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POLYTECHNIQUE MONTRÉAL
affiliée à l'Université de Montréal

A Discrete-Time Markov Chain Approach for Microgrid-Aware Reliability Assessment of Distribution Systems

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Mémoire présenté en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*
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Ce mémoire intitulé :

A Discrete-Time Markov Chain Approach for Microgrid-Aware Reliability Assessment of Distribution Systems

présenté par **Jean-William LAUZON**
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RÉSUMÉ

Assurer l'alimentation en énergie aux clients des réseaux électriques est un enjeu important pour les utilités électriques afin de respecter les exigences des régulateurs d'énergie et d'assurer la satisfaction de la clientèle. Pour y arriver, les utilités électriques réalisent des études de fiabilité sur leurs réseaux de distribution afin de calculer des indices de fiabilité qui permettent d'évaluer la capacité des réseaux à maintenir la continuité du service. Le principal défi lié à l'analyse de fiabilité est la modélisation de la coordination des dispositifs de protection et de sectionnement du système répondant à toutes les fautes qui pourraient potentiellement survenir. Cette modélisation doit inclure toutes les phases d'opération jusqu'au rétablissement du système, soit les phases d'isolation de la faute, de restauration et de réparation de l'appareil en faute.

La fiabilité des réseaux de distribution dépend grandement de la performance des procédures de restauration mises en place par l'utilité électrique afin de réalimenter rapidement la majorité des clients interrompus par l'isolation initiale de la faute. L'avènement des micro-réseaux et la forte croissance des ressources distribuées sur le réseau électrique permettent d'opérer une partie du système en mode îloté en alimentant les clients locaux en énergie grâce à la génération locale des ressources distribuées. L'évaluation de la capacité d'adéquation en puissance des micro-réseaux îlotés, qui revient à évaluer l'impact de cette nouvelle méthode de restauration sur la fiabilité du réseau, est un défi de taille. Cette analyse requiert de modéliser tous les aspects et composantes du micro-réseau îloté, incluant les dépendances temporelles qui le caractérisent.

Dans ce mémoire, nous présentons une méthodologie pour l'analyse de fiabilité qui tient compte des dépendances temporelles des micro-réseaux. Notre approche combine une analyse de la coupe minimum du réseau avec une modélisation par chaîne de Markov à temps discret. L'analyse de la coupe minimal du réseau permet tout d'abord de d'évaluer la fiabilité du réseau de distribution pour tous les événements de fautes possibles tout en compilant ceux qui forcent le micro-réseau à opérer en mode îloté. La construction d'une chaîne de Markov à temp discret nous permet par la suite de simuler l'évolution du micro-réseau îloté. Finalement, les résultats obtenus à l'aide de la chaîne de Markov sont utilisés afin d'ajuster les valeurs de fiabilité initialement obtenues avec l'analyse de la coupe minimal du réseau. Cette approche en trois étapes nous permet de calculer efficacement les valeurs attendues pour les indices de fiabilité du réseau de distribution.

Nous présentons donc une nouvelle méthode analytique pour l'évaluation de la fiabilité des

réseaux de distribution modernes. Tel qu'illustré à l'aide de simulations numériques, notre méthode produit des indices de fiabilité très similaires à ceux obtenus par méthode de Monte Carlo séquentielle. Cette méthode de référence est précise, mais inefficace comparativement à notre approche. Notre travail met aussi de l'avant la nécessité de réaliser une analyse temporelle pour l'évaluation de la capacité du micro-réseau îloté à assurer la continuité du service pour les clients locaux.

ABSTRACT

Ensuring the effectiveness of power systems in providing an uninterrupted power supply to their serviced customers is crucial for electric utilities in order to fulfill regulatory requirements and to maintain customer satisfaction high. To this end, utilities perform reliability assessment (RA) analyses of their distribution networks to evaluate reliability indices which characterize the system's ability to consistently service its customers. The main challenge of RA simulations is to model accurately the protection and switching device behaviours on the system for all possible failure events during the fault isolation, the restoration, and the repair phases before normal system operation is resumed.

The reliability of distribution networks depends heavily on the performance of the restoration scheme(s) used by the utility to operate switching devices to quickly restore interrupted customers after the isolation of a fault. The advent of microgrids and the large deployment of distributed energy resources (DERs) allow for the islanded operation of a portion of the network, even when a failure event disconnects it from the main distribution grid, by supplying local customers with the locally available DERs. Evaluating precisely the power adequacy capability of islanded microgrids, and consequently the impact of this new restoration scheme on the system's reliability, is a considerable challenge. It requires modelling all aspects of the islanded microgrid's operation, including its time-dependant behaviour.

In this Master's thesis, we present an RA methodology that accounts for the time-dependant behaviour of microgrids. Our microgrid-aware RA approach is based on a minimal cut-set (MinCS) analysis combined with a discrete-time Markov Chain (DTMC) model. The MinCS method first computes the reliability performance of the whole distribution system for all possible failure events and compiles the failure events which force the microgrid to operate in islanded mode. The DTMC step then evaluates the expected microgrid evolution during these island-inducing failure events. The DTMC results are finally used to fine-tune the initial MinCS results to obtain accurate reliability indices. This combined approach enables us to efficiently execute the RA simulation to obtain the reliability indices of microgrid-embedded distribution systems.

Our work provides a new closed-form microgrid-aware RA methodology for modern distribution systems. Our method is able to achieve the same level of accuracy as the accurate, but inefficient sequential Monte Carlo simulations. Our research also emphasizes the need for time-based approaches in evaluating precisely the microgrid's ability to provide an alternate power supply to locally serviced customers when disconnected from the main grid.

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LIST OF SYMBOLS AND ABBREVIATIONS

AA	Adequacy Assessment
AIFR	Average Island Formation Rate
ASAI	Average Service Availability Index
BESS	Battery Energy Storage System
CAIDI	Customer Average Interruption Duration Index
CRA	Conventional Reliability Assessment
DDER	Dispatchable Distributed Energy Resource
DER	Distributed Energy Resource
DTMC	Discrete-Time Markov Chain
ENS	Energy Not Supplied
IEEE	Institute of Electrical and Electronics Engineers
LSS	Load Shedding Strategy
MCS	Monte Carle Simuluation
MinCS	Minimal Cut-Set
NDDER	Non-Dispatchable Distributed Energy Resource
NSMCS	Non-Sequential Monte Carlo Simulation
PoA	Probability of Adequacy
PSMCS	Pseudo-Sequential Monte Carlo Simulation
PV	Photovoltaic System
RA	Reliability Assessment
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SMCS	Sequential Monte Carlo Simulation
WT	Wind Turbine

CHAPTER 1 INTRODUCTION

Reliability assessment (RA) is an analysis that evaluates the electric utility's effectiveness at providing a consistent power supply to its serviced customers through the computation of reliability indices [1]. Assessing the ability of the distribution system to reliably supply its customers is a crucial problem faced by distribution planners and operators because they need to ensure that regulatory requirements are met and that customer satisfaction is maintained at an acceptable level. If one of those two elements is violated, then distribution planners and operators have to take action to improve the reliability of the service at a reasonable cost for the utility. Multiple RA techniques have been developed over the years to determine the current and the expected reliability of power systems. In traditional distribution systems, i.e., networks with a centralized power supply providing a one-way transfer of energy from the transmission to the distribution grid, RA methodologies have generally assumed that customers which are electrically isolated during the fault isolation and restoration phases will necessarily be interrupted when evaluating the impact of a specific failure on the system [2].

The rapid ongoing adoption of distributed energy resources (DERs), e.g., photovoltaic systems (PVs), and the advent in the near future of more grid-connected microgrids [3, 4] are quickly transforming the modern distribution grid into a more decentralized system. In this context, the traditional assumption stated above regarding the flow of energy is no longer necessarily valid when evaluating the reliability of distribution systems. Specifically, the key ability of microgrids to allow for the islanded operation of the system when isolated from the main distribution network renders conventional RA techniques inaccurate.

Numerous techniques have been proposed in the literature over the last two decades to include microgrids, and more generally DERs, in the RA analysis of distribution systems [1, 5, 6]. The main challenges faced when including microgrids in RA simulations are the multiple components and time-dependencies that need to be modelled and accounted for during islanded operation to accurately assess the system's power adequacy capability, which, in turn, is used to determine the interruption frequency and duration of the local customers. Expect for sequential or pseudo-sequential Monte Carlo simulations, most of the currently proposed microgrid-aware RA techniques are not able to accurately account for the inherent time-dependencies related to the adequacy assessment of microgrids operating in islanded mode.

1.1 Objective of the Presented Work

This Master's thesis aims to propose a novel time-based analytical technique for microgrid-aware RA simulations of modern distribution systems. By leveraging discrete-time Markov Chains (DTMC), our approach attempts to adequately model the islanded microgrid operation and components during adequacy assessment, including the inherent time-dependencies of the problem. We are then able to integrate our DTMC modelling approach into an existing analytical conventional RA technique, e.g., CYME's power system analysis software's, which is based on a minimal cut-set (MinCS) method of order 1. This combined approach allows us to accurately evaluate the reliability performance of modern distribution systems to offer an alternative to the existing approaches that consider these time-dependencies, which are based on computationally costly Monte Carlo simuations (MCS).

This work also contributes to the development of improved time-based RA techniques, which more accurately model the behaviour of modern distribution systems.

1.2 Structure of the Thesis

The remainder of this Master's thesis is divided into five chapters. First, Chapter 2 presents a review of the relevant literature on microgrid modelling and microgrid-aware RA techniques for distribution systems. Next, Chapter 3 summarizes the research project and the gaps it seeks to fill. The proposed time-based RA framework detailed in an article submitted for publication is presented in Chapter 4. A discussion on the article's impact, its assumptions and its limitations is provided in Chapter 5. Finally, Chapter 6 concludes on some final remarks regarding this thesis work and expands on future potential research perspectives.

CHAPTER 2 LITERATURE REVIEW

In this literature review, we first examine the models that have been developed for each microgrid component relevant to RA simulations. Next, we explore the methodologies that have been put forward to account for the microgrid's reliability impact in modern distribution systems. Finally, we briefly study the indices most commonly used in reliability assessments for distribution systems.

2.1 Microgrids

A microgrid is defined as a bounded system interconnected to the electrical network that contains a group of electrically interconnected DERs and loads which, from the network's point of view, can act as a single controllable unit in either grid-connected or islanded modes [7]. The microgrid control system coordinates the operation of the sectioning devices at the point(s) of interconnection to ensure the disconnection or connection of the microgrid with the main electrical network. This control system preserves the power adequacy inside the system during autonomous operation, viz., in islanded mode, by providing generation dispatch instructions to each DER on the system. In some case, a load shedding strategy (LSS) can be set in the controller to shed and/or curtail some non-critical loads during islanded operation to preserve the power supply of critical loads, and consequently enhance the power balancing capability of the microgrid [8]. Battery energy storage systems (BESSs) can also be installed on the microgrid to ensure the continuous supplying of the load during periods of low power generation capabilities from variable renewable energy resources [1, 9, 10]. The following subsections will investigate the models used in the literature for each microgrid component in RA analyses.

2.1.1 Dispatchable Distributed Energy Resources

Dispatchable distributed energy resources (DDERs) are controllable energy resources, e.g., micro-turbines, fuel cells, and diesel generators. In RA simulations, DDERs are most often considered as power generation sources capable of generating any power output up to their rated power capability at any given point in time [11–16] based on the dispatch command that they receive from the microgrid control system. The generation capability of DDERs is therefore garanteed, except when the generator is unavailable due to scheduled maintenance or unforeseen failure. Power ramping constraints have also been considered in [17, 18] to limit the power output variation of each DDER at any given timestep, thereby providing a more realistic model for this type of generators. A multi-state generation output model has also been used in [19].

2.1.2 Non-Dispatchable Distributed Energy Resources

Non-dispatchable distributed energy resources (NDDERs) are generator types for which the power output capability at any given instant is dependant on the availability and abundance of their primary energy source [6]. Wind turbines and photovoltaic systems are the most known and deployed DERs under this classification in the context of microgrids.

2.1.2.1 Wind Turbine

Wind turbines (WTs) power output is dependent on the wind speed passing through the blades of this generator. It is therefore necessary to characterize the wind speed's probabilistic distribution to be able to determine the power generated on the grid after the system's conversion of energy from mechanical to electrical.

The wind speed's distribution most commonly found in the literature in RA simulations is the Weibull distribution [11,20–25]. In [26], the Gamma distribution has also been employed. Other studies have instead directly relied on historical data [27,28] in the RA simulations, or used an autoregressive-average-moving model based on hourly recorded wind speeds to generate synthetic data [16,18].

Parametric models based on piecewise functions are commonly used in RA simulations to model the conversion of wind speed to the WT's electrical power output. These piecewise functions are based on three operational regions:

1. WT is idled due to insufficient or excessive winds;
2. WT's power generation is a function of the wind speed;
3. WT generates its rated power generation independently of the wind speed.

Specifically, the three proposed piecewise functions models of WTs differ in the mathematical relationship for the second operational region. This relationship is either linear [11,21–23,25, 27–29], quadratic [16,18,30] or cubic [20,24,31]. Figure 2.1 illustrates the three operational regions and the difference between the WT parametric models based on piecewise functions. Lastly, multi-state output models have also been proposed, either correlated with the load [32] or not [13].

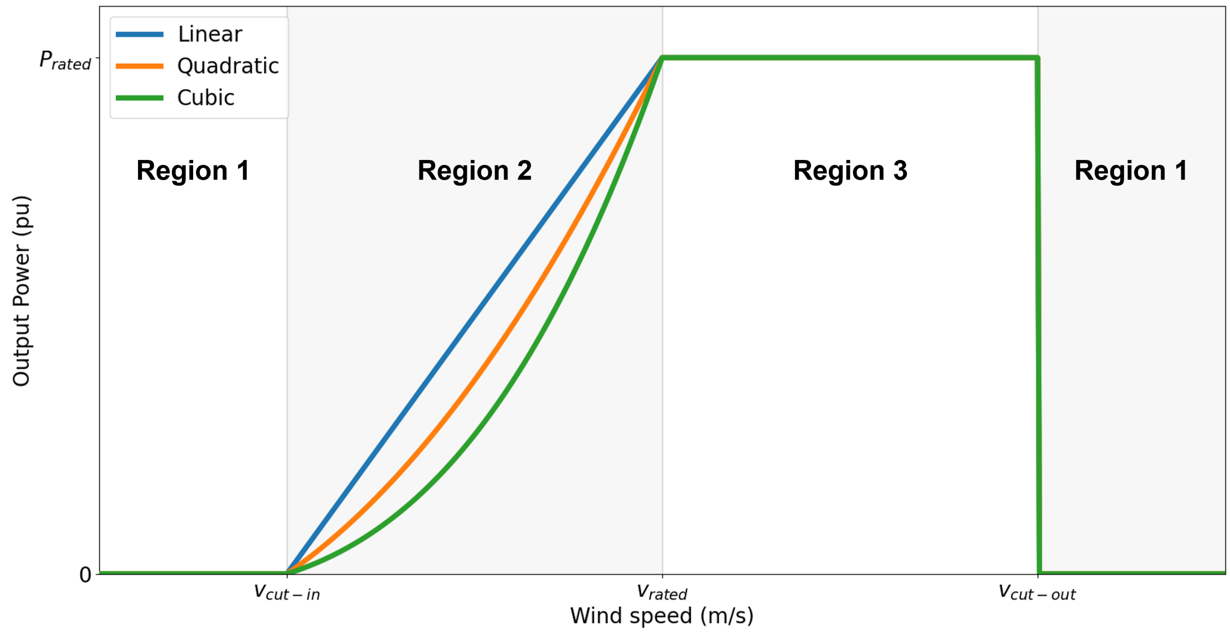

Figure 2.1 Parametric Wind Turbine Output Models Used in Reliability Assessment

2.1.2.2 Photovoltaic System

Photovoltaic systems (PVs) have a power output which is dependent on the solar irradiance (incident and diffuse) at the surface of the panels and on the ambient temperature. Similarly to WTs, caracterizing the PV's output requires to have a model for the system's energy source, i.e., solar irradiance, and the PV's internal model.

Two main approaches based on probabilistic distribution functions have been used to model the available solar energy. The first approach models the irradiance during sunlight hours based on the Beta function [11, 17, 20, 21, 31]. The distribution's α and β parameters are obtained from historical data. The second approach leverages the clearness index distribution [14, 22, 23, 25] proposed in [33]. Instead of modelling the irradiance itself, the clearness index models the fraction of the total solar irradiance which is absorbed by the atmosphere or blocked by clouds. It is then possible to apply the clearness index to the total solar irradiance available at any given hour to obtain the corresponding irradiance at the surface of the PV panels.

The relationship between the available irradiance at the surface of the PV and the produced electrical power on the grid-side of the PV's converter is most often considered to generally be linear when the impact of ambient temperature is ignored. The main distinction between the models in RA simulations is based on if the model includes the temperature impact [21–24] or not [17, 25–28, 31]. The impact of this factor is sometimes neglected because of its limited effect on the resulting power output [28].

2.1.3 Battery Energy Storage System

Battery Energy Storage Systems (BESSs) are modelled by the following set of equations which dictates how the state of charge of the battery varies based on its output power [15, 17, 18, 23, 34, 35]:

$$E_{\mathrm{B}}(t+\Delta t) = E_{\mathrm{B}}(t) + P_{\mathrm{B}}(t)\Delta t \tag{2.1}$$

$$P_{\mathrm{B}}(t) = \begin{cases} \eta_{\mathrm{ch}} P^{\mathrm{ac}}_{\mathrm{B,ch}}(t), & \text{if } P_{\mathrm{L}}(t) < P_{\mathrm{G}}(t) \\ -\dfrac{1}{\eta_{\mathrm{dch}}} P^{\mathrm{ac}}_{\mathrm{B,dch}}(t), & \text{if } P_{\mathrm{L}}(t) \geq P_{\mathrm{G}}(t) \end{cases} \tag{2.2}$$

$$P^{\mathrm{ac}}_{\mathrm{B,ch}}(t) = \min\left(P^{\mathrm{r}}_{\mathrm{B,ch}}, P_{\mathrm{G}}(t) - P_{\mathrm{L}}(t), P^{\max}_{\mathrm{B,ch}}(t)\right) \tag{2.3}$$

$$P^{\mathrm{ac}}_{\mathrm{B,dch}}(t) = \min\left(P^{\mathrm{r}}_{\mathrm{B,dch}}, P_{\mathrm{L}}(t) - P_{\mathrm{G}}(t), P^{\max}_{\mathrm{B,dch}}(t)\right) \tag{2.4}$$

$$P^{\max}_{\mathrm{B,ch}}(t) = \frac{E^{\max}_{\mathrm{B}} - E_{\mathrm{B}}(t)}{\Delta t} \tag{2.5}$$

$$P^{\max}_{\mathrm{B,dch}}(t) = \frac{E_{\mathrm{B}}(t) - E^{\min}_{\mathrm{B}}}{\Delta t}, \tag{2.6}$$

where P_{B} is the BESS power output, Δt is the time interval between each output power update, $\eta_{\mathrm{ch}}(\eta_{\mathrm{dch}})$ is the charging (discharging) efficiency, $P^{\mathrm{ac}}_{\mathrm{B,ch}}(P^{\mathrm{ac}}_{\mathrm{B,dch}})$ is the charge (discharge) power on the AC side, $P^{\mathrm{r}}_{\mathrm{B,ch}}(P^{\mathrm{r}}_{\mathrm{B,dch}})$ is the rated charging (discharging) power, $P^{\max}_{\mathrm{B,ch}}(P^{\max}_{\mathrm{B,dch}})$ is the maximum charge (discharge) power and $E^{\max}_{\mathrm{B}}(E^{\min}_{\mathrm{B}})$ is the maximum (minimum) allowed BESS energy.

