Quantifying Power Distribution System Resiliency Using Code Based Metric

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***Abstract*— It is essential to improve the resiliency of power distribution systems (PDS) with the increase in extreme weather events, number of malicious threats and consumers' need for higher reliability. This paper provides a formal approach to evaluate the operational resiliency of PDS, and quantify the resiliency of a system using a code-based metric. A combination of steady state and dynamic simulation tools is used to determine the resiliency metric. Dynamic simulation tools help with analyzing impact of short-term events, which might affect operational resiliency in long term. The proposed theoretical approach is validated using a simple power distribution system model and simulation results demonstrate the ability to quantify the resiliency using the proposed code-based metric. The time-dependent quantification of resiliency has been demonstrated on a test system of two connected CERTS microgrids.**

Keywords*— Distribution Systems, Distributed Energy Resources, Power System Operations, Renewable Integration, Resilience

I. Introduction

Resilience of Power Distribution System (PDS) has gained significant traction after impact of Superstorm Sandy (2012) on the power grid reliability. However, inadequate theoretical foundations in the definition and metrics relevant to PDS resilience challenge the practical implementation of resilience in electric utilities. PDS resilience is the ability of the network to resist discontinuity of power supply to critical loads during stressful operating conditions, and recover from any damages during the event [1-3]. PDS resilience metrics are important: (i) to justify investments in infrastructural upgrades for higher resilience and (ii) evaluate the suitability of a particular approach to be taken by an operator to adequately enhance the resilience during a contingency or attack.

Threats to normal operations of PDS (i.e., power quality events, momentary interruptions, sustained outages, brownouts, blackouts) are diverse, and have a wide range on the time-scale (i.e., a time-scale of milliseconds to several weeks). It is the objective of resilience-enabling efforts in PDS to maintain power supply to critical loads during emergencies, and maximize the time duration for which this supply can be maintained. Resilience metrics serve to capture the effectiveness of the strategy adopted to meet this objective of utilities.

Resilience metrics developed from network topology can give us an approximate resiliency measure [4], but do not capture availability of distributed energy resources to critical loads accurately in real-time. PDS state variables are susceptible to rapid and unforeseen changes. Events in the distribution system such as pole damage due to a car accident, sudden phase imbalance due to large current drawn by customers charging their electric vehicles, lightning strike, heavy rain followed by sudden drop in temperature, transients due to variable power injections by photovoltaic generation connected to the power grid, voltage spikes, etc. – affect the resiliency of the network indirectly. Most PDS enable resiliency in response to an unfavorable event, and not in anticipation of an event. This results in system downtime, leading to financial losses, safety hazards and public inconvenience. There are several commonly-cited technical barriers to a prognostic approach of enabling resilience, such as – heavy meteorological data requirement, computation expense of processing that data, incorporating artificial intelligence to enable proactive response, and lack of visibility into state parameters of the PDS.

In order to overcome the aforementioned problems, we present an approach to monitor resiliency of PDS in real-time, using steady state and dynamic simulation to study the resilience of a distribution network. Dynamic simulations help us understand unfavorable power systems events in short time-domain, and compute appropriate resilience-enhancing control signals [5]. The proposed method is superior to other decision-making tool based resilience evaluation methods [6-8] based on its ability to preserve information about resilience of the system with respect to a time-scale of an unfavorable event affecting the power system.

The main contribution of the paper is that it provides a time dependent definition of resilience and a generic code-based framework for evaluating operational resilience of a PDS. This metric can be used to compare the resilience of two different network configurations or control mechanisms.

