating modes. However, while other MG-related research has almost exclusively concentrated on the use of renewable-based generation (e.g., solar or wind), which require dedicated energy storage systems due to varied outputs, this paper considers the use of EVs as MG energy sources that can be used to enhance the MG system's reliability.

The presence of EV fleets in the distribution system may improve system reliability as a result of supplying loads in islanded operation, but EV fleets may not be able to fill the demand completely during islanded mode. This is due to the availability and capacity of EVs, which are affected by driving behavior. However, limited research has been conducted to evaluate the impact of EVs on the reliability of the distribution system, and no detailed model exists at present for analysis of related EV impact. The literature does not offer an automated generalized algorithm to evaluate the reliability of a networked power distribution system that includes EVs. Most of the EV reliability studies in the literature were formulated and applied to specific study systems or to radial networks. In order to fill this gap, this paper presents a detailed Markov model of EVs specifically aimed at assessing the reliability of a distribution power system. This work provides a novel contribution to the study of the anticipated transformation of existing electricity networks into future smart grids. A detailed probabilistic model of the stochastic behavior of EVs during normal and emergency operating modes is proposed. Moreover, a novel Markov model also proposed, representing all operating and driving modes considered in this work, was successfully integrated in the reliability model.

Given actual EV and driving behavior data, the model practicality is sound, and the reader can easily relate the simulation to a real case scenario. Moreover, we distinguish our work by the fact that the proposed model takes into account several practical factors such as operating modes (H2V, V2H, G2V, and V2G), driving modes (home-only mode [HO], home–work mode [HW], and home–work–park mode [HWP]), and emergency modes (in-area and out-of-area). We propose wider driving modes and classifications to generalize the concept of the MG in accommodating different operating modes and a different range of customers with different driving patterns.

II. RELIABILITY OF DISTRIBUTION SYSTEMS INCORPORATING EVs

A. DISTRIBUTION RELIABILITY ASSESSMENT

Reliability is a subject of great interest in most manufacturing and services applications [25]. Power distribution engineers have commonly used indexes to count or otherwise quantify the reliability of electric services, the most common being the System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI). Analyzing and evaluating the distribution system's reliability is important for improving the operational and maintenance performance of the system and providing highly reliable and high-quality electricity. In practice, all reliability studies are conducted in relatively small local subsystems because the complete network from the source to the load is enormous. Additionally, it is difficult to collect the necessary data for reliability evaluations; utilities are conservative or sometimes reluctant to release actual reliability data and failure rates. Thus, [26] and [27] investigated methods to collect and categorize data that can be used in reliability studies.

Moreover, the distribution system is in a rapid transition phase, wherein the system is moving from the passive unidirectional mode to becoming more active, with the possibility of bidirectional power flow. One of the main goals of future power systems, or smart grids, is to enhance the reliability of the power system by integrating small-scale resources and reconfiguring the distribution system. The complexity of future distribution systems will require enhanced techniques to evaluate their reliability and minimize the frequency and duration of outages. Conventional methods to evaluate the reliability of future secondary distribution networks are complicated and time consuming. Furthermore, technical and technological changes (emergence of new types of generation, storage, and loads) necessitate both the development of new models and the improvement of traditional reliability approaches, as they might not be (directly) applicable to the future distribution system. In addition, the difficulty of implementing self-restoration in MG-enabled distribution networks is a new initial condition that could vary widely with each outage due to the variability of loads, available renewable energy resources, and levels of stored energy [28], [29].

B. IMPACT OF EVs ON MICROGRID RELIABILITY

In general, EVs cover a wide range of different technologies, with various engines and forms of power. Plug-in EVs have an electric motor and a battery that must be charged from the electrical grid, while plug-in hybrid EVs have both a combustion engine and an electric motor run by energy from a battery that can be charged from the grid. In this paper, and as shown in Fig. 1, the interface between an EV and the electrical system is assumed to follow four different modes: H2V, V2H, G2V, and V2G. Both plug-in hybrid and plug-in EVs have the option to stay connected to the electrical grid while the battery is being charged, thus behaving as an electric load (H2V, G2V), or while the battery is discharged, thus behaving like a generator (V2G and V2H).

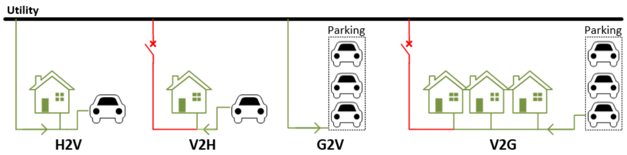

FIGURE 1. Different EV operating modes. EV = electric vehicle.

The charging behavior of EVs is affected by different factors, such as the type of connection (unidirectional or bidirectional), geographic location, the number of EVs being charged in a given vicinity, charging voltage and current levels, battery status and capacity, charging duration, and more. Furthermore, the V2G and V2H modes, increased availability of EVs, and stochastic nature of driving could all introduce reliability benefits and challenges to the system. The main direct contribution of EVs to reliability under the V2G and V2H modes is on the customer side rather than on the utility or system side. The base level of reliability is always provided by the utility, and the EV's role is to boost the level of reliability by supplying the local load during interruptions.

This paper is particularly focused on the reliability and resilience aspects of MGs. For example, off-grid operation of MGs would require fully redefining traditional reliability indexes because the number of interrupted customers and length of interruption time (i.e., standard SAIFI and SAIDI reliability indexes) have to be reassessed due to MG-provided supply to those customers. This will change the ways in which network operators report both frequencies and durations of supply interruption to energy regulators; typically, their low-voltage networks are used for MG operation if the main supply (e.g., from the primary medium-voltage network) has been interrupted. An additional issue is the correct assessment of total interrupted customers and energy not supplied (ENS) because neither all loads nor all customers will be supplied by MGs operating in the off-grid mode (depending on available generation/storage resources).

C. MARKOV MODELING RELIABILITY ASSESSMENT

To evaluate the reliability of a system, a mathematical or graphical model of the system should be used and designed to reflect its reliability characteristics. The model can be either analytical or a simulation. Analytical models represent the system through a set of exact or approximate mathematical models and evaluate reliability based on this mathematical representation of each state. The Markov model is one of the popular analytical techniques to evaluate the reliability of a power system. All transition rates between the states are assumed, making it possible to evaluate the steady-state probability of the states. The Markov chain is one of the best models for representing the dynamic behavior of a system but constructing the transition matrix for a large number of components is also very complicated.

Another widely used technique for reliability assessment in many fields is the Monte Carlo (MC) simulation. In MC simulation, the reliability is evaluated repeatedly using parameters drawn from random distributions to simulate stochastic problems [30]–[32]. Usually, the MC simulation is used when other deterministic methods do not apply, and it can be useful for evaluating the mean time to failure in very complicated or large-scale systems. The advantage of the MC simulation is that it can simulate almost any system and any failure mode. The disadvantages are that it requires long runs (i.e., many samples) and that the accuracy of the output may depend on the number of runs and variables in the system. In applications of complex systems, analytical techniques usually include some simplifications or assumptions. Conversely, the simulation technique can simulate and include any system behavior with less approximation.

