A Framework to Quantify the Value of Operational Resilience for Electric Power Distribution Systems

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***Abstract*—Resilience to the high impact low probability (HILP) events due to extreme weather events is increasingly becoming critical for electric power distribution systems. It is essential to enhance the distribution system's resilience through appropriate operational planing measures such as infrastructure hardening and advanced restoration. Planning distribution system resilience calls for a quantitative metric that can not only model the impacts of non-deterministic catastrophic events but also evaluate the value of the services provided by different planning measures. This paper proposes a resilience metric that quantifies the value of operational resilience of distribution systems in terms of cost of customer interruption. A Monte Carlo based simulation framework is developed to model the probabilistic damage scenarios and to evaluate the resilience metric for different weather intensities. The proposed framework is demonstrated using IEEE 123-bus system.**

***Index Terms*—Distribution systems resilience, Resilience metric, Value of Service, Customer interruption cost.**

I. Introduction

Extreme weather-related events can significantly affect the operation of electric power systems for an extended time with unprecedented consequences [1]. Climate change predictions indicate an increase in the frequency and severity of such events in near future [2]. The power grid, at any hierarchical level, need not only to be reliable to plausible threats but also resilient to HILP events [3]. The impact of Superstorm Sandy (2012) on the power grid has shifted significant traction towards the resilience of power distribution systems. Planning and implementation of distribution system resilience have been challenging for utilities due to inadequate modeling frameworks and relevant metrics that can not only quantify the impacts of potential HILP event on the grid but also help evaluate/compare different planning alternatives for their contribution towards improving operational resilience.

Operational resilience of a distribution system is characterized by its ability to withstand a HILP event and recover to its pre-event state as quickly as possible [4]. Understanding and quantifying the resilience of the distribution system to such HILP events are extremely important in order to justify the investments in infrastructural upgrades to enhance resilience and to evaluate the effectiveness of resiliency enhancing strategies. Towards this goal, several researchers have proposed resilience enhancement techniques using: networked microgrids [5], advanced resource sharing between microgrids [6], and by partitioning the distribution system into multiple microgrids [7]. These approaches, although help enhance operational resilience, but fall short in developing a framework that can quantify the value of the proposed enhancements. Recently, efforts have been made to quantify the resilience based on the availability of resources to supply the interrupted loads [8] and on the ability of the system to restore critical loads [9]. However, the proposed metrics do not consider the probabilistic nature of the HILP events. Also, several optimization-based restoration methods quantify resilience based on the duration and quantity of critical loads restored [10], [11]. However, such methods are scenario dependent and cannot quantify system performance under unprecedented HILP events.

The existing metrics to quantify the operational resilience of distribution grid pose one or more limitations that include: (1) consideration of only post-event measures, (2) not specifically measuring the impacts of the events and (3) not providing a generalized framework to evaluate potential planning measures. In order to overcome these limitations, a few have suggested using risk-based characterization [12] and probabilistic approaches [13] to assess and evaluate resilience in the transmission network. However, there has been little effort towards a risk-based metric that can compare improvements in resilience due to alternate planning measures. Authors of this paper have previously proposed a risk-based metric to quantify the operational resilience of distribution systems [14]. However, the metric does not quantify the monetary value of service improvements for different customer types and hence cannot be used value-based resilience planning.

With these considerations, this paper presents a framework to the characterize system resilience based on the monetary value of customer interruption during a HILP event. The proposed metric can be used to justify the investments in infrastructural upgrades to enhance resilience. The proposed framework is based on Monte-Carlo simulations (MCS) to evaluate the impacts of HILP events on the system's resilience in terms of the customer interruption cost (CIC). The resilience metric CIC is obtained by combining probabilistic damage scenarios with CIC based econometric models (developed from customer surveys conducted across the united states [15], [16]). CIC is extremely informative in value-based planning as it helps in identifying economically efficient strategies for which the cost of improving resilience is less than or equal to the benefits of such improvements. The proposed approach is also extended to quantify the effects of potential threat-management solutions in terms of savings in CIC ($) that can be used by a utility company to assess alternate resilience enhancement solutions.