II. Time-Dependent Definition Of Resilience

There are several working definitions of PDS resilience. Some authors have defined resilience as a function of the probability of attack and the consequence of that attack [9]. Resilience of PDS has also been defined based on the nature of attack on the system [10]. A framework to determine resilience

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based on evaluation of infrastructure, and time taken to restore to service has been proposed in [11]. However, metrics based on inventory assumes all resilience-enabling infrastructures will operate during or after contingency, and cannot be used in real-time. Cost metrics of damages incurred due to an attack has been commonly used to report a lack of resilience in the PDS [2]. The fundamental drawback of each of these definitions of resilience is that these definitions do not consider the durations of unfavorable events affecting the PDS. Consequently, the resilience metric derived using these definitions are meaningful only in the context of a specific attack, network topology, or data availability. In order to evaluate PDS resilience to transient threats (i.e. power system events like a transient voltage spike that can render transformers dysfunctional for days), digital real-time simulation (DRTS) is necessary.

Conventionally, reliability metrics (such as SAIDI, SAIFI, and MAIFI) were adequate to describe the performance of a utility in providing service to consumers. Due to increase in (i) number of reported weather-based or human-induced physical attacks on the PDS [12], (ii) energy mix of renewable and conventional power sources, and (iii) cybersecurity breaches across the power grid [13] – it has become indispensable to make the PDS resilient to these attacks. Though power system reliability and resilience are different concepts [7], they share an inherent dyadic relationship as metrics for evaluating system performance. Irrespective of the nature of the attack, its impact is best assessed by the time taken by a system to recover from the consequences of the attack. A time-domain mathematical formulation of resilience will facilitate mapping between the quantification of system performance by the two independent concepts. There are several other desirable properties in a resilience metric:

a) The resilience metric (say R) should be easily comprehensible and interpretable by operators, so that quick decisions can be made during ongoing contingencies.

b) R should be simple, robust, flexible, scalable, and applicable to any distribution system with minimal modification.

c) Computation of R should not exceed response time of distribution system control actions.

d) Interpretation of sensitivity of R should corroborate to physical changes in the network.

e) Attacks on the power system can disrupt both quality and continuity of service, for varying durations of time. It is important for R to capture both attributes of the effect of the attack on the power system. R should preserve maximum information about all the non-commensurate factors that affect PDS resilience.

f) R should be easy to implement in Distribution Management Systems (DMS), compatible with existing and future data acquisition hardware, and be easy to communicate.

From [11], it can be deduced that PDS system interruptions follow a long-tailed distribution, and impact of resilience inadequacy grows exponentially with outage duration. Thus, resilience of a PDS is function of time duration of outage, as well as the number of loads that are affected by an outage event. In order to capture these two factors, let us propose that the resilience metric of a distribution system be represented as a coded numeric value:

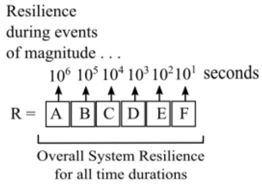

Figure 1: Proposed Resiliency Metric

where and are all variables. R is defined as such in Eq. 1, since it is proportional to power outage duration and power outage magnitude. Each variable corresponds to a time-scale of a power system event corresponding to the magnitude of its duration in seconds. Each variable in the definition of R in Eq. (1) represents the resilience of the system for corresponding duration of time outage, measured in orders of 10.

The proposed approach considers such small time-scale events into resilience evaluation in order to accommodate transient power interruptions can stop or reset operations, leading to lost productivity for long outage durations. In context of resilience, we will consider the fraction of load (*f*) *unaffected* by voltage or current distortion.

$$f = \frac{\text{Load Unaffected by PDS Event(kW)}}{\text{Total Load of PDS (kW)}} \tag{1}$$

where, for events that disrupt power continuity in f fraction of load in the magnitude of 100 seconds, the resilience value is computed on an integer scale of 0 to 9, and stored in the variable F. Similarly, for events lasting in the magnitude of minutes (i.e., 101 seconds), the resilience value is computed on an integer scale of 0 to 9, and stored in the variable E, and so forth for variables D, C, B and A.