To evaluate the reliability of the distribution system using Markov models, first, the time-dependent probabilities are found by solving the Markov differential equations [32]. The general format for the differential equations is as follows:

$$\begin{bmatrix} -\sum_{j=2}^{i}\sigma_{1j} & \sigma_{21} & \cdots & \sigma_{i1} \\ \sigma_{12} & -\sum_{\substack{j=1 \\ j\neq 2}}^{i}\sigma_{2j} & \cdots & \sigma_{i2} \\ \vdots & \vdots & \cdots & \vdots \\ \sigma_{1i} & \sigma_{2i} & \cdots & -\sum_{j=1}^{i-1}\sigma_{ij} \end{bmatrix} \begin{bmatrix} P_1(t) \\ P_2(t) \\ \vdots \\ P_i(t) \end{bmatrix} = \begin{bmatrix} P'_1(t) \\ P'_2(t) \\ \vdots \\ P'_i(t) \end{bmatrix} \quad (1)$$

where Q is the coefficient matrix that can be formed from the transition rates matrix (σ-matrix). Long run (or steady-state) probabilities can be found by solving the set of Markov differential equations (Kolmogorov equations) with the conditions that the sum of all probabilities are equal to 1 and all time derivatives of the probabilities equal 0 [32]. The derivatives can be replaced with a 0 value to solve the set of equations simultaneously:

$$Q \begin{bmatrix} \pi_1 \\ \pi_2 \\ \vdots \\ \pi_i \end{bmatrix} = 0 \quad (2)$$

$$\sum_{j=1}^{i}\pi_j = 1 \quad (3)$$

Equations (2) and (3) are solved to find the steady-state probabilities for all states. The states can be classified based on the system connection as up (working) or down (not working). Then, the steady-state probabilities can be added together for each group to calculate the availability or unavailability of the system.

In addition to finding the steady-state probabilities of the system, it is also useful to find the frequency of occurrence of the down states of the system. To find the expected time of residence for state i, all other states are considered as absorbing states. The expected frequency can then be written as

$$f_i = \pi_i \sum\nolimits_{j=2}^{n} \sigma_{ij}. \tag{4}$$

Equation (4) shows that the expected frequency of any state is the probability of being in that state multiplied by the rates of departure from the same state. Finally, the load and system indexes—such as SAIDI, SAIFI, and ENS—are calculated using the equations in Table 1.

TABLE 1. Charging/discharging modes by location.

Grid Mode	EV Modes	H2V	V2H	G2V	V2G
Normal	HO	•			
	HW	•			
	HWP	•		•	
Emergency (In-Area)	HO		•		
	HW		•		•
	HWP		•		•
Emergency (Out-of-Area)	HO	•			•
	HW	•			•
	HWP	•			•

E = Electric vehicle; H2V = home-to-vehicle; V2H = vehicle-to-grid; G2V = grid-to-vehicle; V2G = vehicle-to-grid; HO = home-only; HW = home–work; HWP = home–work–park.

III. PROPOSED ADEQUACY MODELING OF EV

The paradigm of highly efficient and flexible smart grid networks with adaptable two-way energy flows is perhaps best illustrated by EV chargers and batteries, which may be implemented both as a controlled demand (i.e., for charging of batteries in H2V and G2V applications) and as controlled energy storage (i.e., for discharging stored energy in V2H and V2G applications). In this paper, only residential customers are considered in the distribution system. Accordingly, two distinctive scenarios are considered in this work:

1) Distributed EV charging/interfacing, where individual EVs will charge/discharge at households and similar domestic premises with a dedicated single charging point (e.g., in a private garage).
2) Centralized EV interfacing, where groups and larger numbers of EVs will charge/discharge within shared parking space facilities.

The former case represents homeowners, while the latter represents the development of a wider work-related charging infrastructure, both of which are analyzed in this work in the context of evolving smart grid functionalities. The main aim of this work is to understand how the use of EV storage technologies could provide genuinely new opportunities for increased reliability of the system and reduced vulnerability to faults without reducing end users' comfort.

MGs can operate in two basic modes: grid-connected (normal) and off-grid (emergency). In the off-grid mode, MGs operate autonomously, without connection to the utility grid, while in the grid-connected mode, MGs trade power with the utility grid. Because of certain MG characteristics (e.g., two-way power transfer, the presence of distributed generations, demand side management, and the considerable presence of power electronics), control of the MG in each operating mode and switching between modes are challenges that need to be solved in order to operate MGs efficiently and realize their full potential and benefits.

As shown in Fig. 2, the load is supplied by the utility during normal operation. However, during an emergency, the load is supplied by the EV battery storage. The EV battery restoration capability has two main components: physical availability and state-of-charge (SOC) availability. Physical availability refers to the availability of the car on-site where the restoration is needed. SOC availability refers to the availability of the power in the EV battery. Both are described in this section.

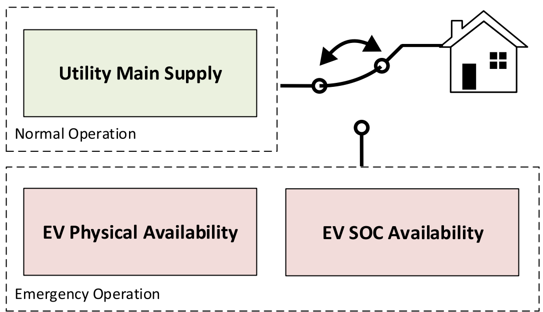

FIGURE 2. Power supply alternatives as seen from the customer side. EV = electric vehicle; SOC = state-of-charge.

For modeling the stochastic behavior of EV driving and changes in MG loads, Markov chain models and MC simulations are used in this work. The stochastic nature of loads and EVs can be adequately described by a Markov process, which is a collection of continuous-time random variables taking discrete values in the state space. This approach is expanded and strengthened by implementing complementary MC simulations targeting specific scenarios and study cases to evaluate stochasticity in the operational performance of the technologies under consideration, behavior of end users, availability of EV storage, and random occurrence of faults and emergency supply conditions. In MC simulations, the states are sampled based on their occurrence in time, which allows for direct correlation with certain changes; for example, in the EV travel distance and duration. In this paper, the effect of EV energy storage on the reliability and smart restoration of MGs is studied by applying both Markov chain modeling and MC simulations. This allows for the calculation of new system and load reliability indexes that are more appropriate/accurate to the analysis of MG operation. Three different models are proposed in this work: the EV mobility, EV available capacity, and EV adequacy models.

A. EV MOBILITY MODEL

EVs have led to concerns about how people must adapt their behaviors to this new technology. These concerns include charging the EV, the limited travel range before charging is needed, adaptations in driving behavior to prevent battery degradation, and changes in energy payments. One of the major benefits of utilizing EV energy storage in power distribution system restoration is the mobility feature of EVs. The role of an EV during interruptions is to supply the demand, and the capability of an EV to contribute is related to driving behavior, SOC characteristics, and the uncertainty of system failures. The availability of an EV supply depends on both physical and storage availabilities. It is a common practice in reliability analyses to assume that the mechanical and electrical systems of the EV battery are 100% reliable. Otherwise, the reliability of the physical EV battery system has to be modeled and reflected as success and failure probabilities.

Due to the uncertain behavior of drivers, several factors affect the available storage capacity of an EV, such as the distance traveled, engine consumption, and the departure and arrival times. The battery capacity of EVs depends on the type of EV and can range from 12 kWh up to 100 kWh. In this study, an average of 24.1 kWh is considered in the base case scenario. Based on the penetration of EVs in the system, and under the assumption that each customer has only one vehicle, the total number of EVs in the system can be calculated by

$$N_{EV} = \sum_{i=1}^{u} \alpha_i N_{c.i} \tag{5}$$

The driving behavior of EV owners is a highly stochastic element that is affected by many social, economic, and psychological factors. In this work, the EV is assumed to be located in three different locations, or states, which are

1) home (H), where daily trips start and end;
2) away (A), where the EV is away from home and not in a parking lot; and
3) parking lot (P), where the EV is parked and can charge or discharge.