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II. Component Level Fragility Modeling

A. Fragility Curve of System Components

A fragility function describes the probability of failure of a system component conditioned to the intensity of the hazard [13]. Since the case study focuses on determining resilience to wind-related events like wind-storms and hurricanes, the fragility curves are modelled with respect to wind speed. Fig. 1a shows an example of a fragility curve that maps the relationship between the failure probability of distribution system component to wind speed. The fragility curve can be mathematically expressed as:

$$P_c(\omega) = \begin{cases} P_c^n, & \text{if } \omega < \omega_{critical} \\ P_c(\omega), & \text{if } \omega_{critical} < \omega < \omega_{collapse} \\ 1, & \text{if } \omega > \omega_{collapse} \end{cases} \quad (1)$$

where, P_c is the failure probability of the c^{th} component as a function of wind speed ω, P_c^n is the failure rate at normal weather condition; $\omega_{critical}$ is the wind speed at which the failure probability rapidly increases. The equipment has negligible probability of survival at $\omega_{collapse}$.

The fragility curve can be constructed using empirical data gathered from previous disaster events. For example, the authors in [17], has developed prototype curve-fit models for percentage damage in structural components as a function of maximum sustained wind speed using observed damage from past storms (see Fig. 1b). The observed damage from the past wind storms can be coupled with infrastructure database and geographical information system to construct an equivalent fragility curve for the component. In this work, fragility curve for components are selected randomly (approximated from [17]). However, empirical data from utility can be used to emulate the real fragility behavior of the components.

B. Component-Level Damage Modeling

The wind-dependent failure probability F_c of the distribution system components is determined from the fragility curves. The operational state of individual system component is obtained by comparing P_c with a uniformly distributed random number, $r_c \sim \mathcal{U}(0, 1)$ as given by 2.

$$F_c(\omega) = \begin{cases} 0, & \text{if } P_c(\omega) < r_c \\ 1, & \text{if } P_c(\omega) > r_c \end{cases} \quad (2)$$

where $F_c$is the failure function of the c^{th} compound, $F_c = 0$ implies that the component has not failed.

The operational states for all the distribution system components obtained for different wind events are used to determine the system level impact and calculate the CIC, which is described in detail in the following section.

III. System level Resilience Assessment

Resiliency has always been a shared responsibility because of its societal benefits, hence investments to improve system resilience should exceed its marginal societal benefits (the economic value of the improvement). Value-based planning is designed to balance the level of investment in improving

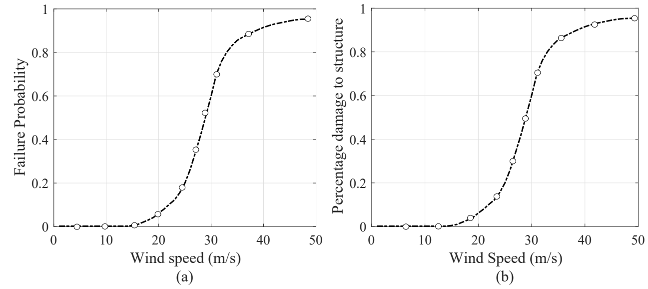

Fig. 1. Component level fragility: (a) fragility curve for a wind profile [13] and (b) prototype curve fit models for percentage of equipment damaged [17]

the service (resiliency in this case) with the societal benefit obtained from the service improvement [15]. Such planning requires a method for estimating customer's economic value of service. This works aims at developing a framework that determines different system resilience states for a probabilistic event and maps them to the econometric model (developed in [15] and updated in [16]) to estimate the net customer interruption costs (CIC_{net}). CIC_{net} is used as a metric for evaluating the value of distribution system resilience.

A. Resilience Curve

A simplified multi-phase resilience curve that demonstrates different resilience states through which a power distribution system transitions in the aftermath of an extreme event is shown in Fig. 2. The transitional states of a distribution system after an event can be chronologically classified as:

1) Phase I - Event progress ($t = t_{1,r} \in t_e, t_{p-e}$): The initial impact of the event on the system depends on the type of threat. A wind-related event may take longer time to degrade the system as it progresses geographically. In the state of event progress, the service loads are interrupted. With reasonable prediction of the extreme event, preventive actions can be applied before the event to reduce the system performance loss and/ or reduce the slope of resilience degradation (see Phase I of Fig. 2). For this work, the duration of this phase has been considered as 2.5 hours.