To demonstrate the computation of each variable in R, let us consider a generic variable m, which is to represent the resilience of the PDS for an event lasting seconds. We propose an empirical equation for unscaled resilience metric as:

$$m' = (\alpha + e^{f})(1 + f) \tag{2}$$

where m' is the unscaled value of the resilience value, c is a binary variable, which stores whether an event actually happened in the considered time frame, and f is the fraction of load unaffected by the PDS event, determined from Eq. (1). Eq. (3) is formulated because resilience of a PDS is proportional to the time duration of impact it can sustain, and the fraction of loads unaffected because of the event in the network. Since fraction of unaffected loads plays a stronger role in determining resiliency of a system in conjunction to the value of (outage duration), an exponential term has been used. The term (1+f) has been used to denote the proportionality of the resilience metric to the fraction of unaffected loads. (1+f) is used instead of f to make the resiliency metric scale from one to nine.

Thus we see that each element of R is a function of time duration of the impact as well as *m'*, which itself is another function of time duration of outage (α), and dependent proportionally and exponentially on fraction of unaffected loads. Thus, in the overall resilience metric R, time duration of impact and unaffected loads has been factored in twice to highlight the importance of these factors in our definition of PDS resilience.

Eq. (2) suggests that the fraction of unaffected load exponentially influences the value of resilience; and, time scale of the event is captured through the range of α. In case of a detected PDS event, the most resilient systems will have:

$$m^{i}_{\max} = (\alpha_{\max} + e^{1})(1+1) = 25.41 \tag{4}$$

$$m^{i}_{\min} = (\alpha_{\min} + e^{0+}) = 1 \tag{5}$$

The unscaled *m'* maximum and minimum resilience value is resolved to an integer value *m* between 1 and 9 (1 for least resilient, 9 for most resilient), as shown in **Error! Reference source not found.**I. If $f = 0$, *m* is forced to store 1. Any case of no event affecting the PDS in the order of 10^{n} seconds under evaluation, *m* is represented as 0. In Eq. (5), $f = 0+$ is used instead of 0 for the most resilient state of the PDS. Otherwise, it would be impossible to distinguish an unfavorable event from non-occurrence of any unfavorable event in the PDS.

TABLE I: SCALING OF RESILIENCE METRICS

m'	1.00-3.71	3.72-6.42	6.43–9.13	9.14–11.85	11.86-14.56	14.57-17.27	17.28-19.98	19.99-22.70	22.71-25.41
m	1	2	3	4	5	6	7	8	9
	Low Resilience			Moderate Resilience				High Resilience	

Example: Consider that a transient surge affects two-thirds of entire PDS customer demand for 6.12×10^{3} seconds. However, Since the event lasts 10^{3} seconds, we have to calculate *C*. Using Eq. (2), $C' = 1(6.12+e^{0.333})\ (1+0.333) = 10.01$. From Table I, *C* is resolved to be 4. In a second event, if only one-third of the PDS customer demand is affected for the same duration due to a transient surge, $C' = 1(6.12+e^{0.667})\ (1+0.667) = 13.44$. From Table I, *C* is resolved to be 5. Thus, we can clearly see the improvement in resilience due to greater percentage of unaffected loads.

Let us assume that for a utility PDS, the resilience metric has been determined to be $R_1 = 112578$. It means that distribution system has low resilience to outages lasting in order to 10^{4} to 10^{6} seconds, but moderate to high resilience to outages lasting 10^{3} to 10^{1} seconds. If another PDS is to be compared, or another configuration of the same PDS is evaluated for resilience using the proposed method, let's say $R_2 = 113689$. The new metric shows that the resilience in continuity of service in the second PDS is higher for events lasting in order of 10^{1} to 10^{4} seconds, but the resilience to power quality events in the power system has declined. The change in resilience could be computed as $\Delta(R_1\text{-}R_2)$.

Evaluating resilience of a PDS is challenging because multiple non-commensurate factors determine resilience of a network. Variety of tools are used to enable the resilience of a PDS, such as: (i) advanced DMS algorithms based on artificial intelligence; and, (ii) devices such as smart switches, reclosers, fault-detection and isolation devices, auto-transfer switches, onsite distributed generation (diesel, natural gas, renewables), and battery storage. However, without a real-time resilience evaluation framework for quantification, it is not possible to gauge the effectiveness of the resilience-enhancement method adopted by the utility.