BESSs are however not often modelled in non-sequential Monte Carlo simulations and in analytical RA techniques. Analytical RAs commonly omit BESSs because these techniques often rely on the enumeration of all possible system states to compute the RA indices. At this time, including BESS in the analysis increases greatly the complexity of tracking all possible states due to the time-varying nature of this microgrid component. In the analytical technique presented in [11], the authors attempt to circumvent the modelling complexity of BESSs in microgrid islanded operations by assuming that the BESS is always fully charged when an islanding event occurs and that its rated capacity is large enough to be able to output its rated discharge power during the total islanded duration. In sum, these assumptions implicitly convert the BESS as a DDER with the BESS's rated power output and without ramping constraints. A more realistic BESS representation based on a multi-state probability model is proposed in [35] to account for the time-series evolution of the storage when assessing the ability of the system to supply its load through time.

2.1.4 Load

The load demand on the system varies greatly throughout time. It is therefore necessary to account for the demand variability when assessing the reliability of the system and the microgrid's islanding capability. In [12, 22, 23, 27], historical or forecasted hourly time-series load profiles are used to model the load. With this approach, the ramping up and down of the load through time is thus captured. Time-series analyses can then provide a more accurate approximation of the real reliability performance of the system.

Multi-state load models have also been proposed and used in non-sequential RA techniques [13, 19, 21, 28, 32, 34]. In these techniques, the microgrid's ability to supply the load is evaluated based on the fixed power demand at the instant of the islanding event.

2.1.5 Load Shedding Strategy

A load shedding strategy can be implemented in the microgrid control system to shed and/or curtail customers load when necessary to achieve local power adequacy within the islanded microgrid. Load shedding and load curtailments are operations applied on one or many customers to reduce the total power demand. The difference between the two operations is that the former fully disconnects the customer(s) from the microgrid while the later drops exclusively a fraction of the customer(s) load. From an RA-perspective, a load shedding therefore interrupts the impacted customer(s) while a load curtailment does not.

Different load shedding strategies have been modelled for islanded microgrids in RA simulations. Two broad categories of LSSs can mainly be found in the RA literature: priority-based load curtailment and curtailment optimization-based methodologies.

In priority-based load curtailment methodologies [11, 20, 23], some customers are shed or curtailed based on a predefined sequence of operations that will be followed until power adequacy is achieved. The LSSs in this category therefore do not rely on the actual load demand of each customer to determine the actions that need to be taken to ensure the supply of the most critical customers. In [23], all non-critial customers are shed at once whenever power adequacy is not achieved during a timestep to maintain the service for all critical customers. All customer loads are ordered based on their supply priority in [20]. When the demand exceeds the total generation capability of the system, the most expendable loads are sequentially disconnected until the total generation output is greater than the remaining load demand. In [19], each load has a predetermined portion of its demand which is curtailable when required.

Curtailment optimization-based methodologies [17,26,32,34] frame the microgrid's power adequacy problem at a given timestep as an optimization problem where the amount of customer load that needs to be shed and/or curtailed is to be minimized. Contrarily to priority-based LSSs, curtailment optimization LSSs also rely on the actual demand of each customer at that instant to determine the shedding/curtailment decision, meaning that assessing which customers will be cut off is not as straightforward as in the priority-based methods. In [26], load flow constraints are also included in the optimization problem.

2.2 Reliability Assessment Techniques

In the context of distribution systems embedded with microgrids, the problem of assessing the reliability of the system can be divided into two subproblems [1, 27]:

1. Determining the network segments that are isolated from the power supply during the failure isolation, the restoration and the repair phases of each possible failure event on the system.

2. Determining the ability of microgrids to operate in islanded mode, and thus supply some or all of their local customers which would have been interrupted otherwise.

Subproblem 1 corresponds to the classical reliability assessment problem of distribution systems. This problem has to be addressed in RA simulations whether microgrids are deployed or not on the system. The solution to this problem relies mainly on the network's topology and the location of the protection and switching devices on the system to determine the interrupted network segments in each operational phase. Thereafter, this subproblem is referred to as the conventional reliability assessment (CRA).

Subproblem 2 refers to the microgrid's capability to reliably adequate the local power demand with its local generation when operating in islanded mode, i.e., when all the microgrid's point(s) of interconnection are disconnected from the power supply. Thereafter, this subproblem is referred to as the adequacy assessment (AA).

RA techniques are typically divided into two main categories of methodologies [1, 5]: analytical techniques and Monte Carlo simulations. This classification also applies to the methodologies addressing the CRA and AA problems. Some RA methodologies can also be considered as being hybrid methods [6] in which one of the subproblem uses a technique from one category, and the other subproblem leverages a method from the other category. Table 2.1 broadly classifies the CRA and AA techniques found in the literature:

Table 2.1 Summary of Reliability Assessment Techniques

CRA	**AA**	**Papers**
Analytical	Analytical	[11–14, 21, 22, 27, 32, 36, 37]
Analytical	MCS	[20, 38]
MCS	MCS	[16, 17, 19, 23, 25, 26, 28, 34, 39, 40]
MCS	Analytical	None

To the best of our knowledge, no MCS-based CRA and analytical AA formulation have been developed. This is due to the fact that this combination does not benefit from the individual method advantages. Current analytical CRA methods are fast and accurate enough to compete with simulation-based techniques. The same cannot be said for analytical AA approaches which are not necessarily as precise as simulation-based counterparts because of the complexity to model the microgrid's islanded operation.

In the next subsections, we provide a brief overview the CRA problem. This will allow for a better understanding of the overall problem before examining in details the methodologies developed to address the AA subproblem, which is the main focus of this Master's thesis.

2.2.1 Conventional Reliability Assessment

The general aim of CRA is to evaluate the impact of interruptions on all serviced customers of the distribution system. To that end, the expected interruption frequency, duration of interruption and energy not supplied to each customer have to be determined. These specific customer reliability results are then aggregated at the distribution network-level to obtain the system's reliability indices (see Section 2.3). This calculation relies on the data availability of the expected failure rates and repair times of all system components in order to properly weight the likelihood and the impact of each interruption event for the customers.

The typical steps in CRA are as follow [1]:

1. **Fault Event:** Simulate a failure at a given location on the system.

2. **Fault Isolation:** Identify the protection device(s) which will operate to isolate the fault and determine the set of initially interrupted customers.

3. **Restoration:** Identify the interrupted customers which can be quickly resupplied by applying the restoration scheme(s) set in place by the utility before repairing the fault.

4. **Results Compilation:** Update the customer-level reliability values based on the simulation results from the previous steps.

After the fault isolation, i.e., during the restoration phase, some or all interrupted customers that are not in the protection zone in which the fault occurs can be quickly restored (restoration phase). There are two non-mutually exclusive restoration schemes to resupply customers: upstream restoration and reconfiguration [41]:

- When a sectioning device exists between the fault location and the upstream protection device which disconnected the fault from the distribution system, then said sectioning device can be opened to better isolate the fault. The triggered protection device can be closed subsequently to resupply interrupted customers in the protection zone(s) between the two operated devices. It follows that customers upstream to the fault and the sectioning device can be quickly restored by reconnecting them to the main power supply, hence the name "upstream restoration" for this restoration scheme.

- When a sectioning device exists between the fault location and the downstream protection zone(s) interrupted due to the operation of the protection device which disconnected the fault, then said sectioning device can be opened and a normally-opened tie-switch downstream to the sectioning device the can be closed subsequently to resupply customers in the protection zone(s) downstream of the sectioning device. Customers downstream to the fault can therefore be quickly restored through a load transfer to one or multiple adjacent feeders, hence the name "reconfiguration" for this restoration scheme.

System reconfigurations are only available if the distribution network has normally-opened tie-switches with adjacent feeder(s), otherwise only upstream restoration can possibly be implemented by the utility. Moreover, reconfiguration might not always be a viable restoration strategy for a specific failure event if there is no load transfer capacity on the adjacent networks given the current loading of the system [27]. It is also possible that only a fraction of the interrupted customers which could technically be resupplied are in fact restored due to the limited capacity margin on the adjacent network.

Figure 2.2 illustrates the interrupted network segments (in purple) during the fault isolation and the restoration phases using a simple two feeder system for a given failure event location.

As mentioned in Section 2.2, the two categories of approaches for CRA are analytical techniques and MCS. In analytical techniques, closed-form mathematical expressions are developed to calculate the expected system reliability indices of the distribution system. These techniques rely on average failure rates and repair times for all components. They then iterate over all possible failure events on the system and generally execute the typical CRA steps presented above to compile the expected load interruption results. An implementation

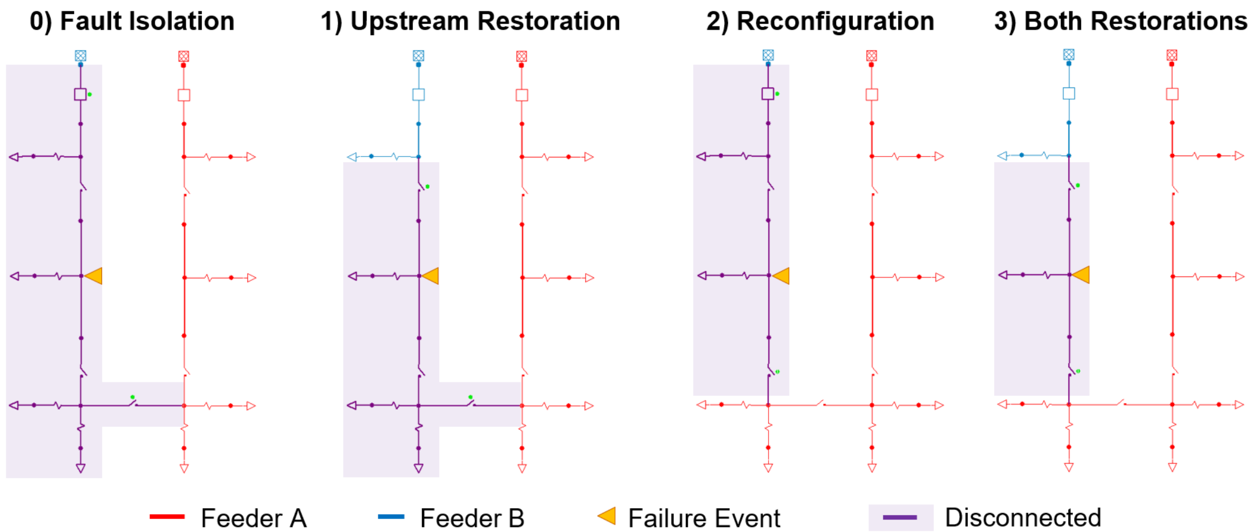

Figure 2.2 Conventional Reliability Assessment Fault Isolation and Restoration

of this type of approach is the Reliability Assessment analysis of CYME's power system analysis software which uses a minimal cut-set (MinCS) method of order 1 to solve the CRA problem [42]. This method iterates over all possible unique concurrent failure event that can occur on the system. It evaluates which customers are impacted by this event and for how long they are interrupted during the fault isolation, the restoration, and the repair phases. On the other hand, MCS-based approaches sample the state (up or down) of all network components to determine the state of the whole distribution system at any given time. Each component is usually modelled using a two-state Markov model with probabilistic distributions for the transition rates, which define the failure rate (transition from up to down) and the repair duration (down to up).

Active distribution networks are expected to streamline the fault location, isolation, and restoration process during failure events, therefore improving the continuity of the power supply to the serviced customers [43]. In this work, the main focus is on the reliability impact of microgrids, i.e., portions of the network which has the ability to operate in islanded mode, rather than on active distribution networks which do not have islanding capabilities.

The restoration phase for distribution systems with embedded microgrid(s) contains a third available restoration scheme [41]: islanded microgrid operation. The inclusion of this scheme will require the development of additional methods to tackle the AA problem encountered when operating autonomously a portion of the system because the power supply cannot be assumed to be fully reliable. This is the focus of the next section.

2.2.2 Adequacy Assessment

The goal of AA is to evaluate the ability of the distribution system's grid-connected microgrid to operate autonomously in islanded mode whenever a failure event occurs on the system which forces the microgrid to be isolated from the main power supply. Contrary to CRA on conventional networks, the microgrid's isolation does not necessarily imply that all isolated customers will be interrupted for the full isolation period. Customers are interrupted based on the microgrid's capability to generate enough power locally to supply completely or partially the local demand. Concretely, the AA analysis validates that the local total generation $P_G(t)$ is greater than or equal to the local total demand $P_L(t)$, i.e., $P_G(t) \geq P_L(t)$. The following factors complexify the analysis:

1. **DER Generation Stochasticity:** Microgrids often have NDDERs, i.e., PVs and/or WTs, installed on the system to provide power generation support [44]. These DERs have a probabilistic power output because of the variable availability and abundance of wind and solar irradiance at any given instant. NDDERs power output is therefore non-deterministic and can greatly fluctuate from one instant to the next. Generation from NDDERs can even become unavailable in some cases, e.g., when there is not enough or too much wind to operate WTs, or when there is no solar irradiance during the night for PVs.

2. **DER Unavailability:** With the demand being supplied exclusively by the local generation of DERs , i.e., no central power supply, loosing one or many DER unit(s) can decrease the ability of the system to provide the generation necessary to supply its local customers during islanded mode. DER unavailability also increases the number of possible system states to consider in the analysis.

3. **Customers Interruption Diversity:** When the microgrid control system implements an LSS in islanded mode, the controller accesses which customers can be supplied and which ones will need to be curtailed or shed at each timestep. This means that the probability of interruption and the expected duration of interruption can vary from one customer to the next, depending on their criticality. This is different to what is assumed in CRA methods because all customers within a protection zone will not experience the same interruptions. The AA solution therefore needs to keep track of the state of each individual customer at every timestep during islanded operation.

4. **Time-Dependencies:** BESSs and LSSs are time-dependant components, i.e., they evolve through time and their current state depends on their previous state. The

current state of these components is also dependant on the current local power adequacy/inadequacy. For BESSs, the state of charge at a given instant is dependant on the previous state of charge and the discharge or charge power that has to be produced, either to ensure power adequacy, or to absorb the excess energy generated by NDDERs. This new state of charge then determines the next discharge power and charge power capability and so on. For instance, if the BESS is completely depleted, then no power can be provided by the component to support the local power adequacy of the microgrid. For LSSs, customers should not be shed repetitively during an islanding event [1, 14]. The LSS therefore has to remember the current state of the loads (supplied, curtailed, shed) during the islanded operation duration. BESSs and LSSs both increase the number of possible states of the system at any given instant, further complexifying the states enumeration in analytical AA methods.

Furthermore, the duration and the timing of interruptions both have a great impact on the system's adequacy capability. The longer the islanding event is, the greater are the chances that the system will not be able to achieve power adequacy during the entire duration of the event [45]. This is especially true when the system relies heavily on the BESS to adequate the local demand. The instant of interruption also has an influence on the system's ability to supply the load. PV's output is greatly correlated with the time of the day and the load demand also fluctuate in a regular pattern through time. There are consequently instances during the year when achieving power adequacy is more likely than in others, leading to different customer interruption results depending on the timing of the islanding event.

Both analytical techniques and MCS methods have been developed to address the AA problem. The remaining portion of this section will focus on the methodologies proposed in the literature and on how well they address the aspects of the problem detailed above.

2.2.2.1 Analytical Techniques

Similarly to analytical CRA techniques, analytical AA approaches aim to derive mathematical expressions to rapidly compute the expected system reliability indices. The main advantage of this type of approach over MCS-based solutions is the lower computational time required to obtain results.

Several proposed analytical AA techniques rely on an enumeration of the possible states to compute an equivalent probability of adequacy (PoA), which is then used to reduce the interruption frequency and duration of interruption calculated based solely on the selected CRA methodology [11, 13, 20–22, 32, 37]. These methods consider the stochastic nature of DERs generation, their possible unavailability and the potential diversity of customer interruption outcomes in the analysis. However, this kind of approach to the problem cannot account for the inherent time-dependencies of the system. BESSs are therefore not modelled using these proposed techniques. Solutions based on a power adequacy probability assume that supplied islanded customers will remain in that state for the entire island duration based on the computation of a single comparison of the available generation and the local demand. This is not an accurate assessment because the available generation and the local demand fluctuate with time. Assuming that power adequacy at the initial time step implies power adequacy for all subsequent time steps leads to an overestimation of the ability of the microgrid to supply its local demand [45].

A similar issue arises with the methodology proposed in [12] in which a Bayesian network with a linearized load flow solution is used to determine the power adequacy of the system. This approach however has the advantage of accounting for the DER island controls as well as allowing for a quick adjustment to the simulation results through a belief update of the Bayesian network without needing to re-simulate the system.

In [36], a Markov Chain approach is proposed for simultaneous CRA and AA evaluation. All possible unique system configuration states are determined, with transitions rates (repair rates and failure rates) between each state (CRA). The load to generation coefficient is used to assess if local power adequacy is achieved or not at a given timestep instead of computing separately the local demand and the generation. These states are then duplicated to allow for both possible outcome of the generation to load ratio, i.e., under or over a given threshold value, depending on the level of load curtailment that is allowed (AA). The reliability results are then computed by analyzing each timestep individually and by aggregating the results. Similarly to the other analytical AA approaches presented above, time-dependencies are not considered with this approach. DER unavailability is also not accounted for.

Finally, [35] presents an AA methodology which is based on probability state vectors for PVs, WTs, and BESSs. To the best of our knowledge, this is the only analytical AA method which accounts for the BESS time-series dependence in its analysis. It also considers the NDDERs stochastic generation and possible unavailability. However, this method has multiple limitations; it does not integrate a CRA analysis and therefore does not calculate the customers expected interruption frequency and duration. Moreover, it does not consider the LSS's influence on the BESS's state of charge evolution and on the overall power adequacy of the system.

2.2.2.2 Monte Carlo Simulations

MCS approaches for AA have commonly been used in the literature because they provide a flexible framework which can possibly consider all factors described in Section 2.2.2. Three main types of MCS have been proposed: sequential, pseudo-sequential, and non-sequential. Contrary to analytical formulations in which deterministic expected results are obtained, MCS-based solutions will inevitably produce non-deterministic results that can therefore vary between runs.