2) Phase II: Post Event degradation State ($t = t_{2,r} \in t_{p-e}, t_{res}$): Following the event, the system enters the post-event degraded stage, where the system damage is evaluated and the available resources and healthy portion of network are identified before restoration. The damage assessment time (DA_e^t) can be calculated from historical information based on prior events. In this work (DA_e^t) is calculated based on (3).

$$DA_e^t = \begin{cases} DA_e^t, & \text{if } \omega \le 20m/s \\ n_1 \times DA_e^t, & \text{if } 20m/s < \omega \le 40m/s \\ n_2 \times DA_e^t, & \text{if } \omega > 40m/s \end{cases} \quad (3)$$

where, DA_e^t, is assumed to be 2 hours, $n_1 \sim \mathcal{U}(1, 2)$ and $n_1 \sim \mathcal{U}(2, 3)$ are random numbers generated within the specified range. However, the accuracy of the metric can be improved using accurate values of DA_e^t provided by the system operator for different intensities of weather event based on prior events.

3) Phase III: Restoration State ($t = t_{3,r} \in t_{res}, t_{i-r}$): After damage assessment, the system restores the disconnected

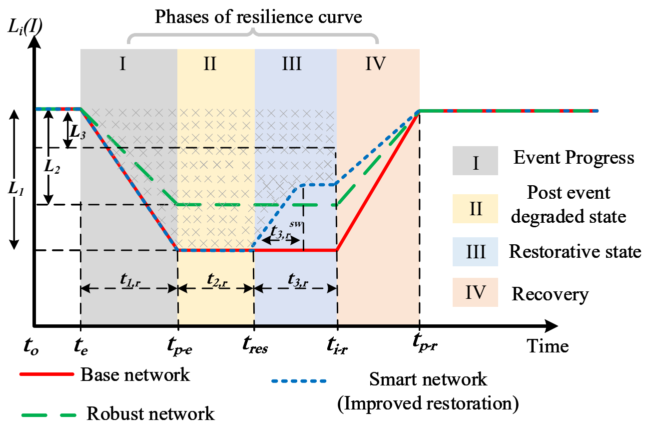

Fig. 2. Approximated resilience curve for an event

loads through feeder reconfiguration, distributed generations and other actions using a proper restoration strategy. Network reconfiguration using remote controlled switches (RCS) and automated islanding driven by utility-owned DGs can help restore the critical loads of the system before infrastructure recovery. This slope of the restorative state (as shown in phase III of Fig. 2) depends on the level of impact, size of DGs available for active islanding, and the number of switching operations required for forming the DG supplied islands. The time required for the switching operations ($t_{3,r}^{sw}$) to reconfigure the network and restore critical loads has been separately considered for modeling the customer interruption duration with more fidelity. The total duration of this phase ($t_{3,r}$) has been considered as 8 hours and $t_{3,r}^{sw}$ depends on the number of switching operations based on restoration.

4) Phase IV: Infrastructure recovery Phase ($t \in t_{i-r}, t_{p-r}$): This phase corresponds to the infrastructural repairs initiated by the operator to bring the system back to pre-event stage. Since the main focus on the work is to quantify, the operational resilience of the system, the infrastructure recovery phase is not included when assessing system resilience.

B. Customer Interruption Cost Model

This Customer interruption cost (CIC) model is based on data-sets from surveys with over 105,000 observations fielded by 10 different utility companies between 1989 and 2012. Some of the utilities surveyed all three customer types, medium and large commercial and industrial (C&I), small C&I, and residential customers [16]. The econometric model that has been developed from the surveys [16] is a two-part regression model. The first part is a probit model to predict the probability that a particular customer will report any positive value (versus zero) for a particular interruption scenario, and the second part is a generalized linear model (GLM) to estimate interruption costs using the same set of independent variables (as shown in eq. 4) used in the probit model for only those customers who report positive costs. Finally, the predicted probabilities from the first part are multiplied by the estimated interruption costs from the second part to generate the final interruption cost predictions (CIC_c) for the customer.

