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Metrics and quantitative framework for assessing microgrid resilience against windstorms

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ABSTRACT

Recent extreme weather events have emphasized the need for new methods and metrics to assess the power system resilience in response to high-impact low-probability (HILP) events. Microgrids (MGs) have been instrumental in such occasions for maintaining the power supply continuity to local customers. This paper provides a quantitative framework for assessing the MG resilience in response to HILP windstorms. The proposed framework jointly employs fragility curves of overhead distribution branches and windstorm profile to quantify the degradation in the MG performance (particularly supplied load in this work). The proposed analytical method is simple and computationally efficient which offers a quick means for getting knowledge about adverse impacts of an approaching windstorm and taking preventive measures accordingly. A set of normalized metrics is defined which provides a comparable tool for assessing the resilience in various operating conditions and power systems. The impacts of restorative actions, the system reinforcement, and the event severity on resilience curves and metrics are also investigated. The effectiveness of the proposed approach in response to an extreme windstorm is examined on a real-scale MG test bed.

1. Introduction

Power systems have conventionally been protected against low-impact high-probability events rendered by equipment breakdowns, human mistakes, or external interferences. The traditional protection schemes often ensured a reasonable level of reliability for power delivery to local customers [1,2]. The high-impact low-probability (HILP) events (i.e., extreme events) may also cause rare power outages with significantly greater damages in which socioeconomic impacts can extensively be stretched to larger and unpredictable parts of the power system [3]. Examples of these events include natural events such as hurricanes, typhoons, windstorms, blizzards, floods, earthquakes, as well as intentional cyber or physical attacks, and cascading failures [4–13]. The power system resilience is the ability of a power system to respond to HILP events and focuses on how rapidly and efficiently the power system can be restored to its pre-event operation state [3–5].

Appropriate metrics and modeling techniques are key elements in quantitative assessment of power system resilience. Unlike routine outages, HILP power outages may not be properly measured by reliability metrics which emphasize the duration and the frequency of power outages or the amount of energy not supplied. Although reliability indices can offer human operators with additional insight on the abnormal behavior of power systems, the static nature of these indices make them unsuitable for measuring the spatiotemporal impacts of HILP events on power grids [4]. New metrics are thus in essence for assessing the power system resilience.

Impacts of weather-originated HILP events on power systems are generally modeled by means of analytical and Monte Carlo (MC) simulation techniques. Analytical techniques are more applicable for small-scale power systems due to their simplicity and computational efficiency while simulation techniques are preferred for complex systems [14].

The literature on the power system resilience was reviewed in [15]. Refs. [14,16] made a comprehensive discussion on impacts of extreme events on the power system resilience. Authors in [14] presented a detailed discussion on modeling techniques for the assessment of adverse impacts on power systems incurred by weather-oriented HILP events. A few references in the literature presented conceptual (qualitative) frameworks for the power system resilience assessment using fragility curves of components [1,4,14,17]. Authors in [18] presented an uncertain risk assessment for catastrophic accidents based on a fuzzy approach. Ref. [19] employed a sequential MC-based time-series simulation method to quantify the adverse impacts of windstorms on power grid resilience. Reliability indices *LOLF* (loss of load frequency)

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Nomenclature

Indices and sets

b	index for distribution branches
s	index for damage scenarios
t	index for time instants
U_s	set of branches in service in scenario s
V_s	set of branches out of service in scenario s

Parameters

DI	degradation index
F_s^{Deg}	power flow result in the degradation phase in scenario s
$F_s^{Res}(t)$	power flow result in the restoration phase in scenario s at time instant t
$F_{exp}(t)$	expected MG performance at time instant t
$M(t)$	system performance at time instant t
M_o	pre-event level of system performance
M_{pe}	post-event level of system performance
M_{pr}	post-restoration level of system performance
MRI	microgrid resilience index
$N_{p,b}$	number of poles in branch b
$P_b(t)$	failure probability of branch b at time instant t
$P_{b,l}(t)$, $P_{b,p}(t)$	failure probabilities of branch b at time instant t due to conductor and pole outages, respectively
$P_{p\_ind}(t)$	failure probability of individual poles at time instant t
$P_s(t)$	probability of scenario s at time instant t
REI	restoration efficiency index
VI	vulnerability index
t_e	starting time of the event
t_d	starting time of the degradation phase
t_{pe}	starting time of the post-event status
t_r	starting time of the restoration phase
t_{pr}	starting time of the post-restoration status
t_{ir}	starting time of the infrastructure recovery
t_{pir}	starting time of the post-infrastructure recovery status