Sequential SMCS has been used repeatedly in AA simulations [16, 17, 23, 39]. This type of MCS simulates the time-series behaviour of each component on the system using sequential state sampling. The technique then iterates through the generated sequence of states, compiles the simulation results, and then computes the expected reliability indices of the system until a given convergence criteria is met, typically based on the value of the coefficient of variation. From the AA's perspective, the DERs unavailability, the timing and duration of the islanding event, the solar irradiance, and the wind speed can all be sequentially sampled in the simulation. The four AA factors are all accounted for in this approach, thereby providing accurate and realistic reliability results. However, the main drawback of this methodology is the high computation cost required to sample and simulate the large number of scenarios required to converge to the final solution. To mitigate this issue, other MCS approaches, like pseudo-sequential and non-sequential MCS, have been proposed.

Different non-sequential MCS approaches [19,25,26,40,40] have been used in AA simulations. In this framework, the system's adequacy is determine by non-sequential state sampling, meaning that the system's outcome is evaluated by generating multiple independent system states instead of generating sequences of states like in sequential MCS, which reduces the computational burden of the method. A large number of scenarios is still required to converge to the final solution, but as demonstrated by [40], using correlated NDDER generation and loading during state sampling can further speed up the simulation while still generating simulation results similar to sequential SMCS. Because of the non-sequential nature of the approach, each evaluate scenario is independant from the others, meaning that time-dependent components such as BESSs and LSSs cannot accurately be considered. Numerous sequences of states still have to be sampled with this approach.

Finally, the pseudo-sequential MCS methodology [28,34] is an hybrid MCS method in which sequential state sampling is used to generate yearly sequence of states which are then randomly sampled to find failure events. The sampled events are then chronologically simulated using the yearly sample sequence, including islanding events if a microgrid is disconnected from the distribution system. This approach allows to compute accurately both the expected frequency and duration of interruption while accounting for all presented AA factors, including all time-dependencies.

2.2.2.3 Summary

The majority of the proposed techniques found in the literature are able to account for the stochastic generation output and the possible unavailability of DERs as well as the diversity of customer interruption when an LSS is implemented. However, the recurring limitation in many proposed methods, especially for analytical techniques and non-sequential MCS, is the lack of modelling of the time-dependent behaviour of the system, mainly LSSs and BESSs. Sequential and pseudo-sequential MCS methods have been favored when considering the time-dependent components of AA simulations. These simulations are able to capture all aspects of the problem and produce accurate, non-deterministic simulation results but at a high computational cost due to the numerous scenarios that need to be simulated to converge to the final results.

2.3 Reliability Indices

This section briefly presents the indices used in RA to characterize the reliability performance of distribution systems and microgrids.

2.3.1 Distribution System Indices

The reliability evaluation is based on the computation of indices developed specifically for each hierarchy of the power system (generation, transmission, and distribution) [46]. In this work, we will mainly focus on the distribution system reliability indices provided by the IEEE 1366-2022 standard [47]. We will briefly examine some of the most commonly used indices in RA simulations of distribution systems.

The System Average Interruption Frequency Index (SAIFI) measures how frequently the average customer on the system can expect to experience a sustained interruption (interruption longer than 5 minutes) over a given period of time, typically over a year. SAIFI is given by [47]:

$$\mathrm{SAIFI} = \frac{\sum\limits_{l \in \mathcal{K}_\mathrm{L}} n_l}{N_T} = \frac{\sum\limits_{l \in \mathcal{K}_\mathrm{L}} \lambda_l N_l}{N_T}, \tag{2.7}$$

where $\mathcal{K}_\mathrm{L}$ is the set of loads on the system, N_l is the total number of customers of load l, n_l is the total number of interrupted customers for load l, λ_l is the expected frequency of interruption for load l in the given period of time, and N_T is the total number of customers on the system.

The System Average Interruption Duration Index (SAIDI) indicates the total expected interruption duration due to sustained interruptions that the average customer on the system can expect to experience over a given period of time, typically over a year. SAIDI is given by the following mathematical expression [47]:

$$\text{SAIDI} = \frac{\sum_{l \in \mathcal{K}_\text{L}} d_l}{N_T} = \frac{\sum_{l \in \mathcal{K}_\text{L}} r_l N_l}{N_T}, \tag{2.8}$$

where d_l and r_l are the total number of customers duration for load l, and the total expected duration of interruption for load l, respectively.

The Customer Average Interruption Duration Index (CAIDI) estimates the interruption duration that the average customer on the system can expect from a single sustained interruption event before restoration. Formally, CAIDI is defined as [47]:

$$\text{CAIDI} = \frac{\text{SAIDI}}{\text{SAIFI}} = \frac{\sum_{l \in \mathcal{K}_\text{L}} d_l}{\sum_{l \in \mathcal{K}_\text{L}} n_l}. \tag{2.9}$$

The Energy Not Supplied (ENS) index computes the total energy that has not been supplied to the system's customers due to sustained interruptions in a given period of time, typically over a year. This index is given by [46]:

$$\text{ENS} = \sum_{l \in \mathcal{K}_\text{L}} e_l = \sum_{l \in \mathcal{K}_\text{L}} r_l P_l, \tag{2.10}$$

where e_l and P_l are the total energy not supplied and the demand of load l, respectively. Note that ENS is not defined in IEEE 1366-2022, but it is commonly used in distribution-level RA analyses [46].

The Average Service Availability Index (ASAI) gives the fraction of the time the average customer has been supplied during a given period of time, typically over a year. ASAI is given by the following mathematical formulation (for a non-leap year, i.e., 8760 hours) [47]:

$$\text{ASAI} = \frac{8760 N_T - \sum_{l \in \mathcal{K}_\text{L}} r_l N_l}{8760 N_T} = 1 - \frac{\text{SAIDI}}{8760}. \tag{2.11}$$

As it can be seen from (2.7)−(2.11), the distribution system reliability indices are obtained from the aggregation of all customers reliability values, i.e., frequency of interruption λ_l and duration of interruption r_l.

2.3.2 Islanded Microgrid Indices

Microgrid-related reliability indices have been proposed in [23] to capture the microgrid's islanded operational performance. These indices are therefore specifically related and obtained from the results of the AA simulation. For instance, [23] proposes the Average Island Formation Rate (AIFR) as a new islanded mode index. AIFR calculates the annual expected number of islanding events that a given microgrid will experience. Standardized guidelines for islanded operation reliability indices, similar to [47] for distribution system indices, have not yet been published by the Institute of Electrical and Electronics Engineers, (IEEE).

CHAPTER 3 DISCUSSION OF THE RESEARCH PROJECT AS A WHOLE AND GENERAL ORGANIZATION OF THE THESIS OR DISSERTATION INDICATING THE COHERENCE OF THE ARTICLES IN RELATION TO THE RESEARCH GOALS

In this Master's thesis, a time-based analytical technique for microgrid-aware RA simulations of distributions systems embedded with microgrid(s) is presented. The main focus of this work is to develop an analytical technique which considers all time-dependencies associated to the AA simulation of islanded microgrids. As presented in Section 2.2.2, the AA problem's time-dependencies are based on the microgrid components, i.e., BESSs and LSSs, as well as on the timing and duration of islanding events. The goal of this research is therefore to provide an alternative RA solution to the existing time-dependant AA methodologies based on sequential MCS or pseudo-sequential MCS, which are computationally costly to run due to the large number of simulated scenarios that are needed to converge to a solution.

In Chapter 4, a DTMC approach is presented to handle the time-based dependencies associated to the AA problem. This solution is combined with CYME's MinCS-based approach for CRA to obtain our RA framework. In this proposed process, our AA analysis can be formulated as evaluating the expected time-series evolution of the microgrid's probability state vector $\mathbf{x}(t)$ during all possible island-inducing failure events, which have a duration with a probability distribution of occurrence, $\lambda_{\text{isl}}(t)$, and an island instant t_0 following a uniform probability distribution. The microgrid state probability vector is updated at each evaluated timestep t with a time interval $\Delta t > 0$ based on:

$$\mathbf{x}(t + \Delta t) = \mathbf{x}(t)\mathbf{P}(t), \tag{3.1}$$

where $\mathbf{P}(t)$ is the 1-step transition matrix based on the probability of power adequacy of the system at time t for all possible state configurations.

The microgrid states included in the probability state vector $\mathbf{x}(t)$ are based on the presence of BESSs and/or LSSs on the microgrid. BESSs and LSSs are hence the state variables in our formulation. Specifically, the algorithm iteratively computes the set of probability state vectors $\mathbf{x}_{t_0}(t)$ for all possible island-inducing failure instants in the simulated time interval of N_T hours, i.e., $t_0 \in \{0, \Delta t, 2\Delta t, \dots, \left\lfloor \frac{N_{\text{T}}}{\Delta t} \right\rfloor \Delta t\}$, and for all islanded operation duration $t \in [0, t_{\max}]$ as:

$$\mathbf{x}_{t_0}(t_{n+1}) = \mathbf{x}_{t_0}(t_n)\mathbf{P}(t_n), \tag{3.2}$$

where $t_{\max}$ is the maximum possible island duration, and $t_n = t_0 + n\Delta t$ with $n = 0, 1, 2, \ldots, \left\lceil \frac{t_{\max}}{\Delta t} \right\rceil$. These microgrid state vectors are then compiled to obtain the expected customer islanded reliability values, and the CRA reliability indices are updated accordingly using $\lambda_{\text{isl}}(t)$.

A DTMC-based approach has been chosen to include AA's time-dependancies because this formulation enables us to model the time-series behaviour of BESSs and LSSs through the state variables $\mathbf{x}_{t_0}(t)$. It also allows us to consider the time-varying output of the local DDER and NDDER generation through the state transition matrices $\mathbf{P}(t)$ which are computed based on the probability that the total available generation is greater than the local demand for all states at time t. The total generation probability distribution can be obtained by leveraging our knowledge of the probabilistic distributions that mirror the natural phenomena on which NDDERs tap into. With this approach, we are able to efficiently enumerate and evaluate the impact of all event sequences during islanding operation while still accounting for the variability of NDDERs output and the inter-dependencies of the microgrid states.

The initial state of the microgrid when transitioning to islanded operation, i.e., the set composed by the LSS state, the BESS state, and the instant of islanded operation, has to be defined in order to determine the evolution of the islanded system. For the LSS, we consider the microgrid to be initially in its nominal operating state, i.e., all customers are supplied. For the BESS, its initial state of charge (which is necessarily uncertain when the BESS is not used exclusively for reliability purposes) can follow any random distribution without increasing the computation time. Finally, each possible instant of island-inducing failure events, i.e., t_0, is iterativaly assessed by executing (3.2).

Although DER unavailability due to unplanned failures or planned maintenance is not directly considered in the evaluation, our proposed method is a first step towards the development of time-based analytical RA techniques. To the best of our knowledge, this is the first analytical RA methodology which attempts to model the time-dependant behaviour of BESSs. This is a crucial component to support the islanded microgrid operation by ensuring that the required level of power generation on the system is met when low NDDER power output occurs. It is therefore highly important to account for it in the reliability assessment of distribution networks embedding microgrid(s).

CHAPTER 4 ARTICLE 1 : MICROGRID-AWARE RELIABILITY ASSESSMENT OF DISTRIBUTION SYSTEMS USING MARKOV CHAINS

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Abstract

Microgrids can improve the reliability and the resiliency of modern distribution systems. The stochasticity of local non-dispatchable distributed energy resources (NDDERs) combined with the time-dependency of battery energy storage systems (BESSs) and load shedding strategies (LSSs) complicate the reliability assessment of distribution networks embedded with microgrids. In this work, a minimal cut-set method using a discrete-time Markov Chain (DTMC) to perform the time-series adequacy assessment is proposed. This reduces the computational burden of currently used approaches based on Sequential Monte Carlo Simulations (SMCS) while accounting for the stochasticity of NDDERs and the time-dependency of BESSs and LSSs. Case studies on a modified IEEE-RTBS Bus2 system assess the accuracy of the method when compared with SMCS.

Keywords. Reliability Assessment, Markov Chains, Microgrids, Distribution Networks, Adequacy Assessment.

4.1 Introduction

Microgrids have the potential of improving the reliability and the resiliency of distribution networks by operating isolated portions of the system autonomously during outage events [8, 44]. Conventional reliability assessment techniques generally assume that customers on electrically isolated sections of the system are interrupted during the entire fault duration. This assumption is no longer valid within the context of microgrids embedded within distribution networks because of their ability to supply local customers by operating in islanded mode. Therefore, the reliability indices computed by conventional techniques are overly conservative because they do not assess the power adequacy of microgrids. Including microgrids in the assessment requires evaluating the microgrid's power adequacy in all circumstances. Specifically, the local distributed energy resources (DERs)'s stochastic generation output, the DERs unavailability, and the time-dependencies inherent to the microgrid, such as the battery energy storage system (BESS) and load shedding strategy (LSS) operations as well as the timing and duration of the island-inducing failure event. Several techniques have already been proposed in the literature to assess the impact of microgrids on the reliability of modern distribution systems. These methodologies can be broadly classified into two main classes [1, 5, 6]: analytical techniques [11–14, 21, 22, 32, 37] and Monte Carlo simulations [17, 19, 23, 24, 28].

Analytical techniques leverage closed-form mathematical formulations to compute the expected values of the reliability indices [1]. These approaches are characterized by relatively fast simulation times compared to the other class of techniques, but they often poorly model or simply omit time-dependent behaviour of BESSs and LSSs, or do not consider the time-varying demand during islanded operations. This modelling issue stems from the complexity of considering all possible scenarios that can occur in the system. Several analytical techniques are relying on the enumeration of all possible microgrid states to compute the expected probability of adequacy (PoA) [11, 13, 21, 22, 32, 37]. This probability is then used to reduce the expected interruption frequency and duration of island-inducing failure events for microgrid customers. This approach overestimate the islanded operation capability of microgrids because it assumes that power adequacy in a given microgrid state imply the survival of the microgrid for the whole duration of the fault [45]. In [35], BESSs are included within the analytical time-series adequacy assessment framework. However, customer interruptions during autonomous operation and LSSs are not considered in the proposed solution.

Monte Carlo simulations, more specifically sequential Monte Carlo simulations (SMCS) [17, 23, 24] and pseudo-sequential Monte Carlo simulutions (PSMCS) [28], allow for a more precise modelling of the system's time-varying behaviour through probabilistic sampling, thereby providing enhanced accuracy in reliability assessments. However this comes at the cost of increased computational burden due to the need for numerous simulations, resulting in stochastic outputs that differs between runs.

This paper presents a new approach for assessing the reliability of distribution systems with microgrids by proposing a decoupled, time-based, and analytical reliability and adequacy assessment methodology. Unlike the existing analytical methodologies, our approach uses a three-step process to account for both islanding operation of microgrids over time and time dependency of generation assets. Our methodology computes PoA based on a power and energy adequacy evaluation, leading to a more accurate representation of the microgrid's true islanding operation capability. To the best of our knowledge, this is the first time that such a comprehensive approach is used in analytical reliability assessment techniques. Our approach is as follows. First, a a minimal cut-set (MinCS) method of order 1 is used to initially assess the reliability of the distribution network by artifichially assuming that embedded microgrids cannot operate in islanded mode. This necessarily leads to inaccurate reliability results for the microgrid's loads. During this initial reliability assessment step, the microgrid's island-inducing fault events are compiled as a yearly equivalent islanding duration probability distribution. This distribution is then used in the second step during which the islanded microgrid's energy adequacy capability is assessed through discrete-time Markov Chain (DTMC)-based computations. The second step is used to assess the islanded operation capability when considering the microgrid's time-dependent behaviour. The resulting microgrid's state vectors for all simulated time steps and failure events are then converted to their corresponding load state before adjusting the initial MinCS indices based on the microgrid's islanded operation performance. Our specific contributions are given next. We:

1. design an analytical adequacy assessment technique which adequately accounts for the time-dependencies of LSSs and DERs, including BESSs, in islanded microgrids.
2. adapt the power system reliability assessment indices to the microgrid-specific context.
3. formulate a reliability assessment methodology that can be readily integrated to conventional analytical reliability techniques that ignore the microgrid's islanding capabilities.
4. present numerical case studies which showcase our decoupled analytical reliability and adequacy assessment methodology.

Section 4.2 details the reliability model of each microgrid component used in the proposed new methodology. Section 4.3 describes the decoupled analytical reliability and adequacy assessment method. Section 4.4 presents numerical case studies and a discussion about the span of solution capabilities of our proposed approach. Finally, Section 4.6 provides a conclusion and future work perspectives.

4.2 Reliability Models of Distribution Systems with Microgrids

This section presents the reliability models used for the microgrid's components, i.e., DERs, LSSs, and customer loads.

4.2.1 Dispatchable Distributed Energy Resources modelling

Dispatchable Distributed Energy Resources (DDERs), e.g., micro-turbines, fuel cells, and diesel generators, are considered from the adequacy assessment perspective as being able to generate their rated active power P_D^{r} at any given time. Let $P_D(t)$ be the discrete random variable representing the DDER's maximum active power generation at time t. The probability mass function (PMF) $f_D(P)$ is:

$$f_D(P) = \begin{cases} 1 & P = P_D^{\mathrm{r}} \\ 0 & \text{else,} \end{cases}$$

4.2.2 Non-Dispatchable Distributed Energy Resources modelling

Non-Dispatchable Distributed Energy Resources (NDDERs), e.g., photovoltaic systems and wind turbines, have unique models in the adequacy assessment because their power generation depends on the natural phenomena on which they tap into.

4.2.2.1 Photovoltaic System

Photovoltaic System (PV) power generation depends on solar irradiance h, which is modelled as a Beta random variable [20,26] with probability density function (PDF) $f_{\mathrm{h}}(\hat{h}, t)$ expressed as:

$$\begin{aligned} \hat{h} &= \frac{h}{h_{\max}} \\ f_{\mathrm{h}}(\hat{h}, t) &= \begin{cases} \dfrac{\hat{h}^{\alpha-1}(1-\hat{h})^{\beta-1}}{\mathrm{B}(\alpha, \beta)}, & t \in \mathcal{K}_{\mathrm{sun}} \\ 0, & \text{otherwise} \end{cases} \\ \mathrm{B}(\alpha, \beta) &= \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}, \end{aligned}$$

where $\hat{h}$ is the normalized solar irradiance based on $h_{\max}$, the maximum recorded irradiance in the analyzed time interval, α and β are the distribution's shape parameters, Γ is the gamma function, t is the hour of the day, and $\mathcal{K}_{\mathrm{sun}}$ is the interval of time between sunrise, t_{rise}, and sunset, t_{set}, i.e., $\mathcal{K}_{\mathrm{sun}} = \{t \mid t_{\mathrm{rise}} \leq t \leq t_{\mathrm{set}}\}$.

The PV active power generation $P_{PV}(h)$ is given by:

$$P_{PV}(h) = N_{\mathrm{s}} N_{\mathrm{p}} F_{\mathrm{F}} I(h) V(h),$$

where N_{s} is the number of PV panels in series, N_{p} is the number of PV panels in parallel, F_{F} is the PV's fill factor, $I(h)$ is the current, and $V(h)$ is the voltage [22]. The full PV model is described in the Appendix.