Three different EV types (trip modes) are also adopted in this work, which reflect charging/discharging EV behaviors. The classification of these three types reflects the behavior of the majority of EV drivers:

1) Home-only (HO): This mode represents the EVs that are used for non-work-related trips. The EVs recharge only at home (H).

$$N_{HO.i} = \alpha_{HO.i} N_{EV.i} \tag{6}$$

2) Home–work (HW): This mode represents the EVs that are used for work-related trips but recharge only at home (H).

$$N_{HW.i} = \alpha_{HW.i} N_{EV.i} \tag{7}$$

3) Home–work–park (HWP): This mode represents the EVs that are used for work and can charge at home (H) and/or at a workplace parking lot (P).

$$N_{HWP.i} = \alpha_{HWP.i} N_{EV.i} \tag{8}$$

Moreover, two grid modes—normal and emergency—are considered in this work. The normal operating mode represents the state of the system/customer when connected to the utility, whereas the emergency mode represents the state of the system when there is a failure and the system/customer is operating in islanded mode. The system is assumed to operate either in normal or emergency operating modes. The normal operating mode is when the system is healthy and does not experience any outages/contingencies and the EV operates in the H2V or G2V modes. During emergencies, either the EV will be in the area where the interruption occurs and will discharge in V2H or V2G mode, or the EV is out of the area where the interruption is and the EV will support the affected area in V2G mode.

The transition from the normal to emergency mode can be represented by the failure rate λ, and the transition back can be represented by the repair rate μ. Both can be calculated by analyzing the system topology and considering all the failure and repair rates of all components as viewed by the customer.

The transitions between the grid states are depicted in Fig. 3. During normal operating mode, the EV can move from H to A with a transition rate of σ_{HA} and back with a transition rate of σ_{AH} or move from H to A with a transition rate of σ_{HA} and then to P with a transition rate of σ_{PA} and back (σ_{PA}, σ_{AH}). Note that A represents the state where the EV is in movement or in a non-parking lot destination. During emergency mode, if the EV is away and within the interrupted area (in-area), the EV is assumed to return to H with a transition rate of σ'_{AH}, as the local V2H restoration mode has a higher priority. If the EV is in a parking lot, the priority will be to support the system and discharge to the grid (V2G). If the system interruption is in a different area (out-of-area), the priority is to head to A with a transition rate of σ''_{HA} and then to P (in the affected area) with a transition rate of σ''_{AP} to participate in the centralized V2G restoration.

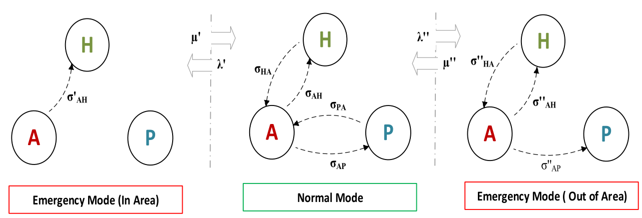

FIGURE 3. Electric vehicle driving behavior model during normal and emergency modes.

To calculate the transition rates shown in Fig. 3, EV drivers' behavior must be analyzed and modeled following two main steps. First, the probability density functions (PDFs) of the departure time, trip duration, arrival time, travel distance, and probability to go to P must be extracted from the EV dataset. Most of the above parameters stochastically follow the normal or Weibull distribution [33]–[35]. The PDF of the normal and Weibull distributions are represented by the following formula:

$$pdf_{normal} : f(x) = \frac{1}{\sqrt{2\pi\sigma_n^2}} e^{-\frac{(x-\mu_n)^2}{2\sigma_n{}^2}} \tag{9}$$

Then, sequential MC simulation can be used to simulate the driving behavior and calculate transition rates between the proposed states in both the normal and emergency modes, as follows:

$$\sigma_{XY} = \frac{Number\ of\ EV\ trips\ from\ X\ to\ Y}{Total\ time\ spent\ in\ X} \tag{10}$$

where X and Y can be H, A, or P.

B. EV AVAILABLE CAPACITY MODEL

EVs can be charged using several modes with varying power. The first option is the use of regular single-phase outlets. A second alternative is three-phase charging, where the third is the fastest mode of charging at the highest power. The battery charging time will depend on the storage capacity, the charging outlet, and the SOC at the beginning of charging. If charging at H, the driver could charge during parked hours, and the energy cost could be added to the regular electricity bill. If charging at P, the driver could charge faster using either the three-phase charger or fast charging stations. During emergencies, the EV can discharge power to H for personal load restoration or to the grid at P to support the system, with the assumption that the EV owner will be compensated.

During normal operating mode, all trip modes can charge at H, and only HWP can charge at P. During emergencies, if the interruption is local (in-area), EVs that are located at H will operate in V2H mode. If the car is located at P (HW and HWP), the priority will be to support the local grid from the centralized parking lot. If the interruption is outside the area (out-of-area), the priority will be to support the neighborhood grid in V2G mode. The total number of EVs participating in in-area and out-of-area restoration can be calculated as follows:

For in-area restoration in region i,

$$N_{IA.i} = \alpha_{IA.HO.i}.N_{HO.i} + \alpha_{IA.HW.i}.N_{HW.i} + \alpha_{IA.HWP.i}.N_{HWP.i} \tag{11}$$

For out-of-area restoration in region i,

$$N_{OA.i} = \alpha_{OA.HO.i}.N_{HO.i} + \alpha_{OA.HW.i}.N_{HW.i} + \alpha_{OA.HWP.i}.N_{HWP.i} \tag{12}$$

Table 1 shows the capability of each location to perform the different EV operating modes.

1) NORMAL OPERATING MODE

During normal operating mode, the consumption of electric energy occurs when the car is away. The SOC_i (i.e., the energy level in the battery) declines during the away period, depending on the distance driven D_D and the consumption when driving C. The charging of the EV will occur when the consumer is at H or P. When charging at a power station of P_c, depending on the charging duration D_c, the SOC_i will increase until the battery is fully charged ($SOC_i = SOC_{max}$) or until the consumer decides to use the car again [36]. To avoid decreasing the lifetime of the battery, the SOC will be limited to a minimum level, which is decided by SOC_{min}.

The starting and returning time of a trip using the EV is decided by the time use data as well as the charging time, which takes place when the car is parked at H or P, connected, and not yet fully charged. The power for charging at H is P_{ch} and at P is P_{cp}. The duration of charging at H is denoted as D_{ch} and at P as D_{cp}.

The battery charge state at any time during normal operating mode is determined by the following equations:

Trip discharging

$$SOC_{i+1} = SOC_i - C \times D_D \quad SOC_i > SOC_{min} \tag{13}$$

H2V charging at H

$$SOC_{i+1} = SOC_i + P_{ch} \times D_{ch} \quad SOC_i < SOC_{max} \tag{14}$$

G2V charging at P

$$SOC_{i+1} = SOC_i + P_{cp} \times D_{cp} \quad SOC_i < SOC_{max} \tag{15}$$

The charging at H or P can follow a certain criterion where the customer can charge immediately after arriving at H or wait until a certain SOC threshold. The probability of recharging at each threshold increases when the SOC decreases.