and *LOLE* (loss of load expectation) are used to assess the effects of different resilience enhancement measures. Authors in [20] employed Markov chain and MC simulation to account for state transitions of power grids with integrated microgrids (MGs) in extreme events and calculate the indices, respectively. Traditional reliability indices including the loss of load probability (*LOLP*) and the expected demand not supplied (*EDNS*) were modified to describe the power grid survivability in extreme events. A multi-factor grid recovery index and a metric accounting for the expected number of lines on outage were also defined. Operational and infrastructure resilience metrics were introduced and calculated via a MC-based simulation method in [21] to assess the resilience of transmission grids to windstorms.

MGs, due to their inherent features, ensure a higher level of resilience against HILP events as discussed in [4,5,22–26]. A numerical assessment tool is in essence to make a judgment about the MG resilience and plan for further measures to improve it, if necessary. However, there is a gap in the literature for a simple and computationally efficient method capable of quantifying the impact of weather-oriented HILP events on MGs. In case of an approaching event (e.g., a windstorm), it is crucial to quickly get knowledge of possible impacts on the MG so that right decisions are made on proactive preventive measures. Simulation-based techniques are hardly computationally tractable entailing no unique outcome. This paper aims to respond to the need for a simple, computationally efficient, and applicable method for the MG resilience assessment. The proposed analytical method provides a probabilistic model for the degradation impacts of extreme windstorms using fragility curves of components. In contrast to simulation methods widely applied for bulk transmission grids in the literature, the proposed method is simple and computationally efficient with less number of inputs. The change in component failure probabilities (presented by fragility curves) due to temporal effects of the windstorm are accounted for which was neglected in previous works. A suite of numerical metrics is also introduced for quantifying the MG resilience. In contrast to available metrics in the literature, proposed metrics are normalized providing a comparable means for assessing the resilience in various operating conditions and MG systems. In addition, in oppose to traditional reliability indices, proposed metrics are capable of assessing the temporal response of MG against the envisaged windstorm. It is worth noting that the proposed metrics could universally be used for different extreme events. However due to inherent differences in the nature of events and impacts on the power grid, minor revisions should be applied per events (other than windstorms) given the generic framework of this paper. Finally, numerical simulations are conducted and impacts of major factors on MG resilience curve and metrics are investigated through case studies.

2. Quantification of resilience concept

The National Center for Earthquake Engineering Research has offered a general viewpoint on resilience which is applicable to critical infrastructures. This framework consists of 4Rs: robustness, redundancy, resourcefulness, and rapidity [4]. Robustness implies the ability of the system to withstand a specified level of stress or disruption without suffering significant degradation or loss of functionality. Redundancy focuses on the availability of systems, mechanisms, or elements to be activated in order to satisfy functional requirements if significant degradation or loss of functionality occurs. Resourcefulness is the potential to mobilize and apply materials, monetary, informational, technological, and human resources for the sake of diagnosing and solving problems in a prioritized manner. Rapidity is the capacity to restore the system functionality and achieve goals in a timely fashion [27]. In fact, redundancy and resourcefulness are means to achieve the stated goals of resilience, i.e., robustness and rapidity.

As the power system is affected by an extreme event, the system attributes may deteriorate form the normal state. The temporal variation of a system attribute in face of an extreme event is recognized as the system performance. Fig. 1 illustrates a typical curve for the system performance associated with an extreme event considering different MoPs (or system attributes) based on system priorities and objectives [4]. Power system performance can be represented by different MoPs such as the percentage of total or critical loads, number of supplied customers or critical customers, number of survived (or failed) components, and technical metrics such as voltage magnitude or frequency. The operator can prioritize MoPs based on the system operation strategy and objectives. Thus in this paper, the system performance is assessed by supplied load and supplied critical load indices due to high importance and priority of sustainable service delivery to customers of MG.

MG may withstand an extreme event without any significant MoP degradation. The extent of this capability depends on strength level of components provided by hardening measures [8,28], proactive measures taken prior to the event arrival [12,29], and severity of the event. Thus, (t_d–t_e) could be interpreted as a measure of system robustness.

Starting from t_d, the system performance will be downgraded before it settles at M_{pe} when the system enters the post-event state at t_{pe}. At the degradation phase, adaptive operation measures provide the system with some degree of flexibility [30], i.e., lessening the vulnerability level, (M_o–M_{pe}). A vulnerability index (*VI*) is simply introduced to