4.2.2.2 Wind Turbine

Wind turbine (WT) power generation depends on wind speed v, which can be modelled as a random variable following a Weibull distribution [25, 49] with PDF $f_{\mathrm{v}}(v)$ provided by:

$$f_{\mathrm{v}}(v) = \begin{cases} \dfrac{k}{\lambda} \left(\dfrac{v}{\lambda}\right)^{(k-1)} e^{-(v/\lambda)}, & \text{if } v \geq 0 \\ 0, & \text{if } v < 0, \end{cases}$$

where k and λ are, respectively, the shape and scale parameters of the distribution.

The WT power generation $P_{WT}(v)$ is given by [20, 24, 29]:

$$P_{WT}(v) = \begin{cases} 0, & \text{if } v \leq v_{\mathrm{in}} \\ P_{WT}^{\mathrm{r}} \dfrac{v^3 - v_{\mathrm{in}}^3}{v_{\mathrm{r}}^3 - v_{\mathrm{in}}^3}, & \text{if } v_{\mathrm{in}} < v \leq v_{\mathrm{r}} \\ P_{WT}^{\mathrm{r}}, & \text{if } v_{\mathrm{r}} < v \leq v_{\mathrm{out}} \\ 0, & \text{if } v_{\mathrm{out}} < v, \end{cases}$$

where P_{WT}^{r}, v_{in}, v_{r}, and v_{out} are, respectively, the wind turbine's rated power generation, the cut-in wind speed, the rated wind speed, and the cut-out wind speed.

4.2.3 Total Generation

The total local microgrid generation $P_{\mathrm{G}}(t)$ is given by the sum of all DDERs and NDDERs power outputs. We remark that $P_{\mathrm{G}}(t)$ is a stochastic process because NDDER's generation is itself a random variable. The PMF and cummulative distribution function (CDF) of $P_{\mathrm{G}}(t)$, $f_{\mathrm{G}}(P,t)$ and $F_{\mathrm{G}}(P,t)$, respectively, are determined in two steps for each hour of the day. First, the PMF of the combined generation of each generation type (viz., f_{PV}^{c}, f_{WT}^{c}, f_{D}^{c}) is computed by summing the power output and the PMF of all generators over discretized values of the domain. We assume the microgrid to be a geographically small system and hence, the energy resources available at any location inside the network are considered identical, i.e., there is full correlation between all generators of a given type. The sum of the total generation for each generator type can therefore be computed by the sum of the generation of each generator of the given type. The resulting PMFs will have variable step size due to NDDERs non-linear power output. A downsampling technique similar to [21] is applied to f_{PV}^{c}, f_{WT}^{c}, and f_{D}^{c}. Finally, assuming that the power output of each generator type is statistically independent [25, 31], $P_{\mathrm{G}}(t)$'s PMF, $f_G(P,t)$ is obtained from the convolution of these functions and its CDF, $F_G(P,t)$ is derived from $f_G(P,t)$. Next, we describe the LSS model.

4.2.4 Load Shedding Strategy

The islanded microgrid's LSS is assumed to be a set of N_S predefined actions that are applied sequentially whenever the microgrid's power demand is not met by the grid, similarly to what has been proposed in [20] and [23]. We define $s = 0$ as the initial LSS state in which no action is implemented. State $s = 1, 2, \ldots, N_\mathrm{S}$ corresponds to the s^{th} action applied to the microgrid. Finally, state $s = \tau$ corresponds to total blackout due to the microgrid's power inadequacy. Let $\mathcal{K}_\mathrm{S} = \{0, 1, \ldots, N_\mathrm{S} - 1, N_\mathrm{S}\}$ be the set of $N_\mathrm{S} + 1$ actively operated LSS states and $\overline{\mathcal{K}}_\mathrm{S} = \mathcal{K}_\mathrm{S} \cup \{\tau\}$ be the set of all $N_\mathrm{S} + 2$ possible LSS states. The set $\mathcal{K}_\mathrm{S}$ is subdivided into two subsets: (i) load shedding operations (subset $\mathcal{K}_\mathrm{S}^\mathrm{s}$) and (ii) load curtailment operations (subset $\mathcal{K}_\mathrm{S}^\mathrm{c}$) such that $\mathcal{K}_\mathrm{S} = \mathcal{K}_\mathrm{S}^\mathrm{s} \cup \mathcal{K}_\mathrm{S}^\mathrm{c}$. We assume that loads cannot be unshed because repetitively interrupting loads during an islanded event can negatively impact customers and could result in them opting out of the load shedding program [1, 14].

4.2.5 Load

The microgrid's loads are modelled using forecasted or historical, i.e., based on actual load measurement, demand profiles with a time step of $\Delta t > 0$. The total demand $P_\mathrm{L}^j(t)$ at t is:

$$P_\mathrm{L}^j(t) = \sum_{l \in \mathcal{K}_\mathrm{L}} m_l(j) P_l(t),$$

where $P_l(t)$ is the active power demand of load l at time t, $\mathcal{K}_\mathrm{L}$ is the set of loads on the microgrid, and $m_l(j) \in [0, 1]$ $\forall$ l, j is the control variable of load l which depends on the current LSS state $s(t) = j$. The demand is assumed to be constant during a time step Δt.

4.2.6 Battery Energy Storage System

Battery Energy Storage System (BESS) energy $E_{\mathrm{B}}(t)$ is modelled by [34]:

$$
\begin{aligned}
E_{\mathrm{B}}(t+\Delta t) &= E_{\mathrm{B}}(t) + P_{\mathrm{B}}(t)\Delta t \\
P_{\mathrm{B}}(t) &= \begin{cases} \eta_{\mathrm{ch}} P^{\mathrm{ac}}_{\mathrm{B,ch}}(t), & \text{if } P_{\mathrm{L}}(t) < P_{\mathrm{G}}(t) \\ -\dfrac{1}{\eta_{\mathrm{dch}}} P^{\mathrm{ac}}_{\mathrm{B,dch}}(t), & \text{if } P_{\mathrm{L}}(t) \geq P_{\mathrm{G}}(t) \end{cases} \\
P^{\mathrm{ac}}_{\mathrm{B,ch}}(t) &= \min\left(P^{\mathrm{r}}_{\mathrm{B,ch}}, P_{\mathrm{G}}(t) - P_{\mathrm{L}}(t), P^{\mathrm{max}}_{\mathrm{B,ch}}(t)\right) \\
P^{\mathrm{ac}}_{\mathrm{B,dch}}(t) &= \min\left(P^{\mathrm{r}}_{\mathrm{B,dch}}, P_{\mathrm{L}}(t) - P_{\mathrm{G}}(t), P^{\mathrm{max}}_{\mathrm{B,dch}}(t)\right) \\
P^{\mathrm{max}}_{\mathrm{B,ch}}(t) &= \frac{E^{\mathrm{max}}_{\mathrm{B}} - E_{\mathrm{B}}(t)}{\Delta t} \\
P^{\mathrm{max}}_{\mathrm{B,dch}}(t) &= \frac{E_{\mathrm{B}}(t) - E^{\mathrm{min}}_{\mathrm{B}}}{\Delta t},
\end{aligned}
$$

where P_{B} is the BESS power output, Δt is the time interval between each output power update, $\eta_{\mathrm{ch}}(\eta_{\mathrm{dch}})$ is the charging (discharging) efficiency, $P^{\mathrm{ac}}_{\mathrm{B,ch}}(P^{\mathrm{ac}}_{\mathrm{B,dch}})$ is the charge (discharge) power on the AC side, $P^{\mathrm{r}}_{\mathrm{B,ch}}(P^{\mathrm{r}}_{\mathrm{B,dch}})$ is the rated charging (discharging) power, $P^{\mathrm{max}}_{\mathrm{B,ch}}(P^{\mathrm{max}}_{\mathrm{B,dch}})$ is the maximum charge (discharge) power and $E^{\mathrm{max}}_{\mathrm{B}}(E^{\mathrm{min}}_{\mathrm{B}})$ is the maximum (minimum) allowed BESS energy.

We discretize the values of $E_{\mathrm{B}}(t)$ and of $P_B(t)$ in $\Delta P > 0$ power intervals and Δt time intervals. We assume that the BESS power output is constant during each Δt intervals. Therefore, we have a corresponding energy interval $\Delta E = \Delta P \Delta t$. The set of possible BESS states is now given by $\mathcal{K}_{\mathrm{B}} = \{E^{\mathrm{min}}_{\mathrm{B}}, E^{\mathrm{min}}_{\mathrm{B}} + \Delta E, \ldots, \overline{E}^{\mathrm{max}}_{\mathrm{B}}\}$ where the maximum discretized energy stored is $\overline{E}^{\mathrm{max}}_{\mathrm{B}} = \Delta E \left\lfloor \frac{E^{\mathrm{max}}_{\mathrm{B}}}{\Delta E} \right\rfloor$ and the number of BESS states in $\mathcal{K}_{\mathrm{B}}$ is $N_{\mathrm{B}} = \frac{\overline{E}^{\mathrm{max}}_{\mathrm{B}} - E^{\mathrm{min}}_{\mathrm{B}}}{\Delta E}$. Let $b \in \mathcal{K}_{\mathrm{B}}$ be a BESS state such that $E_b = E^{\mathrm{min}}_{\mathrm{B}} + b\Delta E$. We then have $E_0 = E^{\mathrm{min}}_{\mathrm{B}}$, $E_1 = E^{\mathrm{min}}_{\mathrm{B}} + \Delta E$, and $E_{N_{\mathrm{B}}-1} = \overline{E}^{\mathrm{max}}_{\mathrm{B}}$. We can define the maximum charging and discharging power knowing that the BESS is in state b as:

$$
P^{\mathrm{max}}_{\mathrm{B,ch}}(b) = \eta_{\mathrm{ch}} \min\left(P^{\mathrm{r}}_{\mathrm{B,ch}}, \frac{\overline{E}^{\mathrm{max}}_{\mathrm{B}} - E_b}{\Delta t}\right) \tag{4.1}
$$

$$
P^{\mathrm{max}}_{\mathrm{B,dch}}(b) = \frac{-1}{\eta_{\mathrm{dch}}} \min\left(P^{\mathrm{r}}_{\mathrm{B,dch}}, \frac{E_b - E^{\mathrm{min}}_{\mathrm{B}}}{\Delta t}\right). \tag{4.2}
$$

The maximum charging and discharging state transition from b is, respectively, given by:

$$
\Delta^{\mathrm{max}}_{\mathrm{ch}}(b) = \frac{P^{\mathrm{max}}_{\mathrm{B,ch}}(b)}{\Delta P} \qquad \Delta^{\mathrm{max}}_{\mathrm{dch}}(b) = \frac{P^{\mathrm{max}}_{\mathrm{B,dch}}(b)}{\Delta P}.
$$

The corresponding maximum charging and discharging accessible states from b are, respectively:

$$d_{\text{ch}}^{\max}(b) = b + \Delta_{\text{ch}}^{\max}(b) \qquad d_{\text{dch}}^{\max}(b) = b - \Delta_{\text{dch}}^{\max}(b).$$

4.3 Reliability Assessment Methodology

The proposed methodology is based on a three-step process. First, a conventional reliability assessment is executed to obtain an initial estimate of the reliability results on all sections of the distribution system including the microgrid(s). All possible interruption events which isolate the microgrid from the grid are compiled during this assessment. Then, the resulting microgrid island-inducing event duration probability distribution is used to assess the islanded operation capability. This step leverages a DTMC-based adequacy assessment which simulates the microgrid operations for the maximum possible islanded duration obtained from the islanding event distribution. Finally, the adequacy assessment results for islanded events are compiled and utilized to adjust the reliability analysis results from the first step.

Without loss of generality, we consider a single microgrid to simplify notation. We remark that our method can be applied to $\mathcal{K}_\Omega$, where $\text{card}(\mathcal{K}_\Omega) > 1$, the set of microgrids on the distribution network by adding a subscript ω on all state variables and executing the analysis for each $\omega \in \mathcal{K}_\Omega$.

4.3.1 Reliability Assessment

A conventional reliability assessment is first executed using a minimal cut-set (MinCS) method of order 1. We use the Reliability Assessment analysis from CYME's power system analysis software [42]. This approach however overestimates the microgrid's reliability indices values because it omits its islanding capability. In traditional approaches, all faults causing the microgrid to be electrically disconnected from the feeder (i.e., to be islanded) are incorrectly registering that the microgrid is in complete blackout (i.e., all customers are interrupted) for the total islanding duration. We add an aggregation step during the MinCS methodology to compile the frequency of microgrid islanded operation $\lambda_{\text{isl}}(t)$ as a function of the failure event's duration t. After MinCS's computation, $\lambda_{\text{isl}}(t)$ contains the probability distribution of equivalent expected yearly islanding frequency for all possible microgrid islanded operation durations.

Let $\mathcal{K}_\lambda = \{t \mid \lambda_{\text{isl}}(t) > 0\}$ be the set of all distinct possible islanded-operation durations recorded for the microgrid as computed by the MinCS approach. The DTMC adequacy assessment calculation then uses the maximum possible island duration $t_{\max} = \max(\mathcal{K}_\lambda)$ to determine the simulation duration.

4.3.2 Discrete-Time Markov Chain Adequacy Assessment

The Markov Chain model used in the adequacy assessment depends on the stochastic process $X(t)$, i.e., the presence of an LSS and/or BESS on the microgrid. A non-stationary, discrete-time, and first-order Markov Chain is used because:

1. the stochastic process state at time t depends exclusively on the system's state at time $t - \Delta t$;

2. the load and generation are assumed to be constant in each interval of duration Δt, and;

3. the local demand $P_{\mathrm{L}}(t)$ and generation $P_{\mathrm{G}}(t)$ are time-varying, i.e., $p_{mn}(t_a) \neq p_{mn}(t_b)$ for $|t_a - t_b| > \Delta t$, where $p_{mn}(t)$ is the probability to transition from microgrid state m to state n between t and $t + \Delta t$.

We assume that the fault event occurs at time t_0, where t_0 is a random variable uniformly distributed throughout the time horizon, i.e., $t_0 \sim \mathrm{U}\left[0, N_{\mathrm{T}} - 1\right]$, where N_{T} corresponds to the number of simulated hours. Considering a step size of duration Δt, we have $t_0 \in \mathcal{K}_{\mathrm{T}} = \{0, \Delta t, 2\Delta t, \ldots, \left\lfloor \frac{N_{\mathrm{T}}}{\Delta t} \right\rfloor \Delta t\}$.

Next, we define the transition probabilities $\mathbf{P}_{mn}(t)$ leading to the 1-step transition matrix $\mathbf{P}(t)$ for (i) LSS-, (ii) BESS-, and (iii) LSS and BESS-equipped microgrid at time t. Given $\mathbf{P}(t)$, the DTMC's $X(t)$ state vector, $\mathbf{x}(t)$, is updated according to:

$$\mathbf{x}(t + \Delta t) = \mathbf{x}(t)\mathbf{P}(t).$$

The microgrid adequacy assessment reduces to evaluating $\mathbf{x}_{t_0}(t)\ \forall\ t_0 \in \mathcal{K}_{\mathrm{T}}$. This corresponds to the computation of $\mathbf{x}(t)$ when the islanded fault event occurs for any given t_0 and for all islanded operation duration $t \in [t_0, t_0 + t_{\max}]$. Hence, $\mathbf{x}_{t_0}(t)$ is evaluated using:

$$\mathbf{x}_{t_0}(t_{n+1}) = \mathbf{x}_{t_0}(t_n)\mathbf{P}(t_n), \tag{4.3}$$

where $t_n = t_0 + n\Delta t$ with $n = 0, 1, 2, \ldots, \left\lceil \frac{t_{\max}}{\Delta t} \right\rceil$. After the adequacy assessment, all $\mathbf{x}_{t_0}(t)$ vectors obtained using (4.3) are used to evaluate the microgrid's islanded capability. We now define $\mathbf{P}(t)$ for each possible case.

4.3.2.1 LSS Case

First, we suppose that the microgrid has a load shedding strategy in place ($N_\mathrm{S} > 0$) and no battery storage installed ($N_\mathrm{B} = 0$). Let $s(t) \in \{0, 1, \ldots, N_\mathrm{S}\}$ and $\mathbf{s}(t) \in [0, 1]^{1\times(N_\mathrm{S}+1)}$ be, respectively, the LSS state and LSS probability state vector at t. We express $\mathbf{s}(t)$ as:

$$\mathbf{s}(t) = \Big[\Pr[s(t) = 0] \;\; \Pr[s(t) = 1] \;\; \ldots \;\; \Pr[s(t) = N_\mathrm{S}]\Big].$$

The LSS state transition depends solely on the microgrid power balance between the total demand $P_\mathrm{L}(t)$ and the total available power generation $P_\mathrm{G}(t)$. Because $P_\mathrm{G}(t)$ is a stochastic process with PMF $f_\mathrm{G}(P, t)$, the microgrid's state (equivalently the LSS state in this case) is defined as the stochastic process $X(t)$. Let $\mathbf{x}_{t_0}(t) \in [0, 1]^{1\times(N_\mathrm{S}+2)}$ be the probability state vector of $X(t)$ expressed as:

$$\begin{aligned}
&\mathbf{x}_{t_0}(t) = [\mathbf{s}(t) \;\; \tau] = [x_0(t) \quad x_1(t) \quad \ldots \quad x_{N_\mathrm{S}}(t) \quad x_\tau(t)]\\
&\mathbf{x}_{t_0}(t)[n] = \Pr[X(t) = X_n] \;\forall\; n \in \overline{\mathcal{K}}_\mathrm{S},
\end{aligned}$$

where $\mathbf{x}_{t_0}(t)[n]$ is the probability to be in the microgrid state X_n at t for an islanding instant $t_0 \in \mathcal{K}_\mathrm{T}$. Let $X_i, X_j \in \overline{\mathcal{K}}_\mathrm{S}$ be the LSS state at t and $t + \Delta t$, respectively. Let:

$$\mathbf{P}_{ij}(t) = \Pr[X(t + \Delta t) = X_j | X(t) = X_i],$$

where $\mathbf{P}_{ij}(t)$ is the state transition probability to go from X_i to X_j, i.e., the element (i, j) in matrix $\mathbf{P}(t)$. Next, we evaluate $\mathbf{P}_{ij}(t)$. We remark that:

1. The LSS is assumed to be an ordered set of actions. To transition from X_i to X_j, it must go through each intermediate state in between, e.g., to transition between the nominal operating state ($s(t) = 0$) to the third LSS state ($s(t) = 3$), the system sequentially applies $s(t) = 1$, $s(t) = 2$, and $s(t) = 3$, respectively.

2. It is possible to transition to all accessible states X_j. A given state X_j is deemed inaccessible from X_i, i.e., $\mathbf{P}_{ij}(t) = 0$, if and only if a load is unshed in one of the intermediate states, e.g., the transition from $s(t) = 3$ to $s(t) = 0$ is impossible if either $s(t) = 1$ or $s(t) = 2$ sheds a customer.