2) EMERGENCY OPERATING MODE

If the EV is in the in-area emergency mode, the car is expected to be connected to H and operating in V2H mode. EVs in the A state are directed to return to H to support the restoration process. In-area cars in the P state contribute to the restoration process through the V2G mode.

For the out-of-area EVs, drivers are requested to contribute to the restoration process by traveling from H to A and then to P in the affected area. The discharge SOC for both H and P are shown below:

V2H discharging at H

$$SOC_{i+1} = SOC_i - P_{dh} \quad SOC_i > SOC_R \tag{16}$$

V2G discharging at P

$$SOC_{i+1} = SOC_i + P_{dp} \quad SOC_i < SOC_R \tag{17}$$

where SOC_R is the reserved SOC level and is determined based on the convenience of the EV owner. It indicates the level of SOC that should remain in the car for the return trip to H. The available SOC in the EV at any point of time can be calculated by

$$SOC_{av} = SOC_i - SOC_R \tag{18}$$

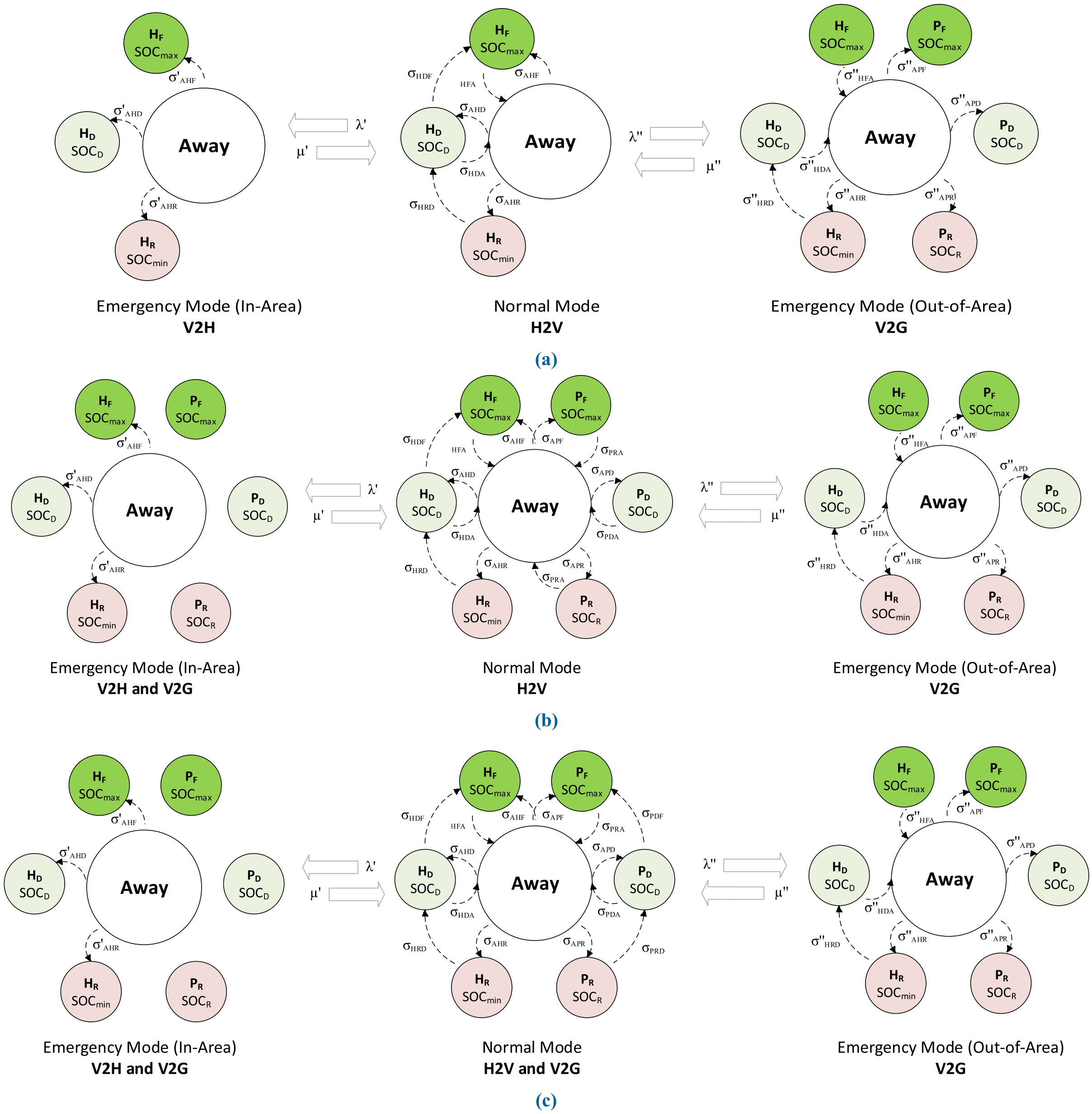

FIGURE 4. The proposed normal and emergency operating models for (a) HO EVs, (b) HW EVs, and (c) HWP EVs. V2H = vehicle-to-home; H2V = home-to-vehicle; V2G = vehicle-to-grid; SOC = state-of-charge.

P_{dh} and P_{dh} are the discharge power at H and P, respectively, and can be calculated as

$$P_{dh} = P_{dp} = \frac{SOC_{av}}{MTTR} \tag{19}$$

where $MTTR$ is the mean time to repair.

Fig. 4 shows, in detail, the transition rate diagrams for all EV trip modes (HO, HW, and HWP). Below is an explanation for the different states,

- H_F and P_F represent the state where the EV is fully charged.
- H_D and P_D represent the de-rated state, where the EV is partially charged.
- H_R and P_R represent the reserve state, where the EV has the preferred lowest level of battery for urgent trips or the return trip to H.

The de-rated and reserved SOC can be calculated using (20) and (21).

$$SOC_D = \alpha_D.SOC_{max} + (1 - \alpha_D)\,.SOC_{min} \tag{20}$$

$$SOC_R = \begin{cases} SOC_{min} & at\ H \\ \alpha_R.SOC_{max} + (1 - \alpha_R)\,.SOC_{min} & at\ P \end{cases} \tag{21}$$

Table 2 shows the transition rate matrix for the HWP EV with all transition rates between all states.

TABLE 2. Transition matrix for the proposed model (HWP EV).

Mode		Normal							Emergency (In-Area)							Emergency (Out-of-Area)						
	State	Away	H_F	H_D	H_R	P_F	P_D	P_R	Away	H_F	H_D	H_R	P_F	P_D	P_R	Away	H_F	H_D	H_R	P_F	P_D	P_R
Normal	Away		σ_{AHF}	σ_{AHD}	σ_{AHR}	σ_{APF}	σ_{APD}	σ_{APR}	λ'							λ''						
	H_F	σ_{HFA}								λ'							λ''					
	H_D	σ_{HDA}	σ_{HDF}								λ'							λ''				
	H_R			σ_{HRD}								λ'							λ''			
	P_F	σ_{PFA}											λ'							λ''		
	P_D	σ_{PDA}				σ_{PDF}								λ'							λ''	
	P_R						σ_{PRD}								λ'							λ''
Emergency (In-Area)	Away	μ'								σ'_{AHF}	σ'_{AHD}	σ'_{AHR}										
	H_F				μ'																	
	H_D				μ'																	
	H_R				μ'																	
	P_F							μ'														
	P_D							μ'														
	P_R							μ'														
Emergency (Out-of-Area)	Away	μ''																	σ''_{AHR}	σ''_{APF}	σ''_{APD}	σ''_{APR}
	H_F		μ''													σ''_{HFA}						
	H_D			μ''												σ''_{HDA}						
	H_R				μ''													σ''_{HRD}				
	P_F							μ''														
	P_D							μ''														
	P_R							μ''														