III. SIMULATION RESULTS & CASE STUDIES

A. *Simple One-Substation, Three Load Case Study*

The proposed resiliency evaluation approach of a distribution network is demonstrated on a PDS using MATLAB/Simulink (shown in Fig. 2). Solar power generation (maximum 5kW) is a renewable energy source. Power sources are system power, solar power generation, and a storage battery (150 V, 30 Ah). The storage battery is controlled by a battery controller, and it absorbs surplus power (if there is surplus power in the PDS) or it supplies insufficient power (if there is a power deficit in the PDS). Three Feeders consume power (2.5kW peak load) as electric loads.

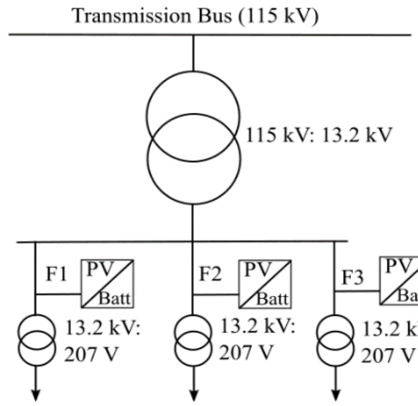

Figure 2: Example Power Distribution System

B. *Simulation Results of Simple System*

In assumed load profile, from 8pm to 4am, solar power generation is 0W. It reaches the peak amount (5kW) between 2pm and 3pm. As a typical load change in ordinary Feeders, the amount of electric power load reaches peak consumption at 9h (6,500W), 19h, and 22h (7,500W). From midnight until noon and from 6pm until midnight, battery control is performed by battery controller. The battery control performs tracking control of the current so that active power, which flows into system power from the secondary side of the pole transformer, is set to 0. Then, the active power of secondary side of the pole-mounted transformer is always around zero. The storage battery supplies the insufficient current when the power of the PDS is insufficient and absorbs surplus current from the PDS when its power surpasses the electric load. From noon until 6pm, battery control is not performed. SOC (State of Charge) of the storage battery is fixed to a constant and does not change since charge or discharge of the storage of the example PDS.

Resilience results from different PDS operating conditions are summarized in Table II. In Table II, by comparing R1 and R2, it can be concluded that addition of PV and Battery to the PDS increases the resilience of the network to long power outage events.

TABLE II: RESILIENCE METRICS OF SIMPLE SYSTEM CASE STUDY

Duration of Event (seconds)	***Affected Loads in simulation scenario***	***Code***	***With No PV, but only Battery***		***With PV and Battery***	
			Resilience Value (m)	***Scaled Value*** **(R_1)**	***Resilience Value***	***Scaled Value*** **(R_2)**
10^6	Feeder 1, Feeder 2, Feeder 3 *[Simulation method: Disconnected from the utility for indeterminate time]*	A	1.67	**1**	6.53	**3**
10^5	Feeder 1, Feeder 2, Feeder 3 *[Simulation method: trip breaker on Feeder 3 and eliminate the section for subsequent simulations]*	B	1.86	**1**	23.78	**9**
10^4	Feeder 2, Feeder 3 *[Simulation method: trip breaker on Feeder 3]*	C	23.78	**9**	23.78	**9**
10^3	Feeder 1, Feeder 2, Feeder 3 *[Simulation method: disconnection of all feeders from substation]*	D	18.56	**7**	23.78	**9**
10^2	Feeder 3 *[Simulation method: timed disconnection and reconnection to PDS of feeder 3 load – battery brought online immediately after disconnection from utility]*	E	1.00	**1**	21.84	**8**
10^1	Feeder 3 *[Simulation method: Rapid application and clearing of fault within few cycles]*	F	1.67	**1**	1.67	**1**

C. Simulation Results on Multiple Microgrid CERTS System

CERTS Microgrid concept was defined as a group of distributed generators and storage with the ability to separate and island itself from the utility grid seamlessly with minimal disruption to the connected loads. Two microgrids, located adjacent to each other (shown in Fig. 3), can be operated together to take advantage of shared resources and maintaining power to critical loads of both microgrids.