3. If the microgrid is in blackout, then it stays in blackout for the remaining duration of the fault, i.e. $\mathbf{P}_{\tau\tau}(t) = 1$ and $\mathbf{P}_{\tau k}(t) = 0 \;\forall\; k \in \mathcal{K}_\mathrm{S}$.

We now derive the state transition probabilities $\mathbf{P}_{ij}(t)$ as a function of $P_{\mathrm{L}}(t)$ and $P_{\mathrm{G}}(t)$:

$$\mathbf{P}_{ij}(t) = \begin{cases} 1 - F_{\mathrm{G}}\Big(P_{\mathrm{L}}^{j}(t), t\Big), & \text{if (a)} \\ F_{\mathrm{G}}\Big(P_{\mathrm{L}}^{j-1}(t), t\Big) - F_{\mathrm{G}}\Big(P_{\mathrm{L}}^{j}(t), t\Big), & \text{if (b)} \\ F_{\mathrm{G}}\Big(P_{\mathrm{L}}^{N_{\mathrm{S}}}(t), t\Big), & \text{if (c)} \\ 1, & \text{if (d)} \\ 0, & \text{else,} \end{cases} \tag{4.4}$$

where we discuss cases (a)-(d) next. Let $j_{\min}(i)$ be the closest LSS state to the nominal operation state ($s(t) = 0$) accessible from $s(t) = i$, i.e., $j_{\min}(i) = i \ \forall \ X_i \in \mathcal{K}_{\mathrm{S}}^{\mathrm{s}}$ and $j_{\min}(i) < i \ \forall \ X_i \in \mathcal{K}_{\mathrm{S}}^{\mathrm{c}}$. First, for $X_i \in \mathcal{K}_{\mathrm{S}}$, we have:

- Case (a): $j = j_{\min}(i)$; $i, j \neq \tau$, is the transition to the LSS state that sequentially reverses all LSS actions until a shedding LSS state is reached.
- Case (b): $j > j_{\min}(i)$; $i, j \neq \tau$, is the transition to any accessible actively operated LSS state other than case (a)'s state.
- Case (c): $i \neq \tau$; $j = \tau$, is the transition to the blackout state when facing power inadequacy in an LSS-equipped microgrid.

Second, for $X_i = X_\tau$, we have:

- Case (d): $i, j = \tau$, reflects that the microgrid blackout lasts for the remaining fault duration.

Lastly, for $X_i \in \overline{\mathcal{K}}_{\mathrm{S}}$, we have:

- The remaining case represents an impossible transition, i.e., a state X_j inaccessible from X_i.

4.3.2.2 BESS Case

We can suppose that the microgrid has a battery storage installed ($N_{\mathrm{B}} \neq 0$) but no load shedding strategy ($\overline{\mathcal{K}}_{\mathrm{S}} = \{0, \tau\}$). Let $b(t) \in \{0, 1, \ldots, N_{\mathrm{B}} - 1\}$ and $\mathbf{b}(t) \in [0,1]^{1\times N_{\mathrm{B}}}$ be, respectively, the BESS state and probability state vector at t. We express $\mathbf{b}(t)$ as:

$$\mathbf{b}(t) = [\Pr[b(t) = 0] \quad \Pr[b(t) = 1] \quad \ldots \quad \Pr[b(t) = N_{\mathrm{B}} - 1]]$$

Similarly to the LSS case, the BESS state is defined as the stochastic process $X(t)$. The set $\overline{\mathcal{K}}_{\mathrm{B}}$ corresponds to all possible microgrid states, including both the actively operating states and the blackout state, i.e., $\overline{\mathcal{K}}_{\mathrm{B}} = \mathcal{K}_{\mathrm{B}} \cup \{\tau\}$. Let $\mathbf{x}_{t_0}(t) \in [0,1]^{1\times(N_{\mathrm{B}}+1)}$ be the probability state vector of $X(t)$:

$$\begin{aligned}\mathbf{x}_{t_0}(t) &= [\mathbf{b}(t) \quad \tau] \\ &= [x_0(t) \quad x_1(t) \quad \dots \quad x_{N_{\mathrm{B}}-1}(t) \quad x_\tau(t)] \\ \mathbf{x}_{t_0}(t)[n] &= \Pr[X(t) = X_n] \ \forall \ n \in \overline{\mathcal{K}}_{\mathrm{B}},\end{aligned}$$

where $\mathbf{x}_{t_0}(t)[n]$ is the probability to be in the microgrid state X_n at t for an islanding instant $t_0 \in \mathcal{K}_{\mathrm{T}}$. Let $X_b, X_d \in \overline{\mathcal{K}}_{\mathrm{B}}$ be, respectively, the microgrid state at t and $t+\Delta t$. The state transition probability to go from X_b to X_d is:

$$\mathbf{P}_{bd}(t) = \Pr\left[X(t+\Delta \mathrm{t}) = X_d | X(t) = X_b\right].$$

Next, we evaluate $\mathbf{P}_{bd}(t)$. We observe that:

1. It is possible to transition from a BESS state X_b to state X_d in Δt as long as the power output discharge/charge constraints given by (4.1) and (4.2) are respected. Any state X_d which does not satisfy the power output constraints is deemed inaccessible from X_b.

2. If the microgrid is in blackout, then it stays in blackout for the remaining duration of the fault, i.e., $\mathbf{P}_{\tau\tau}(t) = 1$ and $\mathbf{P}_{\tau k}(t) = 0 \ \forall \ k \in \mathcal{K}_{\mathrm{B}}$.

We now derive the state transition probabilities $\mathbf{P}_{bd}(t)$ as a function of $P_{\mathrm{L}}(t)$ and $P_{\mathrm{G}}(t)$. Let $P_{\mathrm{L},\delta}^{j,b,d}(t)$ and $P_{\mathrm{B},\delta}^{b,d}$ be, respectively, the microgrid active power discrepency and the BESS discretized active power generation when transitioning from X_b to X_d:

$$\begin{aligned}P_{\mathrm{L},\delta}^{j,b,d}(t) &= P_{\mathrm{L}}^{j}(t) + P_{\mathrm{B},\delta}^{b,d} \\ P_{\mathrm{B},\delta}^{b,d} &= \begin{cases} \eta_{\mathrm{ch}}(d-b+\frac{\delta}{2})\Delta P, & \text{if } d \geq b, \\ \dfrac{-1}{\eta_{\mathrm{dch}}}(d-b+\frac{\delta}{2})\Delta P, & \text{if } d < b, \end{cases}\end{aligned}$$

where $\delta = \{-1, 0, 1\}$ corresponds to, respectively, the lower bound, the midpoint and the upper bound of any given BESS state interval. We note that $j = \tau$ when the microgrid is in blackout, and $j = 0$ otherwise, i.e., for any BESS state in $\mathcal{K}_{\mathrm{B}}$. The state transition probability $\mathbf{P}_{bd}(t)$ is:

$$\mathbf{P}_{bd}(t) = \begin{cases} 1 - F_{\mathrm{G}}(P_{\mathrm{L},-1}^{0,b,d}(t), t), & \text{if (a)} \\ F_{\mathrm{G}}(P_{\mathrm{L},1}^{0,b,d}(t), t) - F_{\mathrm{G}}(P_{\mathrm{L},-1}^{0,b,d}(t), t), & \text{if (b)} \\ F_{\mathrm{G}}(P_{\mathrm{L},-1}^{0,b,d_{\mathrm{dch}}^{\max}(b)}(t), t), & \text{if (c)} \\ 1, & \text{if (d)} \\ 0, & \text{else,} \end{cases} \tag{4.5}$$

where cases (a)-(d) are described next. Note that the definition (4.5) is similar to (4.4). First, for $X_b \in \mathcal{K}_{\mathrm{B}}$, we have:

- Case (a): $d = N_{\mathrm{B}} - 1$; $b, d \neq \tau$, is the transition to the highest possible BESS state of charge accessible from X_b, i.e., $X_{d_{\mathrm{ch}}^{\max}(b)}$.
- Case (b): $d_{\mathrm{dch}}^{\max}(b) < d \leq d_{\mathrm{ch}}^{\max}(b)$; $b, d \neq \tau$, is the transition to any BESS state other than case (a) or the blackout state.
- Case (c): $b \neq \tau$; $d = \tau$, is the transition to the blackout state when facing power inadequacy in a BESS-equipped microgrid.

Second, for $X_b = X_\tau$, we have:

- Case (d): $b, d = \tau$, imposes that the microgrid blackout lasts for the remaining fault duration.

Lastly, for all $X_i \in \overline{\mathcal{K}}_{\mathrm{B}}$:

- The remaining case represents impossible transitions, i.e., moving to a state X_d which is inaccessible from X_b at t.

4.3.2.3 LSS and BESS Case

An islanded microgrid with a load shedding strategy and battery storage possesses two state variables that need to be accounted for. The microgrid's system state can again be expressed as a stochastic process $X(t)$. Because both the LSS and BESS states vary through time during islanding operation, the microgrid probability state vector $\mathbf{x}(t)$ is given by the combination of all LSS states and BESS states. Let $\mathcal{K}_{\mathrm{SB}} = \mathcal{K}_{\mathrm{S}} \times \mathcal{K}_{\mathrm{B}}$ be the set of all possible actively operated microgrid states X_{mn} where the LSS state is m and the BESS state is n. Let

$\overline{\mathcal{K}}_{\text{SB}} = \mathcal{K}_{\text{SB}} \cup \{\tau\}$ be the set of all possible microgrid states and $N_{\text{SB}} = (N_{\text{S}} + 1)N_{\text{B}}$ be the number of states in $\mathcal{K}_{\text{SB}}$. We define $\mathbf{x}_{t_0}(t) \in [0, 1]^{1\times(N_{\text{SB}}+1)}$ as:

$$
\begin{aligned}
\mathbf{x}_{t_0}(t) &= [\mathbf{s}(t) \otimes \mathbf{b}(t) \quad \tau] \\
&= \Big[x_{0,0}(t) \quad x_{0,1}(t) \quad \dots \quad x_{1,0}(t) \quad x_{1,1}(t) \quad \dots \\
&\qquad\qquad x_{N_{\text{S}},N_{\text{B}}-2}(t) \quad x_{N_{\text{S}},N_{\text{B}}-1}(t) \quad x_{\tau}(t)\Big] \\
\mathbf{x}_{t_0}(t)[n] &= \Pr[X(t) = X_{p(n),q(n)}],
\end{aligned}
$$

where $\mathbf{s}(t)$ is the LSS probability state vector, $\mathbf{b}(t)$ is the BESS probability state vector, $\mathbf{x}_{t_0}(t)[n]$ is the probability to be in the microgrid state X_n at t for an islanding instant $t_0 \in \mathcal{K}_{\text{T}}$, and $X_{p(n),q(n)} \in \overline{\mathcal{K}}_{\text{SB}}$ is the microgrid state in which the LSS and BESS states are respectively $s(t) = p(n) = (n \bmod N_{\text{S}})$ and $b(t) = q(n) = (n \bmod N_{\text{B}})$.

Let $X_{i,b}, X_{j,d} \in \overline{\mathcal{K}}_{\text{SB}}$ be, respectively, the microgrid states at t and $t+\Delta t$. The state transition probability to go from $X_{i,b}$ to $X_{j,d}$ is:

$$
\mathbf{P}_{(i,b)(j,d)}(t) = \Pr\left[X(t + \Delta t) = X_{j,d} | X(t) = X_{i,b}\right].
$$

Before evaluating $\mathbf{P}_{(i,b)(j,d)}(t)$, we observe that:

1. The LSS and BESS constraints from Sections 4.3.2.1 and 4.3.2.2 apply to the combined case.

2. Additional LSS actions are taken in state $X_{i,b}$ only when the power discrepancy, $P_{\text{L}} - P_{\text{G}}$, is greater than the BESS maximum power discharge, $P^{\max}_{\text{B,dch}}(b)$.

3. A subsequent LSS state is accessible if and only if the maximum active power discharge is less than $\Delta P^j_{\text{L}}(t)$, the load variation made by applying the LSS action j at time t.

We now relate the state transition probability $\mathbf{P}_{(i,b)(j,d)}(t)$ to $P_{\text{L}}(t)$ and $P_{\text{G}}(t)$. Let $\widetilde{\mathcal{K}}^{i,j,b}_{\text{SB}}(t)$ be the set of all accessible actively operated microgrid states at time t defined as:

$$
\begin{aligned}
&\widetilde{\mathcal{K}}^{i,j,b}_{\text{SB}}(t) = \\
&\begin{cases}
\{X_{j,d} \in \mathcal{K}_{\text{SB}}\}, & \text{if } j = j_{\min}(i) \\
\{X_{j,d} \in \mathcal{K}_{\text{SB}} | P^{\max}_{\text{B,dch}}(b) < \Delta P^j_{\text{L}}(t)\}, & \text{if } j > j_{\min}(i),
\end{cases}
\end{aligned}
$$

where $\Delta P^j_{\text{L}}(t) = P^{j-1}_{\text{L}}(t) - P^j_{\text{L}}(t)$ is the load variation made by applying LSS action j. The condition on $\widetilde{\mathcal{K}}^{i,j,b}_{\text{SB}}(t)$ ensures that not all microgrid states are accessible when additionnal

LSS action(s) are required to reach power adequacy. Recall that the system always attempts to supply the maximum demand possible, i.e., LSS state $j = j_{\min}(i)$ at any given time. This means that the next microgrid states are a subset of all possible states when $j > j_{\min}(i)$. Next, we define $p^{i,b}_{j,d}(t)$ as the probability to be specifically in state $X_{j,d}$ given the current state $X_{i,b}$. Let $p^{i,b}_{j|d}(t)$ be the probability to be specifically in LSS state j given the BESS state d and the microgrid state $X_{i,b}$. Finally, let $p^{i,b}_{\tau^c}(t)$ be the total probability of being in any actively operated microgrid state $X_{j,d} \in \widetilde{\mathcal{K}}^{i,j,b}_{\mathrm{SB}}(t)$ given $X_{i,b}$, i.e., the complementary event probability of being in the blackout state τ. We then have:

$$\begin{aligned}
p^{i,b}_{j,d}(t) &= F_{\mathrm{G}}\Big(P^{j,b,d}_{\mathrm{L},1}(t), t\Big) - F_{\mathrm{G}}\Big(P^{j,b,d}_{\mathrm{L},-1}(t), t\Big) \\
p^{i,b}_{j|d}(t) &= F_{\mathrm{G}}\Big(P^{j-1,b,d}_{\mathrm{L},0}(t), t\Big) - F_{\mathrm{G}}\Big(P^{j,b,d}_{\mathrm{L},0}(t), t\Big) \\
p^{i,b}_{\tau^c}(t) &= \sum_{(j,d)\in\widetilde{\mathcal{K}}^{i,j,b}_{\mathrm{SB}}(t)} p^{i,b}_{j,d}(t).
\end{aligned}$$

Thus, the state transition probabilities $\mathbf{P}_{(ib),(jd)}(t)$ are:

$$\mathbf{P}_{(i,b)(j,d)}(t) = \begin{cases} 1 - F_{\mathrm{G}}\Big(P^{j,b,d}_{\mathrm{L},-1}(t), t\Big) & \text{if (a)} \\ p^{i,b}_{j,d}(t) & \text{if (b)} \\ p^{i,b}_{j,d}(t)\dfrac{p^{i,b}_{j|d}(t)}{p^{i,b}_{\tau^c}(t)} & \text{if (c)} \\ 1 - p^{i,b}_{\tau^c}(t) & \text{if (d)} \\ 1 & \text{if (e)} \\ 0 & \text{else,} \end{cases} \tag{4.6}$$

where the structure of (4.6) is similar to (4.4) and (4.5) , but with the additional case (c). First, for $X_{i,b} \in \mathcal{K}_{\mathrm{SB}}$, we have:

- Case (a): $(j, d) = (j_{\min}(i), N_{\mathrm{B}} - 1)$; $(i, b), (j, d) \neq \tau$, is the transition to the highest possible combined LSS and BESS accessible state, i.e., the minimum number of LSS applied actions and the maximum BESS state of charge from the current microgrid state.

- Case (b): $j = j_{\min}(i); d^{\max}_{\mathrm{dch}}(b) < d \leq d^{\max}_{\mathrm{ch}}(b)$; $(i, b), (j, d) \neq \tau$, is the transition to any BESS state other than the maximum possible state of charge while implementing only the minimum number of LSS actions.

- Case (c): $j > j_{\min}(i); d^{\max}_{\mathrm{dch}}(b) < d \leq d^{\max}_{\mathrm{ch}}(b)$, is the transition to any accessible state when additional LSS actions are required to achieve power adequacy.

- Case (d): $(i, b) \neq \tau; (j, d) = \tau$, is the transition to the blackout state when power adequacy cannot be achieved from the current LSS and BESS state.

Second, for $X_{i,b} = X_\tau$, we have:

- Case (e): $(i, b), (j, d) = \tau$, represents that the microgrid blackout lasts for the remaining fault duration.

Lastly, for all $X_{i,b} \in \overline{\mathcal{K}}_{\mathrm{SB}}$:

- The remaining case represents impossible transitions, e.g., a BESS power output in the interval greater than the charging (discharging) constraints.

4.3.3 Microgrid-Adjusted Reliability Assessment Indices

Following the islanded microgrid's adequacy assessment, we obtain the microgrid probability state vectors $\mathbf{x}_{t_0}(t)$ defined for all possible islanding instants $t_0 \in \mathcal{K}_{\mathrm{T}}$ and all islanded operation durations $t \in \{\Delta t, 2\Delta t, \ldots, \left\lceil \frac{t_{\max}}{\Delta t} \right\rceil\}$. We convert $\mathbf{x}_{t_0}(t)$ into the aggregated LSS probability state vector $\hat{\mathbf{x}}_{t_0}(t)$. Next, we map the state of each microgrid load, i.e., supplied, curtailed, or shed, for all LSS actions in $\hat{\mathbf{x}}_{t_0}(t)$. Based on $\lambda_{\mathrm{isl}}(t)$, we convert the load states into microgrid load's islanded reliability values, i.e., frequency of interruption, duration of interruption and energy not supplied during islanding operation for all islanding instant t_0. We can next recompile these islanded reliability values into yearly expected results by assuming that all islanding instants t_0 have the same probability of occurrence, i.e., a uniform distribution, as stated in Section 4.3.2. Given that the MinCS analysis overrestimates the microgrid's loads interruption during any islanding event because it always assumes the microgrid to be in the blackout state, we recast these load islanded yearly expected reliability values into the reliability values adjustment that should be made, i.e., the equivalent number of supplied islanded customers n_l^{isl}, the equivalent number of supplied islanded customers duration d_l^{isl} and the equivalent islanded energy supplied e_l^{isl}. These reliability values, n_l^{isl}, d_l^{isl}, and e_l^{isl}, are then subtracted from the MinCS total number of interrupted customers n_l^{MinCS}, total number of interrupted customers duration d_l^{MinCS}, and total energy not supplied e_l^{MinCS} for each load $l \in \mathcal{K}_{\mathrm{L}}$, respectively, as follows:

$$\begin{aligned}
\overline{n}_l &= n_l^{\mathrm{MinCS}} - n_l^{\mathrm{isl}}, \\
\overline{d}_l &= d_l^{\mathrm{MinCS}} - d_l^{\mathrm{isl}}, \\
\overline{e}_l &= e_l^{\mathrm{MinCS}} - e_l^{\mathrm{isl}},
\end{aligned}$$

where $\overline{n}_l$, $\overline{d}_l$, and $\overline{e}_l$ are, respectively, the adjusted total number of interrupted customers, the adjusted total number of interrupted customers duration, and the adjusted total energy not supplied for load l inside the microgrid. Finally, the reliability indices, e.g., SAIFI, SAIDI, ENS, ASAI, etc. [47], are computed based on $\overline{n}_l$, $\overline{d}_l$, and $\overline{e}_l$ instead of n_l^{MinCS}, d_l^{MinCS} and e_l^{MinCS}, leading to indices values which adequatly account for the microgrid's islanded operation.