C. EV ADEQUACY MODEL

The amount of energy that can be contributed by an EV (SOC_{av}) is determined by its state-of-charge (SOC_i) at the beginning of a contingency. SOC_i shows the amount of energy stored in a battery pack. Considering the constant power approach to charging, the SOC of an EV at the time of an outage is calculated by

Available SOC at H,

$$SOC_{av.H} = \pi_{HF}.\left(SOC_{max} - SOC_{\min}\right) + \pi_{HD}.\left(SOC_D - SOC_{\min}\right) \quad (22)$$

Available SOC at P,

$$SOC_{av.P} = \pi_{PF}.\left(SOC_{max} - SOC_{\min}\right) + \pi_{PD}.\left(SOC_D - SOC_{\mathrm{R}}\right) \quad (23)$$

Utilizing the EV available SOC at P given by (23), the cumulative in-area and out-of-area EV available energy capacities are given by

$$SOC_{av.IA} = \frac{\sum_{n=1}^{N_{IA.i}} SOC_{av.P.n}}{N_{C.i}} \quad (24)$$

$$SOC_{av.OA} = \sum_{m=1}^{u} \frac{\sum_{n=1}^{N_{OA.i}} SOC_{av.P.n}}{\sum_{k=1}^{u} N_{C.k}} \quad m \neq i,\ k \neq m \quad (25)$$

To model the adequacy of the EV power output to meet the load demand, the adequacy transition rate is calculated. In Fig. 5, the state transition diagram is given for the system adequacy model, incorporating the EV, where E_n, E_x, and E_o represent full, partial, and zero EV adequacy to supply the load. The E_n state is the only state that can improve the duration and frequency of interruptions, while the E_x state improves only the ENS.

The total EV available capacity for each customer in the system during interruption can be calculated using

$$E_{n.i} = \begin{cases} SOC_{av.H.n} + SOC_{av.IA.n} + SOC_{av.OA.n} & 0 < n \leq N_{EV.i} \\ SOC_{av.IA.n} + SOC_{av.OA.n} & N_{EV.i} < n \leq N_{C.i} \end{cases} \quad (26)$$

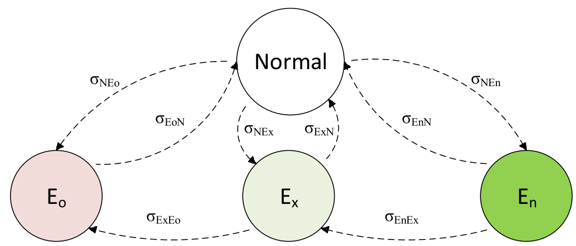

FIGURE 5. Adequacy model for an MG utilizing EVs.

Based on the adequacy of the EV available capacity given in (26), ENS, SAIFI, and SAIDI can be calculated as follows:

$$ENS_i = \sum_{n=1}^{N_{c.i}} \left(LD_{n.i} - E_{n.i}\right) \quad (27)$$

$$SAIFI_i = \frac{\left(N_{C.i} - N_{R.i}\right).\lambda_i}{N_{C.i}} \quad (28)$$

$$SAIDI_i = \frac{\left(N_{C.i} - N_{R.i}\right).MTTR_i.\lambda_i}{N_{C.i}} \quad (29)$$

In summary, to assess the reliability of an electric MG utilizing EVs, different tasks should be executed, as shown in the flowchart in Fig. 6. The following steps are involved in the proposed algorithm for modeling EV behavior and its impact on the reliability of the MG:

1) Collect the EV data (charging/discharging, mobility, participation).
2) Model the stochastic behavior of the following parameters:
    a) EV home departure and arrival time
    b) EV trip distance
    c) EV parking arrival and departure times
    d) EV parking duratio
3) Simulate the driving behavior of the different EV trip modes in normal and emergency scenarios using Sequential Monte-Carlo simulation.
4) Compute the transition rates for each EV.
5) Construct the transition rate matrix for each EV.
6) Compute the steady-state availability for each state.

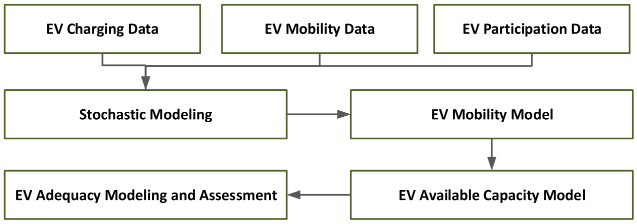

FIGURE 6. The restoration model flow chart.

7) Compute the available SOC for each EV and parking lot.
8) Analyze the system reliability indexes, including EV.

IV. ANALYSIS AND RESULTS

A. EV AND STUDY SYSTEM DATA

In this study, the Roy Billinton Test System (RBTS) Bus 2 was used to evaluate the reliability in different scenarios. The RBTS has been referenced in the body of literature for many reliability studies and evaluation techniques. A description of the RBTS and system data can be found in [37]. Table 3 lists all the data related to the study system. The system is divided into four regions/feeders, where each region has its own EV fleet and parking structure.

TABLE 3. Study system data.

	R1	R2	R3	R4
Number of Customers	800	450	750	1200
Penetration of EVs	0.31			
Participation Factor	0.3			
Load (KW)	Normal (2.5,0.2)			
Failure Rate (f/y)	10			
Repair Time (h/f)	5			

EV = Electric vehicle; kW = kilowatt.

The following comments are related to the RBTS under study in this report:

- It is assumed that adequate capacity is installed in the system for normal operation and all failure scenarios. All the lines and components are within the capacity limits.
- The initial state of the test systems is assumed to be in normal operating mode, where all the components and lines in the system work properly.
- The average load given for each load point is the average load seen at each load point based on the average consumption over a year.

Some simplifications were made in the model to make feasible iterations for the simulation. It was assumed that one EV exists in each household and only one of the residents drives it. It was also assumed that the driver only charges the vehicle at H or P. Only the EV sedan battery size, with an average capacity of 24.1 kWh [38], was considered in this work. However, different battery sizes are also considered to assess the sensitivity of reliability indexes to the EV battery size. The charging power was based on two different charging rate possibilities—a regular charging mode at H and a fast three-phase charging mode at P.

TABLE 4. EV data – base case.

EV Category	**HO**	**HW**	**HWP**
Number of EVs	400	300	300
In-Area Participation Factor	0.8		
Out-of-Area Participation Factor	0.4		
SOC_{max} (kWh)	24.1		
SOC_{min} (kWh)	12.05		
$SOC_{Derated}$ (kWh)	20.00		
$SOC_{Resereve}$ (kWh)	16.02		
Consumption (kWh/km)	0.17		
P_h (kW)	3.7		
P_p (kW)	11		
Charging Threshold 1 Probability	0.1		
Charging Threshold 2 Probability	0.5		
Charging Threshold 3 Probability	1		

EV = Electric vehicle; HO = home only; HW = home–work; HWP = home–work–park; SOC = state-of-charge; kWh = kilowatt hour; km = kilometers.

Table 5 lists all the relative EV data used in the proposed model [34], [35], [38]. The efficiency of the EV charger is assumed to be 100%. The data in Table 4 pertain to a base case to show the basic analysis; further sensitivity analyses will be considered to cover a wider range of data.