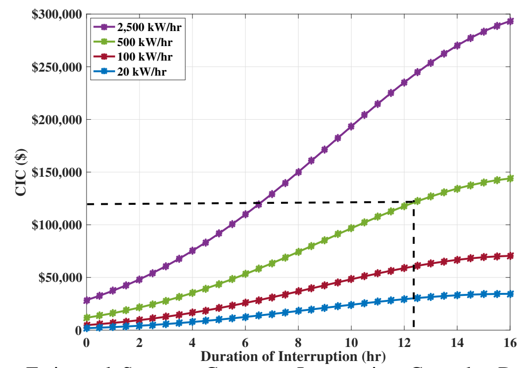

Fig. 3. Estimated Summer Customer Interruption Costs by Duration and Average Demand (kW/hr) - Medium and Large C&I

The total cost of interruption (CIC_{net}) for the probabilistic event is the cumulative sum of CIC_c for all the interrupted customers.

$$\begin{cases} f(ln(MWH_y), t_c, t_c^2, ln(MWH_y) \times t_c, ln(MWH_y) \\ \quad \times t_c^2, szn^*, ind^*), \text{ for large and medium C\&I} \\ f(ln(MWH_y), t_c, t_c^2, ln(MWH_y) \times t_c, szn^*, ind^*, \\ \quad backup^*, t_{od}*), \text{ for small C\&I} \\ f(ln(MWH_y), t_c, t_c^2, inc_c^*, szn^*, t_{od}^*), \text{ for residential} \end{cases} \tag{4}$$

where, $ln(MWH_y)$ is the natural log of average annual consumption of the customer, t_c is the duration of the customer interruption, szn is the season of interruption, ind denotes the customer business type, $backup$ denotes the presence of backup equipment at facility, t_{od} is the time of day, inc_c is the annual household income. The variables marked with $*$ have been incorporated with their average values obtained from [16]. Fig. 3 shows the variation of CIC with the duration of interruption for large and medium C&I having different energy consumption. The duration of interruption for a particular customer is determined using eq. (5) depending on its restoration status. Finally, the cost of a particular customer interruption (CIC_c) is obtained by mapping the duration of interruption, the customer type of the interrupted loads and the average annual consumption of the loads ($base_{load}*demand_{factor}*24*365$) into the CIC functions defined in (4).

$$t_c = \begin{cases} \frac{t_{1-r}}{2} + t_{2-r} + t_{3-r} & \text{if load is not restored} \\ \frac{t_{1-r}}{2} + t_{2-r} + \frac{t_{3-r}^{sw}}{2} & \text{if load is restored} \end{cases} \tag{5}$$

IV. Framework for Characterizing Distribution System Resilience

The framework for computing the resilience metric is based on Monte-Carlo simulation (MCS) to model the probabilistic system damage scenarios for different weather intensities. The framework would require historical outage data, probabilistic weather data and current asset conditions.

A. Monte Carlo Simulations to Characterize Resilience

MCS techniques have been adopted in the framework to evaluate the probabilistic impact of the weather related event because of their non-deterministic nature. For a particular