We recall that our methodology is applicable for distribution networks with multiple microgrids. In this case, the frequency of islanded operation for each microgrid $\omega \in \mathcal{K}_\Omega$ is compiled in $\lambda_{\text{isl}}^{\omega}(t)$ during the conventional reliability assessment. Then, the DTMC and state/indices aggregation steps are executed iteratively for each microgrid because all microgrid DTMCs results are independent.

4.4 Numerical Case Studies

This section presents a numerical case study to showcase the accuracy and advantges of our methodology.

4.4.1 Case Study

We use a modified version of the IEEE-RTBS Bus 2's feeder F1 system [50] to showcase our methodology. Th modified system is illustrated in 4.1. Specifically, the spot load LP7 has been replaced by a microgrid composed of 3 equivalent loads (LP7-1, LP7-2, and LP7-3) and 3 DERs (micro-turbine (MT), PV, and BESS). The tie-switch between feeders F1 and F2 has been removed, meaning that only upstream restoration is available for feeder F1 during the restoration phase of any failure event on the system. The microgrid load characteristics are shown in Table 4.1. The microgrid DER characteristics are provided in Table 4.2. The load shedding strategy is detailed in Table 4.3. The preset LSS will first try to curtail non-critical loads LP7-1 and LP7-2 (states 1 and 2). If power adequacy is still not achieved, then these non-essential loads will be shed (states 3 and 4) to ensure that critical load LP7-3 remains online. Finally, if LP7-3 cannot be supplied, then the microgrid is then forced into blackout (state 5). The reliability parameters used are listed in Table 4.4. These reliability parameters are applied to both feeder F1 and microgrid LP-7. An inspection time of 30 minutes/km is used. Table 4.5 defines the simulation scenarios we performed to illustrate the different cases of our approach. The sunrise and sunset are, respectively, set to 8:00 AM and 6:00 PM. The irradiance Beta distribution parameters are set to $\alpha = 1.92$ and $\beta = 2.68$. The initial BESS state of charge at the islanding instant is considered to follow a uniform distribution between 50% and 80% of the BESS rated capacity. The simulation is executed over the span of an

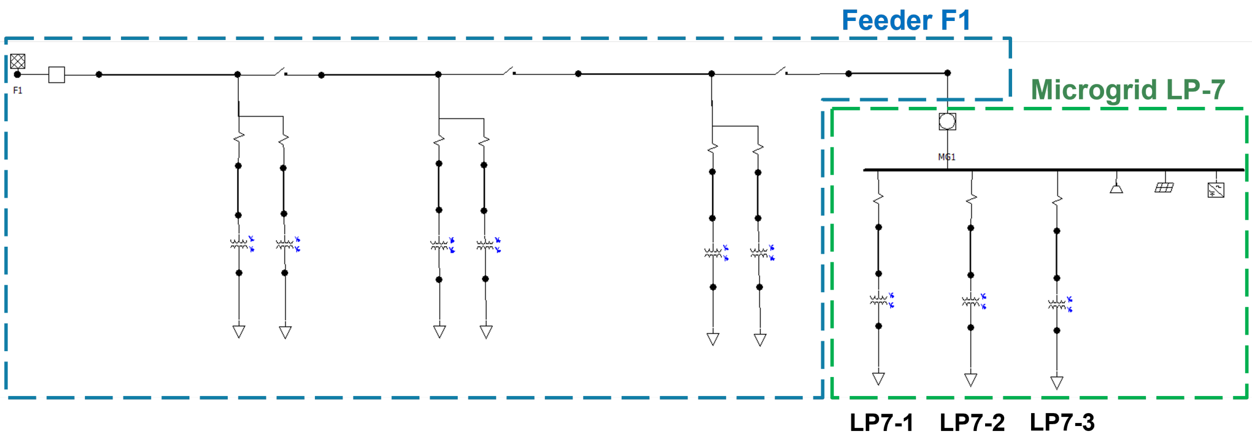

Figure 4.1 Modified IEEE-RTBS Bus 2 F1 Feeder

entire year, i.e., $N_\mathrm{T} = 8760$, with a time step $\Delta t = 1$ hour.

To validate the proposed methodology's results during the adequacy assessment, an SMCS is used to simulate the microgrid's islanded operation. The simulation stops when a confidence level of 95% is reached, indicating that the microgrid load reliability results are all within 1% of their true value.

Finally, we note that the proposed microgrid is small, but the size of the system does not have an impact on the simulation time because the total load and generation are aggregated in our methodology. Hence, it scales straightforwardly to more general distribution systems.

4.4.2 Results

The microgrid's reliability indices obtained for each simulated scenario are presented in Table 4.6. Note that the SMCS results for each scenario are also displayed in gray in the table.

In Scenario 0, microgrid islanding capabilities are neglected, i.e., a conventional reliability

Table 4.1 Microgrid Loads Specifications

Customer	**Average Load** (kW)	**Maximum Load** (kW)	**Number of Customers**
LP7-1	81.5	398.9	5
LP7-2	192.0	293.3	3
LP7-3	180.5	275.6	2
Total (LP7)	**454.0**	**792.4**	**10**

Table 4.2 Microgrid DER Specifications

MT	BESS	PV
$P_D^{\mathrm{r}} = 250$ kW	$E_{\mathrm{B}}^{\max} = 1000$ kWh $E_{\mathrm{B}}^{\min} = 50$ kWh $\eta_{\mathrm{ch}} = \eta_{\mathrm{dch}} = 100$ % $P_{\mathrm{ch}} = P_{\mathrm{dch}} = 1000$ kW $\Delta P = 10$ kW	$N_{\mathrm{s}}N_{\mathrm{p}} = 2250$ $T_{\mathrm{NOCT}} = 45°\mathrm{C}$ $T_{\mathrm{a,ref}} = 25°\mathrm{C}$ $T_{\mathrm{stc}} = 25°\mathrm{C}$ $h_{\mathrm{stc}} = 1000\ \mathrm{W/m^2}$ $V_{\mathrm{mpp}} = 54.7$ V $I_{\mathrm{mpp}} = 5.76$ A $I_{\mathrm{sc}} = 6.14$ A $V_{\mathrm{oc}} = 64.6$ V $\alpha_{\mathrm{sct}} = 0.057\%/°\mathrm{C}$ $\beta_{\mathrm{oct}} = -0.273\%/°\mathrm{C}$

Table 4.3 Microgrid Load Shedding Strategy

State	Customer	Action	Curtailment Factor
0	All	None	0.00
1	LP7-1	Curtail	0.25
2	LP7-2	Curtail	0.50
3	LP7-1	Shed	1.00
4	LP7-2	Shed	1.00
5	All	Blackout	1.00

assessment methodology is executed to compute reliability indices. We observe from Table 4.6 that such an approach overestimates the microgrid's reliability indices when compared to the other scenarios, especially with Scenario 4 in which both an LSS and a BESS are available. Deploying an LSS (Scenario 2) on the system has a positive but somewhat limited impact on the reliability values compared to installing a BESS (Scenario 3). Indeed, a decrease in SAIFI, SAIDI, and ENS by, respectively, 52%, 58%, and 45% is observed between Scenario 1 and 2 while a corresponding decrease of 60%, 71%, and 71%, respectively, is observed between Scenario 1 and 3. The greater reliability effect of the BESS over the LSS on the microgrid

Table 4.4 Reliability Assessment Parameters

Element	Interruption Frequency (int/yr-km)	Repair Time (h)
Overhead Line	0.10	5.0
Transformer	0.02	10.0
Breaker	0.01	4.0

Table 4.5 Simulation Scenarios

Scenario	**DTMC**	**MT & PV**	**LSS**	**BESS**
0		✓		
1	✓	✓		
2	✓	✓	✓	
3	✓	✓		✓
4	✓	✓	✓	✓

Table 4.6 Scenarios Microgrid Reliability Indices(*SMCS Results in Gray*)

Scenario	**SAIFI** (int/cust-yr)	**SAIDI** (h/cust-yr)	**CAIDI** (h/int)	**ENS** (kWh/yr)
0	0.335	2.189	6.534	994.0
1	0.331	2.010	6.063	905.0
	(0.331)	(2.009)	(6.064)	(902.9)
2	0.161	0.849	5.289	495.2
	(0.161)	(0.849)	(5.289)	(495.0)
3	0.132	0.578	4.372	266.3
	(0.132)	(0.577)	(4.372)	(265.9)
4	0.077	0.404	5.237	184.0
	(0.075)	(0.398)	(5.302)	(181.6)

is explained by the limited impact that the LSS has during night islanded operation because the PVs are not producing during that period, as seen in Figure 4.2. The improvement in Scenario 2 is therefore mostly related to fewer shedded customers and fewer blackout events during the day. This is because the LSS is able to reduce the overall demand by applying its sequence of actions to achieve local power adequacy in the microgrid. In Scenario 3, the BESS can contribute day and night to the total available local generation, thus increasing the likelihood of achieving successful islanded operations. Equipping the microgrid with both an LSS and a BESS (Scenario 4) combines the positive effect of the two components, i.e., reducing the overall load demand when needed and increasing the total available generation, respectively, leading to an even greater reliability improvement.

CAIDI is not improved as much even though interruptions are less likely, especially in Scenarios 2, 3 and 4. This low improvement of CAIDI is explained by the system being not able to supply the total load during multiple hours of the night, i.e., when the system depends on the MT and BESS generation. Therefore, the majority of blackout events end up during the night, which means that even if interruptions are much less frequent, their duration is not significantly reduced.

We note that in Table 4.6, the maximum error between the SMCS results and the proposed methodology is 2.7% (SAIFI - Scenario 4) across all reported values. This error is greater than the maximum error of 0.17% (SAIDI - Scenario 3) recorded in the other three simulated scenarios but is still deemed acceptable.

Figure 4.2 illustrates the time-dependency between the average microgrid customer's expected interruption duration and the time at which the island-inducing failure event occurs. We observe no time-dependency between the expected interruption duration and the time of the failure event in Scenario 0 because the microgrid is assumed to be incapable of islanded operation. This corresponds to the worst possible case for the expected interruption duration. In Scenario 1, the installed MT and PV are able to provide enough generation to reduce slightly the expected interruption duration during the day. However, the microgrid will still end up in blackout for the vast majority of the time. We also note that the MT is capable of providing some power adequacy capability during low demand hours, e.g., around midnight. The limited islanded microgrid operation capability in Scenario 1 is also due to the fact that the total demand is relatively high compared to the readily available generation at any hour of the day. The deployment of an LSS on the microgrid (Scenario 2) enables the system to modulate its total demand throughout the islanded operation to better achieve power adequacy at any time step. This leads to significant improvements during hours of higher available generation, i.e., between sunrise and sunset, or low demand, i.e., in the middle of the night. However, the microgrid remains vulnerable to prolonged and more widespread interruptions whenever the failure event occurs at times of high demand and low available generation, i.e., in the morning during sunrise when customers are waking up and soon after sunset when customers are coming back home from work. On the other hand, installing a BESS on the microgrid (Scenario 3), greatly reduces the expected customer interruption duration, especially during low demand of night hours because the total available generation is increased. We observe that the microgrid remains susceptible to long expected interruptions when the failure event occurs during the highest demand period of the evening when the PV generation does not contribute to the total microgrid generation. Equipping the microgrid with both a BESS and an LSS (Scenario 4) results in the fewest and shortest interruptions for all scenarios.

Figure 4.3 presents the percentage of reliability improvement made by each simulated scenarios in terms of the yearly expected frequency of interruption, interruption duration per interruption, and energy not supplied in comparison to Scenario 0's results used as the reference for each microgrid customer load, i.e., LP7-1, LP7-2, and LP7-3, during islanded events. We see from the results that the LSS (Scenarios 2 and 4) modulates the microgrid loads expected reliability values because the likelihood of LP7-3 (critical load) to be interrupted is

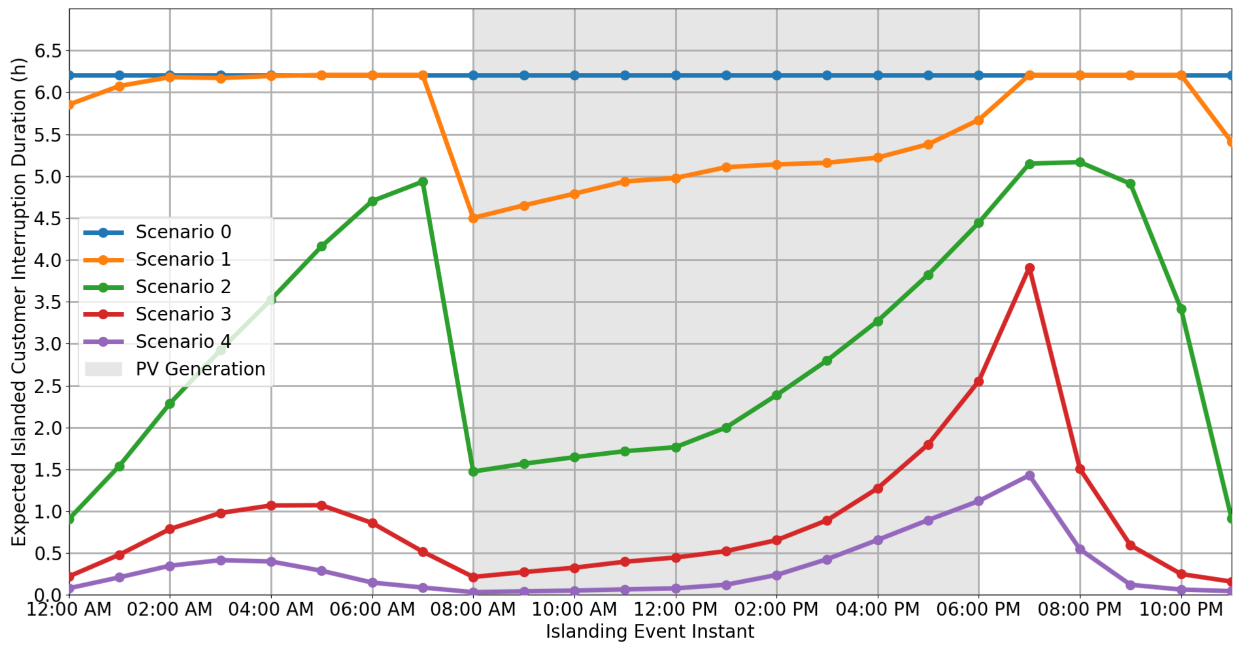

Figure 4.2 Microgrid Customer's Expected Interruption Duration During Islanding Events

less than LP7-2 and LP7-1 (non-critical loads). The microgrid loads reliability values are the same in Scenarios 1 and 3 because no LSS is implemented to curtail or shed some or all of the non-critical loads until achieving power balance, leading to the same interruption results for all microgrid loads. This leads to worst reliability results for critical load LP7-3 in both Scenarios 1 and 3 when compared to Scenarios 2 and 4, respectively. Because all microgrid loads are either fully supplied or in blackout when no LSS is implemented, the likelihood of islanded interruption is higher for load LP7-3. We remark that the energy not supplied (ENS) to all microgrid loads is greatly reduced in Scenarios 3 and 4 in which a BESS is installed on the system. This is the index most positively affected by the microgrid's islanding capability across all simulated scenarios.

4.4.3 Assumptions

The proposed adequacy assessment method is based on steady-state simulation assumptions. This means that the dynamic behaviour of all components is ignored, such as the possibility of unsuccessful switching operation during island formation [19, 51]. Moreover, DERs availability during islanded operation is assumed to be guaranteed. Considering these factors will reduce the microgrid's islanding operation capability.

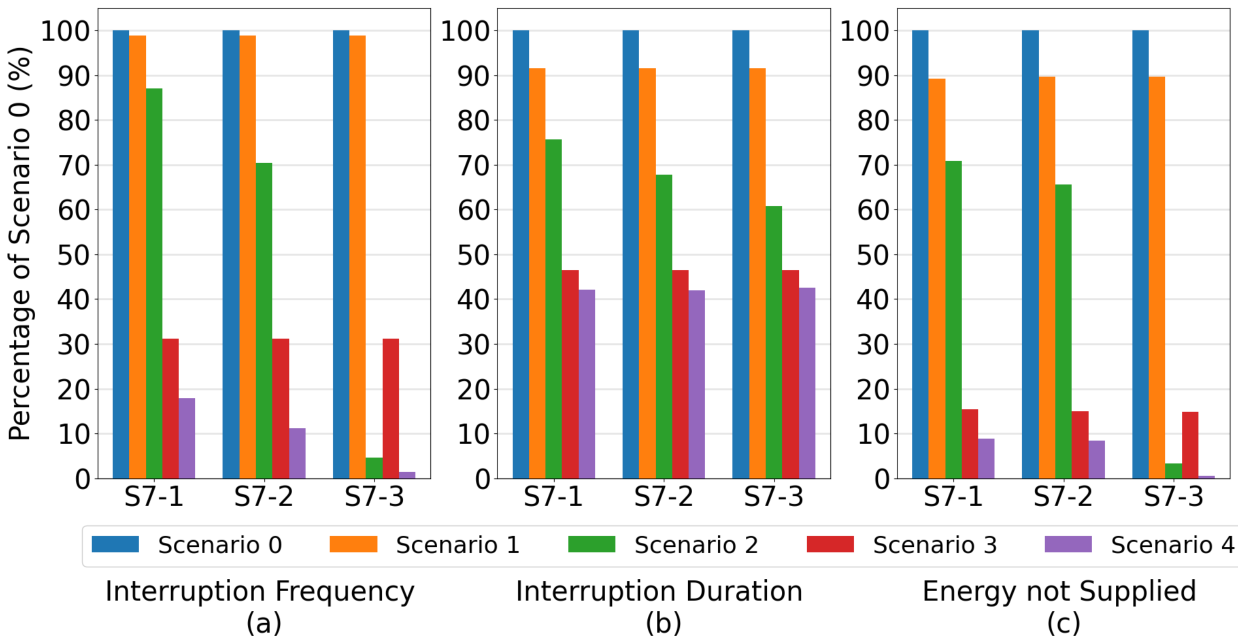

Figure 4.3 Microgrid Load's Islanded Expected Yearly Reliability Results Comparison

4.5 Discussion

Our approach has no limitations nor restrictions on the DERs generation and on the natural phenomena on which they tap into, as long as a total generation probability distribution can be evaluated. The number of simulated timesteps and the time-uniform interruption probability can also be modified. Therefore, our methodology is compatible with more refined models in regards to these aspects. For example, an hourly-based irradiance distribution could be utilized instead by using the clearness index probability density function [33] and the irradiance at the top of the atmosphere to model the time-varying behaviour of the irradiance during the day [23]. A distinct total generation probability distribution would then be calculated and then used for each hour of sunlight in the DTMC step.