TABLE 5. EV data – base case.

	HO	**HW and HWP**
Departure Time (h)	Normal (12.88,4.56)	Normal (7.22, 1.89)
Arrival Time (h)	Normal (15.67, 4.11)	Normal (16.68,1.97)
Distance Traveled (km)	Normal (9.01,4.51)	Normal (30,15)

HO = Home only; HW = home–work; HWP = home–work–park; h = hours; km = kilometers.

The distance traveled, departure time, and arrival time to H or P were all modeled by random variables. Arrival at and departure from H and P times were collected and processed [39]. A time scale of 1 minute from 00:00 to 24:00 was used. In Fig. 7, the PDFs for the EV departure and arrival times are for both the HO EVs and the HW/HWP EVs. All PDFs were modeled as normal distribution, which was better suited than other distributions. Table 5 lists all the PDFs and travel distances.

B. EV MOBILITY MODELING

In this section, the stochastic behavior of the EV mobility is modeled using MC simulation. Fig. 8 and 9 show the EV travel time and distance for 10 arbitrary HO EVs and HW EVs. It is worth noting that the HW and HWP EVs have the same travel distance and time characteristics, and the main difference lies in the ability of the EV to be recharged at P. During the MC simulation, the SOC for each EV was computed sequentially and the transition rates between all states were counted in order to be included in the EV capacity model.

The driving pattern for an arbitrary EV HW for three consecutive days is shown in Fig. 10. The three days are

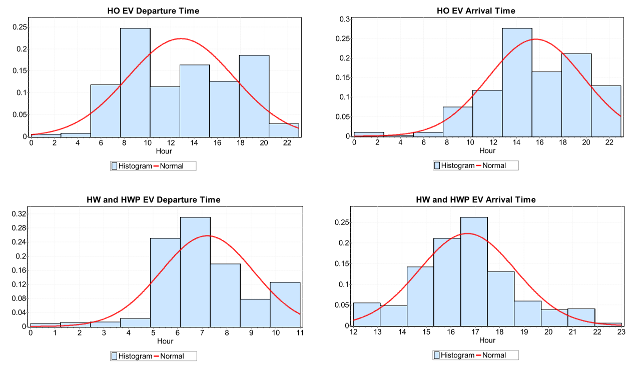

FIGURE 7. PDF modeling for HO, HW, and HWP EV departure and arrival times. PDF = probability density function; HO = home-only; HW = home–work; HWP = home–work–park; EV = electric vehicle.

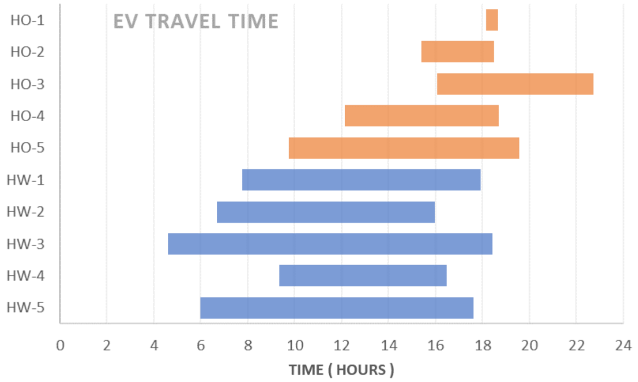

FIGURE 8. EV travel time for 10 arbitrary HO and HW EVs. EV = electric vehicle; HO = home-only; HW = home–work.

simulated to show the different EV behaviors and possible transitions between states.

- Day 1: Normal operation.
- Day 2: An in-area outage occurs at 18:00 for 5 hours.
- Day 3: An out-of-area outage occurs at 6:00 for 5 hours.

Two outages are simulated in Fig. 10, an in-area outage on the second day and an out-of-area outage on the third day. At the beginning of the in-area outage, the EV is at H, fully charged and shifted to the V2H state to restore the service. At the end of the outage, the EV is at HR state, shifted to the H2V operation. As of the second outage, the EV is at H at the beginning of the outage. To support the affected area, the EV is moved to the away state and taken to P to operate in V2G mode.

C. EV AVAILABLE CAPACITY MODELING

At this stage, the EV SOC capacity is modeled using MC simulation and Markov modeling. In Fig. 11, the SOC for different types of EVs are shown for 10 consecutive days. All SOC charging follows the recharging threshold probabilities mentioned in Table 5. The HWP is clearly more charged because the EV has the option of charging at either H or P. The HO EV is less depleted over time because the distance traveled every day is less than the HW and HWP.

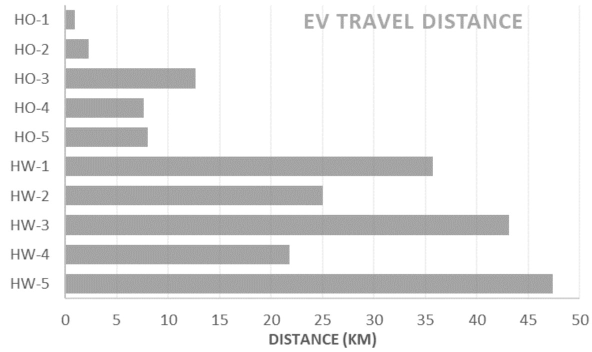

FIGURE 9. EV travel distance for 10 arbitrary HO and HW EVs. EV = electric vehicle; HO = home-only; HW = home–work; km = kilometers.

In Fig. 12, the cumulative available EV parking capacity for different numbers of EVs (5, 10, and 20) in one arbitrary day is shown. The EVs arrive and depart stochastically, and the number of EVs available differ from one time to another. Note that the maximum capacity of the parking lot occurs at around 12:00, when the parking lot can supply the maximum energy.

Tables 6 and 7 give the transition rates and steady-state probabilities, respectively, for an HWP EV. The largest probability is the state where the EV is at H and fully charged (H_F). Then, the steady-state probabilities were used to compute the reliability system indexes for all customers in the study system.

TABLE 6. Transition rates – base case.

σ_{AHF}	36438	σ_{HDF}	11273	σ'_{AHR}	12668
σ_{AHD}	17660	σ_{HRD}	13149	σ''_{AHR}	12668
σ_{AHR}	12668	σ_{PFA}	1034	σ''_{APF}	33260
σ_{APF}	33260	σ_{PDA}	1003	σ''_{APD}	16587
σ_{APD}	16587	σ_{PDF}	30753	σ''_{APR}	13479
σ_{APR}	13479	σ_{PRD}	36279	λ'	10
σ_{HFA}	612	σ'_{AHF}	36438	λ''	30
σ_{HDA}	588	σ'_{AHD}	17660	$\mu,' \mu''$	1752

TABLE 7. Steady-state probabilities – base case.

Normal	A	0.00572	Emergency (In-Area)	A	0.00001	Emergency (Out-of-Area)	A	0.00027
	H_F	0.58116		H_F	0.00330		H_F	0.00017
	H_D	0.01511		H_D	0.00010		H_D	0.00003
	H_R	0.00599		H_R	0.00004		H_R	0.00024
	P_F	0.36029		P_F	0.00206		P_F	0.01136
	P_D	0.00640		P_D	0.00004		P_D	0.00270
	P_R	0.003000		P_R	0.00002		P_R	0.00196

D. EV ISLANDED SYSTEM ADEQUACY ASSESSMENT

In this section, the adequacy of the EV capacity to supply the demand during interruptions is assessed. Three reliability indexes are considered: ENS, SAIDI, and SAIFI.