TABLE III: CERTS MICROGRID LOAD & GENERATION PARAMETERS

Source	Node	Capacity (kVA)		Microgrid
DG1	8	262		1
DG2	16	262		2
Priority	**Load Node**	**P (kW)**	**Q (kVAR)**	**Microgrid**
Normal	5	48.8	36.6	1
Critical	7	84.5	64.5	
Normal	9	77.3	58.9	
Normal	11	79.9	59.9	
Normal	15	46.6	34.5	2
Normal	17	52.5	39.4	
Critical	19	81.1	60.8	
Normal	21	69.8	52.3	

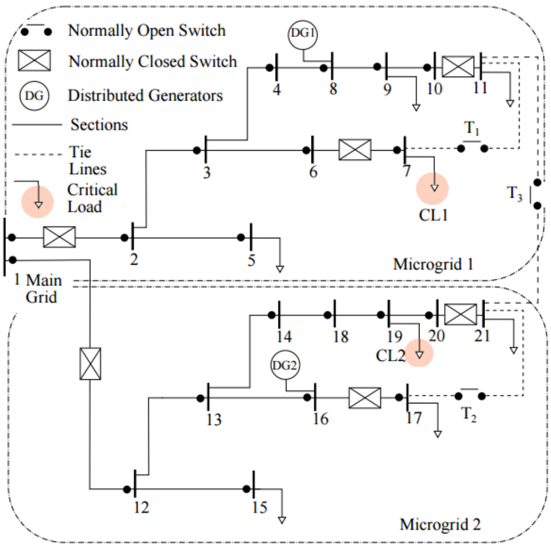

Figure 3: Multiple CERTS Microgrid Systems connected to same substation

The concept of multiple microgrids (or 'multi-microgrids') was introduced by the EU MORE Microgrid projects with the objective of enhancing the resiliency of distribution systems [15].

TABLE IV: RESILIENCE QUANTIFICATION IN MODIFIED CERTS MULTIPLE MICROGRID WITH DIESEL GENERATOR POWER BACKUP

Duration of Event (seconds)	*Affected Critical Loads in simulation scenario*	*Code*	*With* **No** *Distributed Generation or Battery backup in any load*		*With Non-renewable diesel generator Distributed Generation*	
			Resilience Value (m)	*Scaled Value* **(R_1)**	*Resilience Value*	*Scaled Value* **(R_2)**
10^6	CL1, CL2 Scenario: Islanded from the grid due to transmission line problems	A	1.07	**1**	11.03	**4**
10^5	CL1, CL2 Scenario: Triple line to ground fault in Section 1-2	B	1.43	**1**	13.73	**5**
10^4	CL1, CL2 Scenario: Single Line to Ground Fault in Section 3-6, and Single Line to Ground fault in 14-18	C	1.43	**1**	24.71	**9**
10^3	CL2 Scenario: Single Line to Ground fault in 14-18. Fault caused delay in loads to function again at peak, leading to increase in effective fault duration	D	1.43	**1**	23.56	**9**
10^2	CL1 Scenario: Single Line to Ground Fault in Section 3-6, that required resetting of relay settings	E	1.43	**1**	23.09	**9**
10^1	CL1, CL2: Scenario: Fault in Section 1-2 cleared within 5 cycles.	F	22.71	**9**	22.71	**9**