4.6 Conclusion

In this work, we developed a new time-based analytical reliability assessment framework for distribution systems with microgrids. Our adequacy assessment approach uses discrete-time Markov Chains to account for all microgrid components and their time-varying behaviour during the simulation. The time-dependant reliability and adequacy performance of the microgrid's islanded operation were exemplified through numerical case studies. It was also demonstrated through these cases that the proposed methodology leads to the same results as those of an equivalent, but time consuming, SMCS. Future work includes the design of the LSS and the sizing of BESS using reliability indices-based optimization and our reliability assessment approach.

4.7 Appendix - Detailed PV Model

The PV active power generation $P_{PV}(h)$ is given by [22, 23]:

$$\begin{aligned} T_\mathrm{c} &= T_\mathrm{a} + h\left(\frac{T_\mathrm{NOCT} - T_\mathrm{a,ref}}{0.8}\right) \\ \Delta T_\mathrm{c} &= T_\mathrm{c} - T_\mathrm{stc} \\ I &= I_\mathrm{sc}\frac{h}{g_\mathrm{stc}}(1 + \alpha_\mathrm{sct}\Delta T_\mathrm{c}) \\ V &= V_\mathrm{oc}(1 + \beta_\mathrm{oct}\Delta T_\mathrm{c}) \\ F_\mathrm{F} &= \frac{V_\mathrm{mpp} I_\mathrm{mpp}}{V_\mathrm{oc} I_\mathrm{sc}} \\ P_{PV}(h) &= N_\mathrm{s} N_\mathrm{p} F_\mathrm{F} I V, \end{aligned}$$

where T_c is the solar cell temperature, T_a is the ambient temperature, T_NOCT is the normal operating cell temperature, $T_\mathrm{a,ref}$ is the reference ambient temperature, T_stc is the temperature in standard test conditions (STC), g_stc is the irradiance in STC, α_sct is the short-circuit current temperature coefficient in STC, I_sc is the short-circuit current in STC, β_oct is the open-circuit voltage temperature coefficient in STC, V_oc is the open-circuit voltage in STC, V_mpp is the voltage at the maximum power point, I_mpp is the current at the maximum power point, N_s is the number of PV panels in series, N_p is the number of PV panels in parallel, F_F is the PV fill factor, I is the current, and V is the voltage.

Acknowledgment

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CHAPTER 5 GENERAL DISCUSSION

The contributions of our method presented in Chapter 4 can be broken down into the following elements. We developed a time-based, decoupled CRA-AA, analytical RA methodology which:

- accurately models BESSs and LSSs time-dependencies in an analytical microgrid-aware AA framework. To the best of our knowledge, no other analytical AA technique considers the time-varying behaviour of both components simultaneously.
- provides reliability indices to calculate PoA which accounts for the time-series power adequacy of the system. This contrasts with existing analytical AA techniques which calculate the reliability indices based exclusively on a single time power adequacy.
- is flexible enough to be integrated to any existing conventional approach and is therefore not dependant on a specific CRA solution. However, the island-inducing failure event compilation process executed during the initial CRA-step could possibly need to be adapted depending on the selected CRA approach, especially in the case of an MCS-based technique. The core of our solution would still remain relevant.
- is able to provide deterministic RA indices with the same accuracy as sequential MCS's non-deterministic results when considering BESSs and/or a priority-based LSS during islanded operation.

5.1 Assumptions

Our proposed RA method rely on multiple assumptions, which are either central to the solution formulation or simplifying assumptions which can be circumvented by applying minor modifications to the framework. For each simplifying assumption, a description of the modification(s) to the algorithm to account for the more general case will be presented.

Failure Occurrence A failure always has the same probability of occurrence at all time during the year, i.e., the distribution of island-inducing failure events is uniform. In our proposed methodology, this entails that the DTMC's aggregated results are compiled based on the average of all individual results from the simulated island inducing failure events.

This is however not a mandatory assumption of the analysis. If the failure events distribution is non-uniform, then the DTMC aggregated results would instead be computed as a weighted average based on the known distribution of the events. For instance in Quebec, weather does have an impact on the expected interruption frequency of distribution systems. Icing and snow storms increase the likelihood of tree branches to fall under the additional weight on overhead lines. Therefore, it is reasonable to assume that in some geographical settings the failure event distribution can vary from one period of the year to the next.

Failures Correlation There is no correlation between failure events, meaning that one failure event does not change the probability of another failure event to occur. This assumption enables us to evaluate independently the impact each possible fault on the system.

Failure Duration The duration of a failure event is relatively short, i.e., it is calculated in terms of hours, not days. This is related to the fact that we are interested in the system's reliability, i.e., we are evaluating low impact, high probability events such as an overhead line short-circuit, not its resiliency, which focuses on evaluating high impact, low frequency extraordinary events, e.g., extreme weather events such as hurricanes [52].

This assumption is consequently inherent to the type of analysis at hand.

Simultaneous Failures Multiple failure events, and therefore also multiple island-inducing failure events, do not occur simultaneously. This assumption is reasonable as power distribution networks are fairly reliable systems. This means that the probability of a failure event occuring at any given instant is already low, and as stated above already, its duration is relatively short. The probability of two or more simultaneous events which would also be overlapping in their interrupted zones during the fault isolation and/or restoration phases can be considered as negligible.

DDER Energy Resource Availability The primary source of energy used by DDERs to supply the system is considered to always be available. This means that the resource consumption of DDERs can be ignored and that these generators are always able to generate up to their rated capacity at any given instant, independently of the islanding duration. This modelling assumption is consistent with the *Failure Duration* assumption.

DER Availability DERs are considered to be fully reliable during islanded operation. In this context, this refers not to the availability of the source of energy they tap into, i.e., wind speed and solar irradiance, but rather to the fact that these microgrid components are always ready for operation at any given instant.

The DER unavailability could be modelled in our framework by multiplying the number of executions of the DTMC method to execute by the combinations of DER availability states. This is however impractical as the required number of simulations grows exponentially (2^n where n is the number of DER units which can individually fail).

A more reasonable approach would be to execute the simulation for a given number of DER availability states such that the total probability of these states is over $X\%$, similarly to [11]. Considering the reliability figures given in [28] for NDDERs reliability, each PV and WT unit would be down 1.6% and 2.7% of the year, respectively. A small number of DER availability states should suffice to obtain a given level of precision, without the need of enumerating all possible combinations.

Microgrid Operational Mode Transition After electrical disconnection from the main grid, a microgrid quickly, i.e., in under five minutes, transitions to islanded operation.

This is not a mandatory assumption, but transitions in over 5 minutes mean that microgrid customers would be considered as experiencing a sustained interruption as per the IEEE1366-2022 standard [47], and consequently that SAIFI would be unaffected by microgrid island operation, i.e., it would remain at the value computed by CRA.

Microgrid Load Shedding Strategy If the microgrid control system implements an LSS, then the strategy is based on a predetermined sequence of load curtailment/shedding operations, i.e., priority-based LSS. Our methodology rely on strategies for which the number of possible states is finite and the applied sequence of shedding/curtailment actions are known before running the analysis. This ensure that the enumeration of all possible LSS states is achievable and include them in the microgrid's state vector prior to the analysis execution.

Microgrid Spatial Distribution Embedded microgrids in distribution systems are considered to be geographically localized systems, i.e., the available energy resources is considered to be the same for all microgrid NDDERs. This means that a perfect positive correlation exists between the energy resources available at any NDDER location.

This is not a mandatory assumption. If the correlation is not 1, then historical data can be leveraged to calculate the correlation in energy resource available at every NDDER location and obtain a more realistic representation of the total power output of a given NDDER type. The method proposed in [26] could be used to that effect.

Solar and Wind Correlation Wind speed and solar irradiance are considered to have no correlation.

This assumption was made in Chapter 4 and is similar to the *Microgrid Spatial Distribution* assumption. It allows us to use a convolution to compute the probabilistic distribution of the total microgrid available generation. The algorithm proposed in [26] could again be used to calculate the correlation between these variables if no correlation cannot be assumed.

Steady-State Simulation The microgrid adequacy assessment is based on steady-state simulation assumptions. Transient phenomena, e.g., switching transition to disconnect the microgrid, and frequency/voltage drops or rises, are not considered.

There are some limitations with our RA solution based on the assumptions described above. First, ignoring to assess the feasibility of the switching operation during island formation means that the algorithm tends to be too optimistic regarding the microgrid's islanded operation [23]. Furthermore, the steady-state assumption also imply that frequency control and voltage control during islanded operation are not considered in the analysis because the time interval between evaluated timesteps is far greater than the time horizon in which these controls operate. For instance, the DER ramping rate constraints could lead to additional shedding or curtailment of loads during islanded operation. Assuming DER availability at all time is also a slightly optimistic assumption. Some DER units could be out for maintenance or for repair. The local generation capacity of the system would then be lower than in nominal operating conditions.

Considering the aforementioned factors would reduce the evaluated islanded microgrid's PoA. Our methodology therefore underestimates to some extent the number of interrupted customers and the duration of interruption for each one of them. Consequently, our RA technique will overall provide slightly optimistic reliability indices compared to what is really expected.

5.2 Other Considerations

An important aspect to consider with our proposed approach is the impact of the BESS discretization that is applied to reduce the state space of the BESS-equipped microgrid. This discretization could affect the accuracy of the simulation results. The discretization error depends on multiple factors, such as the energy step size ΔE, the contribution of the BESS in the overall local generation, the minimum load relief achieved by applying an LSS action, etc. The energy step size used in a simulation has to be calibrated to offer a realistic model of the evolution of the BESS state of charge without increasing too much the number of possible states because more BESS states consequently require more time to initialize the transition matrices.

Figure 5.1 provides an example of the average error made by our approach on the microgrid's AA results (expected number of interrupted customers, number of interrupted customers duration and energy not supplied) depending on the number of modelled BESS states (which is inversely proportional to the step size of ΔE) when taking the average sequential MCS results obtained over 15 executions as the ground truth. This figure was obtained by using Scenario 3 of the case studies presented in Chapter 4, i.e., a BESS-equipped microgrid with no LSS, with a simulated time horizon of $N_T = 24$ hours.

As we can see from Figure 5.1, the average error made depends heavily on the number of BESS states. After a given threshold value, the average error on the AA results obtained with our solution remains under 2%.

The transition matrices generation presented in Chapter 4 is based on an element-based initialization. This approach is inefficient as it would require n^2 element-wise initializations for each one of the N_T matrices required by the simulation. There are however symmetries and patterns in our problem formulation that can be leveraged to more efficiently create these matrices. For instance, in the BESS-equipped microgrid case, the number of required element-wise initializations can be reduced down to at worst $3n$.

Finally, our methodology is also applicable to users that do not have time-series loading data readily available. In this case, the number of transition matrices to construct will be greatly reduced and our approach will still be able to consider approximately the time-dependence of the interruption duration on the microgrid's PoA, which is still an improvement on many analytical RA techniques which do not consider time-dependencies.

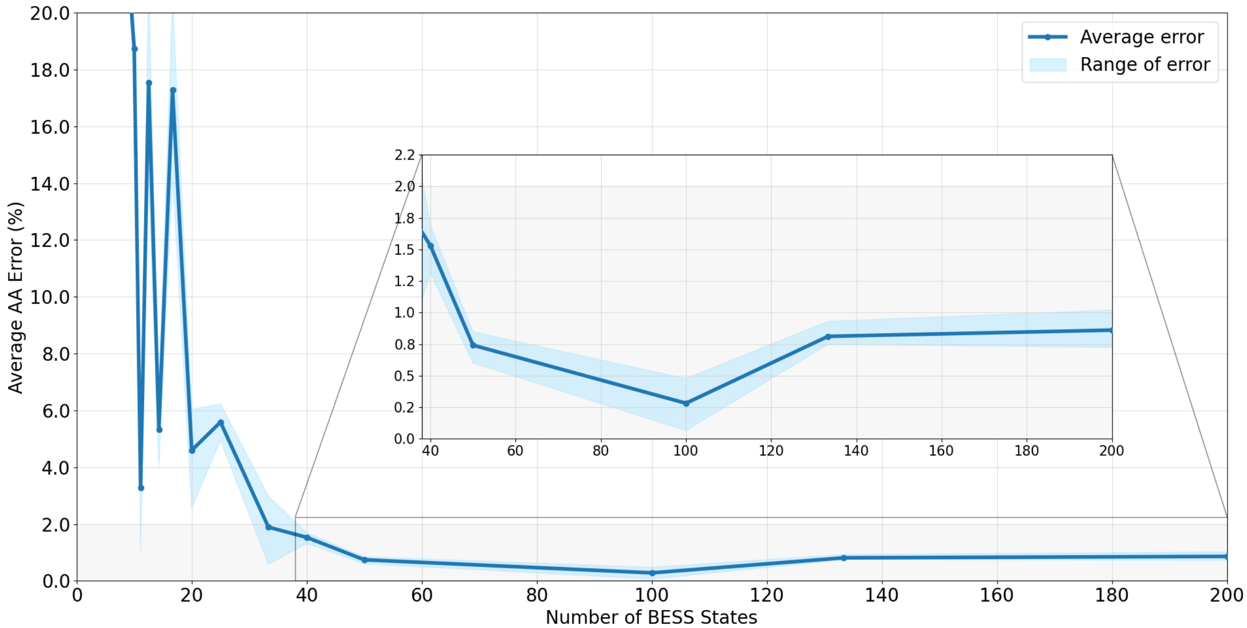

Figure 5.1 Adequacy Assessment Average Error Depending on the Number of BESS States

CHAPTER 6 CONCLUSION AND RECOMMENDATIONS

In this Master's Thesis, we propose a novel decoupled, time-based, and analytical reliability and adequacy assessment methodology for distribution systems embedded with microgrids. Our approach combines a MinCS approach with a DTMC to evaluate the system's reliability. The MinCS-based CRA technique first evaluates the distribution system's reliability by artificially assuming that all microgrid customers are necessarily interrupted whenever a fault on the network causes the microgrid to be electrically isolated from the main power supply. The microgrid islanded power adequacy capability is then evaluated using a DTMC approach to consider the inherent time-dependencies of this system. Finally, results from the DTMC simulation are used to adjust MinCS method's initially computed reliability indices to obtain the actual expected reliability indices of the modern distribution network. As demonstrated in our numerical case studies, our analytical time-based AA approach leads to the same results as the equivalent sequential MCS approach.

Our work emphasizes the need for time-based reliability assessment techniques when evaluating the impact of microgrids within the power grid. Ignoring the impact of time dependant factors of islanded microgrid operation, such as the interruption instant and duration, the BESS state of charge, the LSS state and the sequence of time-varying demand, will inevitably produce inaccurate reliability results, leading distribution planners and operators to take inadequate decisions related to the overall system's expected reliability performance.

The only RA methods put forward in the literature to consider these factors are MCS-based solutions, i.e., sequential MCS and pseudo-sequential MCS. However, these approaches have a high computational burden due to the need for numerous simulations. Furthermore, MCS methods necessarily produce different results in each run because of the repeated random sampling required by these algorithms. Our methodology is able to tackles both of these issues. First, it does not rely on the evaluation of large number of scenarios to compute the indices, leading to a lower expected computational cost for our solution. Second, our formulation produces repeatable and deterministic results for the same input conditions. These two advantages of our approach are crucial for a practical software implementation of a microgrid-aware RA methodology, such as in CYME's power system analysis software, to ensure the usability of the analysis and the confidence in the results for the user. As mentioned previously, our framework is also flexible and can be adapted based on the amount of information known about the systems and its natural phenomena.

Finally, there are multiple research opportunities to enhance our solution or to leverage it in other types of analyses. These future work perspectives are presented next.

6.1 Future Work

Our work has established a time-series analytical RA framework to tackle the AA problem of islanded microgrids. Future research avenues could include the operationalization of our simulator to optimally size the microgrid's BESS, the calibration of the BESS energy step size, the inclusion in our solution of a time-series CRA method, and the enhancement of our AA formulation by considering active and reactive power demand and constraints, as well as developing a multi-phase adaptation of our approach. Finally, our proposed algorithm could be enhanced to improve its computational time and memory usage. These considerations are discussed next.

6.1.1 Optimal Microgrid Battery Energy Storage System Sizing

Our RA method could be leveraged for microgrid BESS optimal sizing, both in terms of its rated capacity and its rated discharge power, i.e., its C-rate. The optimization would be based on the total costs and benefits of the BESS. More specifically, it would consider the total BESS cost (material, installation, operation, decommissioning) and the expected additional revenues made through energy sales based on the reduction in ENS during islanded operation resulting from the enhanced BESS-equipped microgrid's adequacy capability. This optimization problem would leverage our method to quickly compute ENS for a given set of BESS specifications.

Note that this proposed analysis would provide a first approximation of the BESS sizing required for maximal positive return on investment based on the increased reliability provided by the component in islanded operation. The practical implementation of such a system would still have to be thoroughly evaluated through transient and steady-state simulations in divers scenarios to ensure the feasibility of the BESS project.

6.1.2 BESS States Calibration

The BESS states discretization is currently an input parameter of our approach, similarly to [35]. This is not ideal as this should not be left to the user to define this because the determination of this value depends on multiple factors, some of which have been presented in Chapter 5. It would, therefore, be interesting to enhance our methodology by developing a closed-form expression, or at least an empirical rule, which would allow us to properly calibrate the value of ΔE such that the number of BESS states is approximately minimized while still ensuring a reasonable level of accuracy in the obtained AA results. In the example presented in Figure 5.1, it is evident that, in this context, a minimum of around 40 BESS states are required for accurate simulation results. The marginal benefit of increasing the number of BESS states over this value is limited as illustrated in Figure 5.1.

The problem would most likely require an analysis of the BESS characteristics, the local available generation, and the total demand at all simulated time and in all possible LSS states, to determine the minimum value required. Moreover, this value could also potentially be determined based on the impact that the microgrid islanded operation has on the overall system reliability results. In this case, if the interruption results initially computed for island-inducing fault events in the CRA simulation for the microgrid account for a negligible fraction of the system's results, the required AA accuracy could be decreased by reducing further the number of required BESS states, thereby lowering also the simulation time.