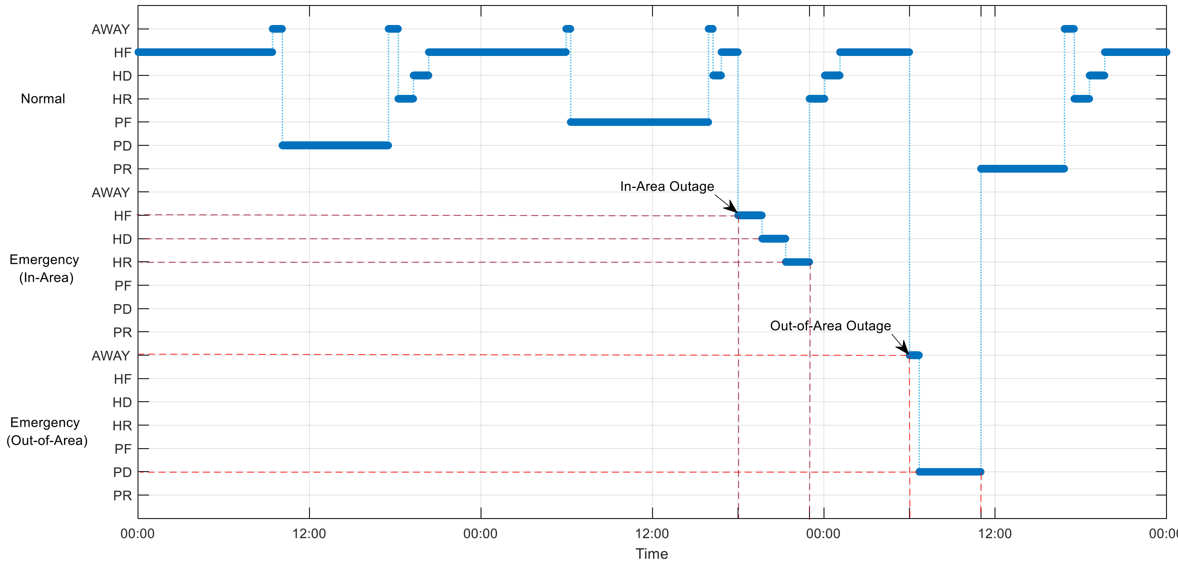

FIGURE 10. EV HW simulated driving pattern for three consecutive days with in-area and out-of-area outages.

TABLE 8. System reliability indexes – base case.

		R1	*R2*	*R3*	*R4*	*Overall System*
ENS (kWh)	***Base***	100.1	56.4	94.1	150.3	400.9
	V2H	62.3	33.5	55.7	88.9	240.3
	Percentage	−37.8	−40.7	−40.8	−40.9	−40.1
	V2H+V2G	44.7	19.0	41.2	74.1	179.0
	Percentage	−55.4	−66.3	−56.2	−50.7	−55.4
SAIDI (h/y.c)	***Base***	50.0	50.0	50.0	50.0	50.0
	V2H	31.1	29.5	29.5	29.4	37.6
	Percentage	−37.9	−40.9	−41.0	−41.1	−24.9
	V2H+V2G	22.3	16.7	21.8	24.5	27.0
	Percentage	−55.5	−66.5	−56.4	−50.9	−46.0
SAIFI (f/y.c)	***Base***	10.0	10.0	10.0	10.0	10.0
	V2H	9.9	9.8	9.9	9.8	9.84
	Percentage	−0.6	−2.0	−1.2	−1.7	−1.5
	V2H+V2G	8.0	6.3	7.9	8.7	8.0
	Percentage	−20.0	−36.9	−21.3	−12.8	−20.0

V2H = Vehicle-to-home; V2G = vehicle-to-grid.

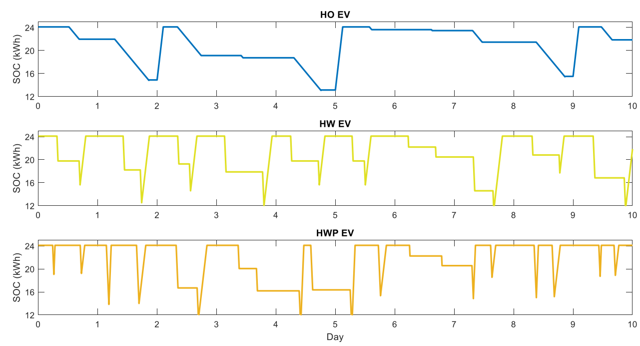

FIGURE 11. SOC for different EV types over 10 consecutive days. SOC = state-of-charge; EV = electric vehicle; HO = home-only; HW = home–work; HWP = home–work–park.

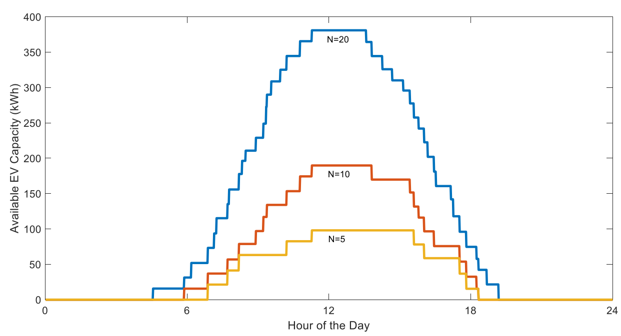

FIGURE 12. The cumulative available EV parking capacity for different numbers of EVs. EV = electric vehicles.

Fig. 13 shows the load energy consumption, the EV available capacity in the three different modes (V2H, in-area V2G, and out-of-area V2G), and considering four arbitrary customers with no EV, HO EV, HW EV, and HWP EV. It is clear from the figure that the HO EV can provide more energy to the load during interruptions because the EV is more available at H, and the travel distance is less compared to HW and HWP EVs.

In Table 8, the reliability indexes (EN, SAIDI, and SAIFI) are shown for each region in the study system as well as for the overall system. Three different cases are considered—the base case with no EV participation at all, with only V2H, and with V2H and V2G. The percentage of change is also shown for each scenario. The percentage of change in ENS is −40.1% for the overall study system when considering only V2H restoration mode and −55.4% when considering both V2H and V2G. In SAIDI, the change is −24.9% and −46%, respectively. SAIFI is slightly affected when only considering V2H, with a percentage of −1.5%, and the change is −20% when considering both V2H and V2G. This is expected because the impact of EV support is greater on the ENS and

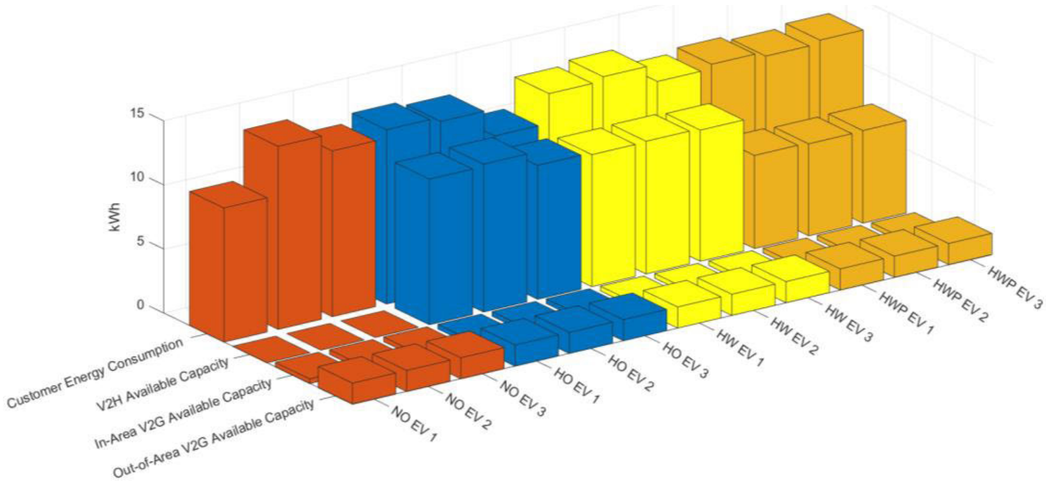

FIGURE 13. Load energy consumption, with the EV available capacity in the three different modes (V2H, in-area V2G, and out-of-area V2G). kWh = kilowatt hours; V2H = vehicle-to-home; V2G = vehicle-to-grid; EV = electric vehicle; HO = home-only; HW = home–work; HWP = home–work–park.