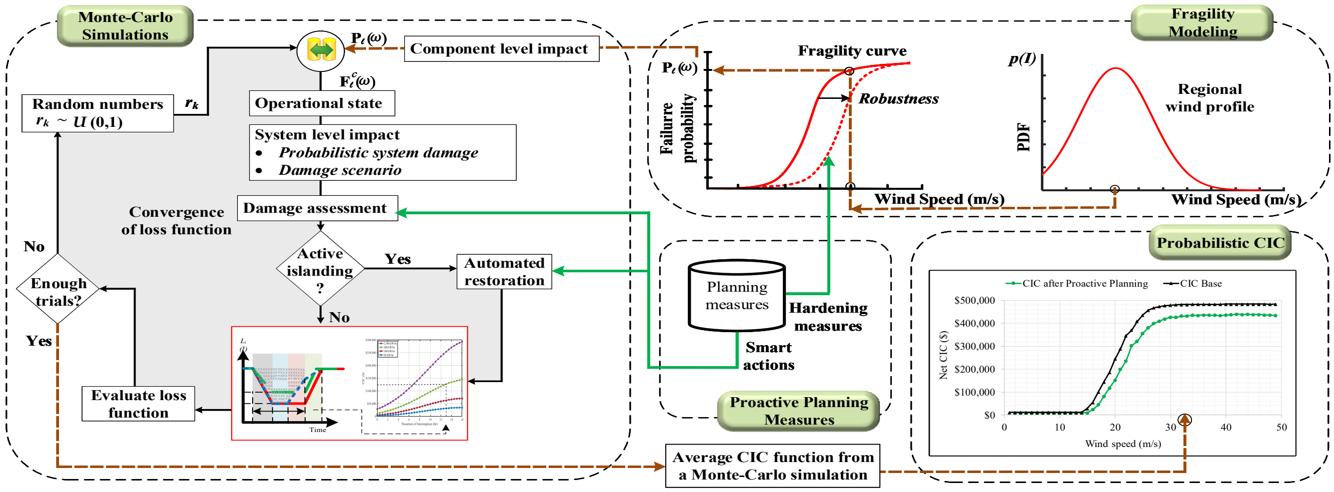

Fig. 4. Framework for fragility modeling and characterizing system resilience

MCS trial, the operational state of all the system components are determined by mapping the probability distribution function (see Fig. 4) of the wind profile to the component fragility curves (shown in Fig. 1). The generated damage scenario is then used to determine the total cost of interruption (CIC_{net}). Several trials of MCS are conducted to obtain statistically representative results. The process is repeated for multiple wind speeds (see Fig. 4).

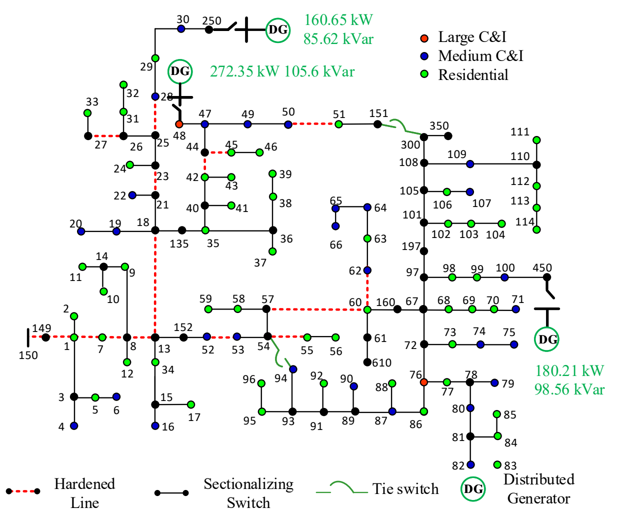

Fig. 5. Modified IEEE 123-bus test system with DGs and tie switches

B. Proactive Planning Measures

Proactive planning can enhance the operational resilience of the system by reducing the impact of the event on the customers. Two specific proactive planning measures has been incorporated in the framework and the value of planning service is evaluated using CIC_{net}.

1) Robust Network - Line Hardening/ Under-grounding: Distribution line hardening, although expensive, is one of the most efficient methods to protect the system against extreme wind events by reducing the interruption level. In terms of fragility, hardening would decrease the fragility of the components by lowering its failure probability for higher wind speeds (see Fig. 4). This decreases the number of customer interrupted and hence increases the resilience of the system, as characterized by the green curve in Fig. 2.

2) Smart Network - Automated Restoration: The smart network solution enhances the operational resilience of the system through automated restoration of critical loads. RCSs and grid forming DGs facilitates the is-landing to supply critical loads prior to infrastructure recovery (phase IV of Fig. 2). The framework incorporates the smart restoration algorithm (that has been developed in [11]) as a mixed-integer linear program (MILP) with the objective of maximizing the load restored using available resources. The planning measure quickens damage assessment and the smart restoration reduces the outage duration by restoring critical loads. The blue curve in Fig. 2 characterizes resilience for the smart network.