TABLE V: RESILIENCE QUANTIFICATION IN MODIFIED CERTS MULTIPLE MICROGRID WITH PV DISTRIBUTED GENERATION

Duration of Event	*Affected Critical Loads in simulation scenario*	*Code*	*With PV/Battery based Distributed Generation (Day-time, peak load)*		*With PV/Battery based Distributed Generation (Night-time average load)*	
			Resilience Value (m)	*Scaled Value* **(R_1)**	*Resilience Value*	*Scaled Value* **(R_2)**
10^6	CL1, CL2 Scenario: Islanded from the grid due to transmission line problems	A	16.89	**6**	11.23	**4**
10^5	CL1, CL2 Scenario: Triple line to ground fault in Section 1-2	B	22.91	**9**	14.46	**6**
10^4	CL1, CL2 Scenario: Single Line to Ground Fault in Section 3-6, and Single Line to Ground fault in 14-18	C	24.71	**9**	24.71	**9**
10^3	CL2 Scenario: Single Line to Ground fault in 14-18. Fault caused delay in loads to function again at peak, leading to increase in effective fault duration	D	23.56	**9**	23.56	**9**
10^2	CL1 Scenario: Single Line to Ground Fault in Section 3-6, that required resetting of relay settings	E	23.09	**9**	23.09	**9**
10^1	CL1, CL2: Scenario: Fault in Section 1-2 cleared within 5 cycles.	F	22.71	**9**	22.71	**9**

Thus, a system that is engineered for higher reliability is suitable system for studying quantification of resiliency. The DGs has been located at nodes 8 and 16, capable of serving 165.6 kW critical load demand of the network. The remaining capacity of the generators are used to feed remainder of the normal loads in the same feeder as critical loads. The critical loads CL1 and CL2 are identified at nodes 7 and 19, as shown in Fig. 3. There are six normally closed sectionalizing switches and it is possible to install three tie-lines with normally open switches (T1, T2 and T3) in network between nodes 7-11, 17-21, and 11-21. It has been assumed that a smart reconfiguration algorithm has been in the distribution system. If the restoration algorithm had not been implemented by default, the resiliency values for an events of duration 10^1 to 10^4 seconds (i.e., events that range in seconds to several hours) would have been modified further which is beyond the scope of this paper, and can be studied in a future work.

Several operating and fault conditions have been simulated for the multiple CERTS microgrid system. Table IV and V summarizes the fault duration, and corresponding resiliency of the system depending upon availability of backup power resources. Since many microgrids are being designed with a focus on high penetration of renewable energy resources, all the DGs shown in Fig. 3 have been studied as both conventional diesel generators as well as PV panels integrated with battery storage. The PV and battery models are the same as in [16], and modified to be of equal rating as the diesel generator DGs. The differences in resiliency value in systems with only diesel DG and systems with PV are computed by comparing corresponding columns in Table IV and Table V.

Tables IV and V shows the simulation results for resiliency values in different operating conditions for CERTS microgrid. It can be observed that the proposed approach effectively captures the ability of a system to maintain acceptable performance, during potential outages that can last from seconds to several days. For outages lasting a few hours, gas-fired DGs show significantly higher resiliency, however if such DGs are replaced with solar PV modules of equivalent capacity, the resiliency in such systems are higher during outage for longer durations.

IV. Conclusions

This paper presents a novel, and feasible framework for quantifying, monitoring and leveraging resilience metrics of Power Distribution System (PDS). The developed metrics formulation quantifies the ability of the system to supply critical loads with reduced resources. Though the metrics have been developed for electric utility and power system, the metrics can be generalized to any flow networks. Based on resilience values under several operating and planning scenarios, cost-benefit analysis of distribution system investments can be justified.

The information derived from the proposed resilience metric can be used to design PDS to serve consumers with higher reliability. The proposed time-dependent resilience metric is scalable to different PDS topologies, preserves diverse non-commensurate information, and easily interpretable by operators. The case studies presented in this work assume either 100% renewable or 100% diesel generator DGs. In real distribution systems, there will be a mix between renewable and non-renewable power sources to enable resilience of the system. This will be studied as future case studies.

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