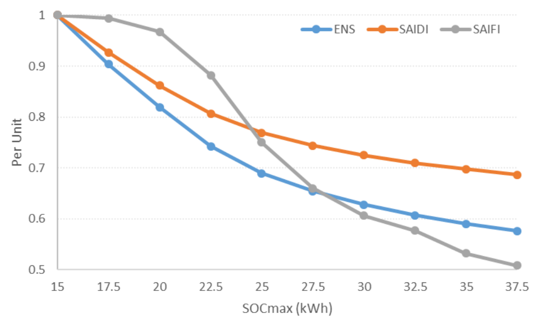

FIGURE 14. ENS, SAIDI, and SAIFI for different SOC_{max} values. ENS = energy not supplied; SAIDI = System Average Interruption Duration Index; SAIFI = System Average Interruption Frequency Index; SOC_{max} = maximum state-of-charge; kWh = kilowatt hours.

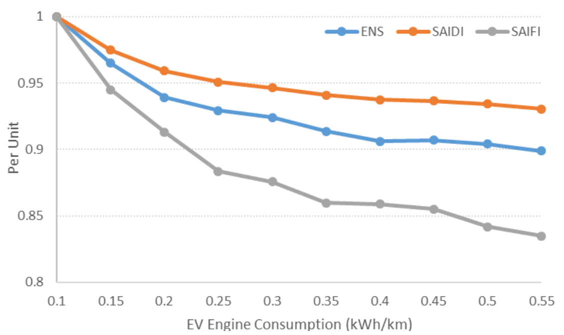

FIGURE 15. ENS, SAIDI, and SAIFI for different engine consumption values. ENS = energy not supplied; SAIDI = System Average Interruption Duration Index; SAIFI = System Average Interruption Frequency Index; EV = electric vehicle; kWh = kilowatt hours; km = kilometer.

SAIDI. The EV can either restore part of the load or the full load for a certain duration during the outage, unlike SAIFI, where full restoration is required for improvement.

E. SENSITIVITY ANALYSIS

The reliability indexes also help the utilities evaluate their networks and improve these reliability indexes for providing

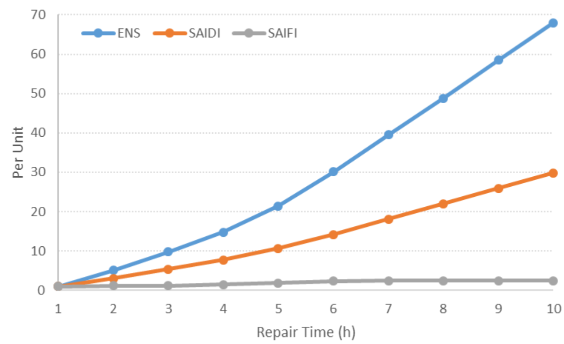

FIGURE 16. ENS, SAIDI, and SAIFI for different MTTR values. ENS = energy not supplied; SAIDI = System Average Interruption Duration Index; SAIFI = System Average Interruption Frequency Index; MTTR = mean time to repair.

better service. Many factors can impact the reliability performance, such as EV SOC_{max}, SOC_{min}, outage duration, failure frequency, and more. In this section, different key parameters are incremented to show the sensitivity of the reliability indexes. Fig. 14 shows the effect of EV SOC_{max} on the system reliability indexes. The indexes decrease as the SOC_{max} increases due to the added capacity during restoration.

In Fig. 15, the EV engine consumption is increased from 0.1 to 0.55 kWh/km. All indexes decrease when the engine consumption increases because the available capacity is less during interruptions.

In Fig. 16, the repair time increases from 1 to 10 hours/failure. The ENS and SAIDI increase with the repair time, and the SAIFI is steady.

V. CONCLUSION

Electric power systems are currently experiencing major changes in their architecture and principles of operation. Increased integration of renewable energy sources, energy market restructuring, greater environmental awareness, and rising concerns about the security of the energy supply impose new challenges. These challenges were traditionally addressed by adding new system resources and capacities, with investments in the field of large size generation and transmission infrastructures, in particular. Recently, the increasing penetration of EVs connected to the utility distribution grids have attracted significant interest in modeling and formulating the potential of EV storage to support the customer side during outages. Since EVs mainly affect local distribution systems, previous studies have mostly tried to determine how different distribution system characteristics will be affected by EVs. Analyzing the reliability of distribution systems incorporating EVs is a challenging issue, especially considering the stochastic driving behavior and increased utilization of EVs.

This paper focused particularly on the reliability and resilience aspects of MGs incorporating EVs. V2G and V2H modes, the increased availability of EVs, and the stochastic nature of driving can all introduce reliability benefits and challenges to the system. The main direct contribution of EVs to reliability under the V2G and V2H modes is on the customer side rather than on the utility or system side. V2G technology achieves two-way interaction between the distribution system and EVs and helps provide more flexible and reliable operation. This paper quantitatively analyzed the stochastic behavior of the EV and available energy capacity. Moreover, an innovative and practical Markov-based reliability analysis method including EV participation was developed and illustrated. The model proposed is algorithmic and does not introduce bias in the calculation of reliability. Therefore, the method appears suitable for the evaluation of alternative microgrid restoration plans incorporating EVs. The stochastic natures of EV driving and charging behavior were integrated successfully into the proposed reliability model, and adequacy transition rates were extracted from the EV available capacity and load demand and used in the Markov model analysis. However, EVs' available capacity may not be able to completely supply the demand during outages. This is due to the ratio of available EV capacity to the load demand, especially if the EV is in HW or HWP mode, because the work driving distance is longer, which consumes more of the SOC.

The results and outcomes of this work will benefit network operators with improved reliability, security, and power quality of their networks during emergency/fault supply conditions. Customers will also benefit by participating in different system support and energy balancing schemes because they will be empowered through MG operation to take control of their energy flow and gain full independence from the main grid supply in case of system faults. Owners and operators of EV batteries will also be able to negotiate tariffs, incentives, and compensations for all offered functionalities and services, thereby gaining additional returns on their investments.

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MOHAMMAD AL-MUHAINI (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical engineering from the King Fahd University of Petroleum and Minerals (KFUPM), in 2004 and 2007, respectively, and the Ph.D. degree from Arizona State University (ASU), Tempe, AZ, USA, in 2012. He is currently an Assistant Professor with the Electrical Engineering Department, King Fahd University of Petroleum and Minerals (KFUPM), Saudi Arabia. His research interests include evaluating the reliability of power distribution systems, Markov model applications in power systems, and smart grids and secondary distribution networks.