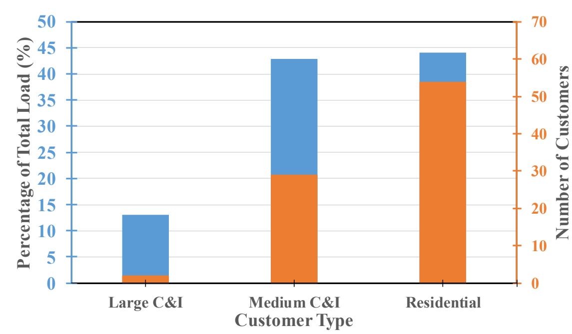

Fig. 6. Customer distribution of net system load

V. Results and Discussions

IEEE 123-bus test system is used to demonstrate the framework proposed in this work. For the base case, the distribution system components are modeled using same fragility curves assuming that the distribution system spans a small geographic area and observes homogeneous weather event. In order to model proactive threat-management solutions for smart network, two tie switches, 54-94 and 151-300 are included in the model to create different restoration scenarios and line 93-94 is upgraded to three-phase. Three utility-owned DGs with grid-forming inverters are employed for active islanding to assist with the restoration process. The tie switches and

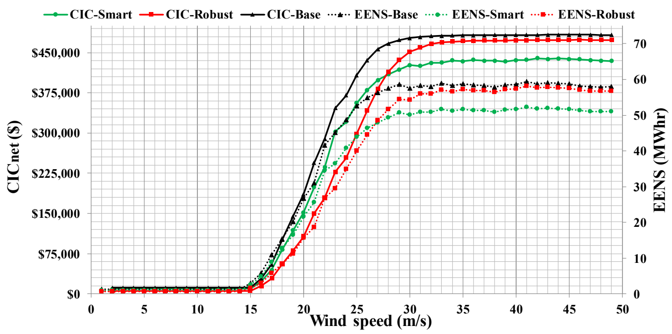

Fig. 7. CIC_{net} and $EENS$ for different wind speeds

DG specifications are shown in Fig. 5. 16 overhead lines are randomly selected and hardened (shown in Fig. 5) to model proactive threat-management solutions for robust network. Loads are modeled as static loads with pre specified peak-load demand. In order to determine CIC for the specific interrupted load, different customer types has been assigned to each load (as shown in Fig. 5) and the average load has been obtained using a demand factor of 0.4. Fig. 6 summarizes the distribution of load among different customer types.

The proposed resilience metric (CIC_{net}) is computed by averaging the results for 1000 MCS trials for a specified wind speed. The process is repeated for multiple wind-speeds sampled from the wind-speed probability distribution function (obtained from [13]) to model the system resilience for different wind intensities. Fig. 7 shows a comparison of CIC_{net} between the two proactive planning scenarios with the base case. It is clear that for the simulated use-case, the value of enhancing resilience using smart network is close to $50,000 for extreme wind speeds. The figure also shows that the robust network results in an increased value for resilience during moderate wind speeds (close too $100,000 for wind speed 23-27 m/s). However, the value of resilience for the robust network decreases (close to $10,000) during extreme wind speeds. Fig. 7 also shows a comparison of the metric, expected energy not supplied ($EENS$), for different wind intensities. The $EENS$ metric, proposed in [14], is obtained from the area under the resilience curve in Fig. 2. Note that $EENS$ shows a similar behavior as CIC_{net} for the smart and robust networks as the number and type of customers interrupted and their duration of interruption directly influence their CIC_c.

$EENS$ quantifies resilience in terms of energy lost but does not consider the impact for different customer types. Hence it cannot be directly correlated to justify economically efficient investment for resilience planning. CIC_{net} is a practical metric that help compare the value of investment in improving resilience as a function of the savings in customer interruption cost. Hence, CIC_{net} can be used by utility companies in making economically efficient investment decisions when planning the distribution systems for resilience.

VI. Conclusions

In this work, a value-of-service-based resilience metric, CIC_{net}, is proposed for quantifying the resilience of power distribution systems. The proposed metric quantifies the system resilience for different weather-events in terms of cost of customer interruption; the case study is presented for wind-related events. The resilience metric is calculated using a framework that models probabilistic damage scenarios for different intensities of weather events. The effects of two planning measures viz. deployment of DGs (smart network) and grid hardening solutions (robust network) on the resilience enhancement are quantified using the proposed resilience metric. It is demonstrated that the metric is suitable for comparing the value-of-service provided by the different resilience enhancement strategies and can help assist with the cost-benefit analysis for resilience-driven investments.

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