Another interesting line of research would be to assess if it could be beneficial to modulate this discretization of states used in the simulation. This modulation could potentially accelerate the simulation by modelling fewer BESS states during certain segments of the analysis where precise BESS state of charge modelling would not really impact the interruption results, e.g., islanded operation during periods of high DER generation to load ratio, while using many BESS states in some other cases, e.g., during islanded operation periods where the BESS contribution is critical to the microgrid's survival.

6.1.3 Time-Based Conventional Reliability Assessment

The CRA technique currently used in our proposed method is based on the RA analysis provided by CYME's power system analysis software. This analysis is currently executed on a static network model (i.e., single network model, single network configuration, single loading state, etc.) to compute the CRA's yearly expected reliability indices. To the best of our knowledge, the RA techniques available in the literature all assume a static network model in the assessment, similarly to CYME's current RA analysis. This approach leads to accurate results when doing a short-term RA because the as-built network during the simulated period will not differ significantly from the simulated network model. However, this approach has two main limitations for mid- to long-term planning purposes.

First, the distribution system does not remain static through time. New customer interconnections (new loads and new DERs), topological changes (load transfers) based on seasonal loading or mitigation projects, planned projects (e.g., installation of new protection and sectioning device(s)), system expansions (e.g., new feeder), etc. will impact the system's behaviour from a reliability standpoint. These changes will happen at different instants in the future. The timing of these modifications to the distribution system, and the influence that they will have on the system's reliability are non-negligible and should therefore be included in the assessment, especially when determining the expected future reliability performance of the system.

Second, when the reconfiguration restoration scheme is used by the utility, basing the RA analysis on single demand state will neglect the time-varying capacity margin of the adjacent feeder(s) to supply momentarily interrupted customers during a failure event [28]. There is therefore a correlation between the system's loading through time and its expected reliability indices over that same period.

To resolve the two limitations above, the evolution of the network model through time has to be considered in the CRA methodology. The development of such a technique would be interesting to explore in future research.

6.1.4 Adequacy Assessment Formulation

The power adequacy capability of the microgrid at any given timestep in our presented methodology is currently determined by comparing the *active power* demand with the available *active generation* of the installed DERs. To the best of our knowledge, all AA techniques for islanded microgrid operation evaluate the microgrid's power adequacy based solely on active power, similarly to what was presented in this Master's thesis. This, however, ignores the reactive power adequacy from the power balance, which could be a constraining factor depending on the local DDERs active, reactive, and apparent power ratings. Assessing the microgrid's power adequacy while considering both active and reactive power would therefore improve the accuracy of the simulation.

The AA techniques found in the literature, including ours in its current formulation, compute the microgrid's power adequacy capability based on the total generation compared to the total demand at a given time. The calculation therefore assumes implicitly that the system is balanced. However, distribution networks are unbalanced systems, both in terms of the load demand and of the installed DER generation. The RA results currently obtained are therefore optimistic, because they do not consider that the power balance has to be achieved on every phase of the microgrid. Moreover, the applied load curtailment/shedding LSS actions will not have the same load relief on each phase. Developing a multi-phase formulation of our method could thus also be a key future research opportunity to increase its modeling accuracy.

Finally, the load shedding strategy considered in our proposed method is based on a predefined list of actions that can be applied on non-critical and controllable loads. This, however, does not consider specifically the behavior of thermostatically controlled loads. The LSS could therefore be enhanced the more accurately model this type of load.

6.1.5 Algorithm Enhancements

The previous sections have already presented ways to improve the required computation time and memory usage of our proposed method, such as strategically initializing the transition matrices by taking advantage of its structure, and calibrating and/or modulating the number of BESS states simulated. There are additional approaches to further enhance the implementation of our DTMC-based algorithm:

1. The periodic nature of the customers load demand through time could be leveraged by clustering the customers time-series load profiles, e.g., creating a 24-hour typical day profile for each simulated month. This would reduce the number of islanded instants t_0 that would need to be iterated during simulation because multiple hourly islanded instants would be linked to the results of a single DTMC calculation at a given t_0 value. Reducing the required number of islanded instants to simulate also mean that the number of transition matrices to initialize is also reduced, thereby accelerating the analysis execution.

2. Window sliding could be leveraged in our proposed algorithm instead of pre-computing all transition matrices before simulating the microgrid state evolution for all possible islanded-instants in the simulated time interval. The algorithm would still iterate sequentially through every possible islanded-instant t_0 in the simulated time interval, but only the transition matrices relevant for the currently computed specific microgrid state evolution would be kept in memory, thereby reducing significantly the memory usage of the method as shown in Figure 6.1.

3. Multiprocessing can easily be implemented in our proposed algorithm to improve the computational time because the microgrid state evolution simulation at islanded instant

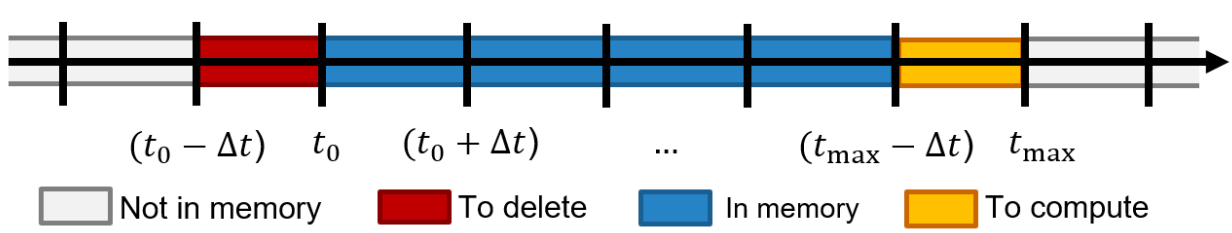

Figure 6.1 Sliding window for a given DTMC calculation at islanded instant t_0

t_0 is independent from all other islanded instants simulations. The set of islanded instants to simulated could thus be separated evenly across all utilized central processing units to parallelize the calculation.

4. Practical microgrid projects are sized to be able to met the local power demand in most circumstances. In this context, simulating every possible islanded instant might be a waste of computational resources as the power adequacy might be guaranteed in some scenarios. A preprocessing step could be added to our method to strategically determine the set of islanded instants which should be simulated to evaluate the power adequacy capability of the islanded system. The islanded instants which would not be in that set would be ignored during the analysis. This additional step would allow to reduce the number of instants to simulate, and therefore the number of transition matrices to initialize, thereby reducing the computational time required by the method.

The algorithmic enhancements detailed above along with those discussed in the previous sections could all jointly be implemented in our proposed method to greatly reduce the computational time and memory usage.

REFERENCES

[1] A. Escalera, B. Hayes, and M. Prodanović, "A survey of reliability assessment techniques for modern distribution networks," *Renewable and Sustainable Energy Reviews*, vol. 91, pp. 344–357, Aug. 2018.

[2] A. Pregelj, M. Begovic, and A. Rohatgi, "Recloser allocation for improved reliability of DG-enhanced distribution networks," *IEEE Transactions on Power Systems*, vol. 21, no. 3, pp. 1442–1449, Aug. 2006.

[3] J. Shi, L. Ma, C. Li, N. Liu, and J. Zhang, "A comprehensive review of standards for distributed energy resource grid-integration and microgrid," *Renewable and Sustainable Energy Reviews*, vol. 170, p. 112957, Dec. 2022.

[4] K. Horowitz, Z. Peterson, M. Coddington, F. Ding, B. Sigrin, D. Saleem, S. E. Baldwin, B. Lydic, S. C. Stanfield, N. Enbar, S. Coley, A. Sundararajan, and C. Schroeder, "An overview of distributed energy," *Renewable Energy*, 2019.

[5] J. L. López-Prado, J. I. Vélez, and G. A. Garcia-Llinás, "Reliability evaluation in distribution networks with microgrids: Review and classification of the literature," *Energies*, vol. 13, no. 23, p. 6189, Jan. 2020.

[6] C. L. T. Borges, "An overview of reliability models and methods for distribution systems with renewable energy distributed generation," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 6, pp. 4008–4015, Aug. 2012.

[7] "IEEE Standard for the Specification of Microgrid Controllers," *IEEE Std 2030.7-2017*, pp. 1–43, Apr. 2018.

[8] N. N. A. Bakar, M. Y. Hassan, M. F. Sulaima, M. N. Mohd Nasir, and A. Khamis, "Microgrid and load shedding scheme during islanded mode: A review," *Renewable and Sustainable Energy Reviews*, vol. 71, pp. 161–169, May 2017.

[9] E. Zarate-Perez, E. Rosales-Asensio, A. González-Martínez, M. de Simón-Martín, and A. Colmenar-Santos, "Battery energy storage performance in microgrids: A scientific mapping perspective," *Energy Reports*, vol. 8, pp. 259–268, Nov. 2022.

[10] S. Koohi-Fayegh and M. A. Rosen, "A review of energy storage types, applications and recent developments," *Journal of Energy Storage*, vol. 27, p. 101047, Feb. 2020.

[11] Y. Guo, S. Li, C. Li, and H. Peng, “Short-term reliability assessment for islanded microgrid based on time-varying probability ordered tree screening algorithm,” *IEEE Access*, vol. 7, pp. 37 324–37 333, 2019.

[12] A. A. Eajal, A. El-Awady, E. F. El-Saadany, K. Ponnambalam, A. Al-Durra, A. S. Al-Sumaiti, and M. M. A. Salama, “A bayesian approach to the reliability analysis of renewables-dominated islanded DC microgrids,” *IEEE Transactions on Power Systems*, vol. 36, no. 5, pp. 4296–4309, Sep. 2021.

[13] S. Conti, R. Nicolosi, and S. A. Rizzo, “Generalized systematic approach to assess distribution system reliability with renewable distributed generators and microgrids,” *IEEE Transactions on Power Delivery*, vol. 27, no. 1, pp. 261–270, Jan. 2012.

[14] K. Zou, A. P. Agalgaonkar, K. M. Muttaqi, and S. Perera, “An analytical approach fo reliability evaluation of distribution systems containing dispatchable and non-dispatchable renewable DG units,” *IEEE Transactions on Smart Grid*, vol. 5, no. 6, pp. 2657–2665, Nov. 2014.

[15] J. L. López-Prado, J. W. González-Sánchez, J. I. Vélez, and G. A. Garcia-Llinás, “Reliability assessment in rural distribution systems with microgrids: A computational-based approach,” *IEEE Access*, vol. 10, pp. 43 327–43 340, 2022.

[16] W. Wangdee and R. Billinton, “Considering load-carrying capability and wind speed correlation of WECS in generation adequacy assessment,” *IEEE Transactions on Energy Conversion*, vol. 21, no. 3, pp. 734–741, Sep. 2006.

[17] X. Song, Y. Zhao, J. Zhou, and Z. Weng, “Reliability varying characteristics of PV-ESS-based standalone microgrid,” *IEEE Access*, vol. 7, pp. 120 872–120 883, 2019.

[18] P. Wang, Z. Gao, and L. Bertling, “Operational adequacy studies of power systems with wind farms and energy storages,” *IEEE Transactions on Power Systems*, vol. 27, no. 4, pp. 2377–2384, Nov. 2012.

[19] L. F. Rocha, C. L. T. Borges, and G. N. Taranto, “Reliability evaluation of active distribution networks including islanding dynamics,” *IEEE Transactions on Power Systems*, vol. 32, no. 2, pp. 1545–1552, Mar. 2017.

[20] O. A. Ansari, N. Safari, and C. Y. Chung, “Reliability assessment of microgrid with renewable generation and prioritized loads,” in *2016 IEEE Green Energy and Systems Conference (IGSEC)*, Nov. 2016, pp. 1–6.

[21] Y.-F. Li and E. Zio, "A multi-state model for the reliability assessment of a distributed generation system via universal generating function," *Reliability Engineering & System Safety*, vol. 106, pp. 28–36, Oct. 2012.

[22] Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, R. Seethapathy, M. Assam, and S. Conti, "Adequacy evaluation of distribution system including wind/solar DG during different modes of operation," *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 1945–1952, Nov. 2011.

[23] S. Wang, Z. Li, L. Wu, M. Shahidehpour, and Z. Li, "New metrics for assessing the reliability and economics of microgrids in distribution system," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 2852–2861, Aug. 2013.

[24] M. M. Ghahderijani, S. M. Barakati, and S. Tavakoli, "Reliability evaluation of stand-alone hybrid microgrid using Sequential Monte Carlo Simulation," in *2012 Second Iranian Conference on Renewable Energy and Distributed Generation*, Mar. 2012, pp. 33–38.

[25] G. Tina, S. Gagliano, and S. Raiti, "Hybrid solar/wind power system probabilistic modelling for long-term performance assessment," *Solar Energy*, vol. 80, no. 5, pp. 578–588, May 2006.

[26] Z. Qin, W. Li, and X. Xiong, "Incorporating multiple correlations among wind speeds, photovoltaic powers and bus loads in composite system reliability evaluation," *Applied Energy*, vol. 110, pp. 285–294, Oct. 2013.

[27] X. Xu, J. Mitra, T. Wang, and L. Mu, "Evaluation of operational reliability of a microgrid using a short-term outage model," *IEEE Transactions on Power Systems*, vol. 29, no. 5, pp. 2238–2247, Sep. 2014.

[28] G. Celli, F. Pilo, and G. G. Soma, "Reliability assessment in smart distribution networks," *Electric Power Systems Research*, vol. 104, pp. 164–175, Nov. 2013.

[29] X. Han, Y. Qu, P. Wang, and J. Yang, "Four-dimensional wind speed model for adequacy assessment of power systems with wind farms," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 2978–2985, Aug. 2013.

[30] P. Giorsetto and K. F. Utsurogi, "Development of a new procedure for reliability modeling of wind turbineg enerators," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-102, no. 1, pp. 134–143, Jan. 1983.

[31] S. Sarkar and V. Ajjarapu, "MW resource assessment model for a hybrid energy conversion system with wind and solar resources," *IEEE Transactions on Sustainable Energy*, vol. 2, no. 4, pp. 383–391, Oct. 2011.

[32] C. Chen, W. Wu, B. Zhang, and C. Singh, "An analytical adequacy evaluation method for distribution networks considering protection strategies and distributed generators," *IEEE Transactions on Power Delivery*, vol. 30, no. 3, pp. 1392–1400, Jun. 2015.

[33] K. G. T. Hollands and R. G. Huget, "A probability density function for the clearness index, with applications," *Solar Energy*, vol. 30, no. 3, pp. 195–209, Jan. 1983.

[34] L. Yu, S. Gao, and Y. Liu, "Pseudo-sequential Monte Carlo simulation for distribution network analysis with distributed energy resources," in *2015 5th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT)*, Nov. 2015, pp. 2684–2689.

[35] P. Paliwal, N. P. Patidar, and R. K. Nema, "A novel method for reliability assessment of autonomous PV-wind-storage system using probabilistic storage model," *International Journal of Electrical Power & Energy Systems*, vol. 55, pp. 692–703, Feb. 2014.

[36] S. Kennedy, "Reliability evaluation of islanded microgrids with stochastic distributed generation," in *2009 IEEE Power & Energy Society General Meeting*, Jul. 2009, pp. 1–8.

[37] S. Conti, S. A. Rizzo, E. F. El-Saadany, M. Essam, and Y. M. Atwa, "Reliability assessment of distribution systems considering telecontrolled switches and microgrids," *IEEE Transactions on Power Systems*, vol. 29, no. 2, pp. 598–607, Mar. 2014.

[38] S. Conti and S. A. Rizzo, "Monte Carlo simulation by using a systematic approach to assess distribution system reliability considering intentional islanding," *IEEE Transactions on Power Delivery*, vol. 30, no. 1, pp. 64–73, Feb. 2015.

[39] X. Song, Y. Sun, F. Wang, and W. Xu, "A novel sequential sampling algorithm for reliability assessment of microgrids," *IEEE Access*, vol. 8, pp. 134 468–134 479, 2020.

[40] Z. Shu and P. Jirutitijaroen, "Latin Hypercube Sampling Techniques for power systems reliability analysis with renewable energy sources," *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2066–2073, Nov. 2011.

[41] P. M. Costa and M. A. Matos, "Assessing the contribution o microgrids to the reliability of distribution networks," *Electric Power Systems Research*, vol. 79, no. 2, pp. 382–389, Feb. 2009.

[42] R. E. Brown, *Electric Power Distribution Reliability*, 1st ed. New York: CRC Press, 2002.

[43] S. Repo, S. Lu, T. Pöhö, D. D. Giustina, G. Ravera, J. M. Selga, and F. A.-C. Figuerola, "Active distribution network concept for distributed management of low voltage network," in *IEEE PES ISGT Europe 2013*, 2013, pp. 1–5.

[44] A. Hirsch, Y. Parag, and J. Guerrero, "Microgrids: A review of technologies, key drivers, and outstanding issues," *Renewable and Sustainable Energy Reviews*, vol. 90, pp. 402–411, Jul. 2018.

[45] S. Conti, G. Faraci, A. La Corte, R. Nicolosi, S. A. Rizzo, and G. Schembra, "Effect of islanding and telecontrolled switches on distribution system reliability considering load and green-energy fluctuations," *Applied Sciences*, vol. 6, no. 5, p. 138, May 2016.

[46] R. Billinton and W. Li, *Reliability Assessment of Electric Power Systems Using Monte Carlo Methods*. Boston, MA: Springer US, 1994.

[47] "IEEE Guide for Electric Power Distribution Reliability Indices," *IEEE Std 1366-2022 (Revision of IEEE Std 1366-2012)*, pp. 1–44, Nov. 2022.

[48] J.-W. Lauzon, I. Kocar, and A. Lesage-Landry, "Microgrid-aware," *IEEE Transactions on Power Systems*.

[49] A. Leite, C. Borges, and D. Falcao, "Probabilistic wind farms generation model for reliability studies applied to brazilian sites," *IEEE Transactions on Power Systems*, vol. 21, no. 4, pp. 1493–1501, Nov. 2006.

[50] R. Allan, R. Billinton, I. Sjarief, L. Goel, and K. So, "A reliability test system for educational purposes-basic distribution system data and results," *IEEE Transactions on Power Systems*, vol. 6, no. 2, pp. 813–820, May 1991.

[51] M. Roos, M. Faizan, P. Nguyen, J. Morren, and J. Slootweg, "Probabilistic adequacy and transient stability analysis for planning of fault-initiated islanding distribution networks," in *2021 IEEE Madrid PowerTech*, Jun. 2021, pp. 1–6.

[52] A. M. Stanković, K. L. Tomsovic, F. De Caro, M. Braun, J. H. Chow, N. Čukalevski, I. Dobson, J. Eto, B. Fink, C. Hachmann, D. Hill, C. Ji, J. A. Kavicky, V. Levi, C.-C. Liu, L. Mili, R. Moreno, M. Panteli, F. D. Petit, G. Sansavini, C. Singh, A. K. Srivastava, K. Strunz, H. Sun, Y. Xu, and S. Zhao, "Methods for analysis and quantification of power

system resilience," *IEEE Transactions on Power Systems*, vol. 38, no. 5, pp. 4774–4787, Sep. 2023.