Technology Planning for Electric Power Supply in Critical Events Considering a Bulk Grid, Backup Power Plants, and Micro-Grids

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***Abstract*—This paper discusses a risk assessment approach to infrastructure technology planning aimed at improving power supply resiliency to natural disasters or other critical events. Cost as well as power supply availability are both fundamental decision factors considered in the study. The proposed planning process spans three phases during which the critical loads under study are subject to the effects of the extreme event: during the event, the immediate aftermath until potential infrastructure damage is repaired, and the long term aftermath until the load has recovered the same level existing before the critical event. The combined risk of these three phases is calculated considering likelihood of the critical event to occur, expected impact, and system vulnerability. This risk is then added to the system capital and normal operational costs to yield a lifetime cost that is used to compare technological options. Micro-grids are identified as a relevant technology with potential to achieve enhanced power supply during critical events. The analysis provides indications on how to better configure micro-grids in order to achieve high availability through diverse local distributed generation sources.**

***Index Terms*—Critical event, disasters, micro-grid, power supply, risk assessments, technology planning.**

I. Introduction

THIS paper presents a risk assessment planning framework to objectively determine suitable technology options for electrical power supply systems that are resilient to critical events, such as hurricanes. The systematic technology evaluation process proposed here considers costs resulting from the expected critical event effects on system operation and output. Although electrical power supply is a critical need when a disaster happens, traditional electric grids show little resiliency to external actions from such events. As it is exemplified with the effects of 2008 Hurricane Ike summarized in Figs. 1 and 2, grid outages may affect for a long period almost all or all customers in an extensive region where no more than 1% of the power grid infrastructure is damaged. These outages may jeopardize human lives and delay community recovery efforts by hindering many society critical services, such as financial, and health services. Communication networks are particularly affected by power supply deficiencies in these events as attested by the fact that most of their outages have power related causes [1]–[4].

Despite the recognized importance of improving power supply resiliency during critical events, few works seem to have been published focusing on this topic [4]–[10]. Although significant work, particularly in civil engineering—e.g., [11]—has been dedicated to study planning issues when extreme events may affect critical infrastructures, most studies rely on risk assessment methods after the infrastructure is installed [12] and not during the initial planning stages. In this sense, there seems to exist little past work addressing the issue of how to systematically and objectively plan new or replacement power supply infrastructure deployment in areas that are prone to critical events. One is [13], but it is mostly based on a qualitative analysis. In contrast, this paper presents a quantitative planning framework based on risk analysis with some similarities to that suggested in [14] in terms of considering system characteristics as an important part. Yet, many differences exist, such as the applied focus in here. Furthermore, although micro-grids—small electric distribution grids powered by local generation sources with a total capacity of a few MW—have been identified as a suitable technology to improve power supply availability [15], no past works focused on how to design micro-grids able to sustain operation during an extreme event. The risk analysis planning framework presented here allows determining not only if micro-grids are a suitable technology option, but also how to engineer them so they are more resilient to critical events.

II. Preliminary Notions

A. Power Supply Alternatives

The proposed framework supports evaluation of suitable technologies in order to achieve a resilient power supply for a given load confined to a limited physical space, such as a building—a data center or industrial campus—or an area with a maximum radius of 500 m, such as a neighborhood or part of it. This confined space with a given load defines a *service area* in which the load can be powered based on three *powering approaches* or *technology options* (TOs):

TO A) the traditional approach of using the bulk power grid without any local power backup alternatives (Fig. 3),
TO B) same as TO A, but with a local backup power plant with batteries and a diesel generator (Fig. 4),
TO C) a *micro-grid* with varying alternatives for the local distributed generation (DG) power sources (Fig. 5).

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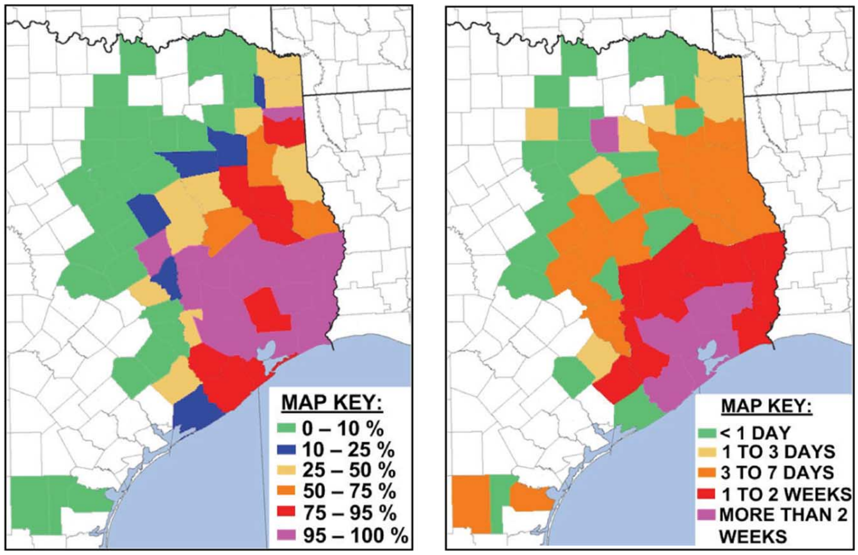

Fig. 1. Left: Power outage incidence caused by Hurricane Ike in Texas. Right: 95% restoration time for Hurricane Ike in Texas.

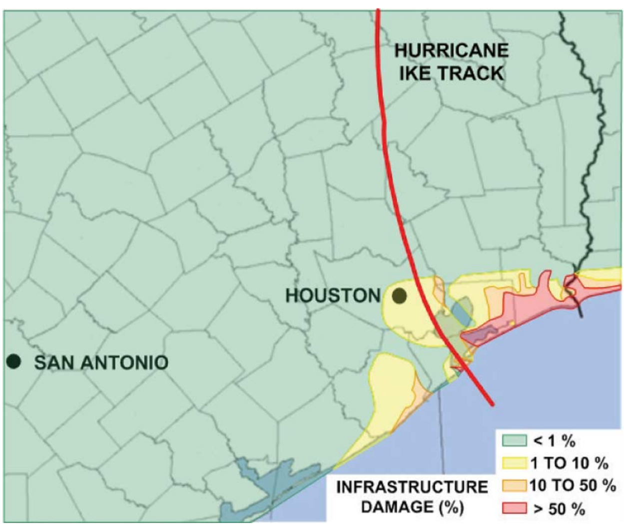

Fig. 2. Percentage of power infrastructure damage caused by Hurricane Ike.

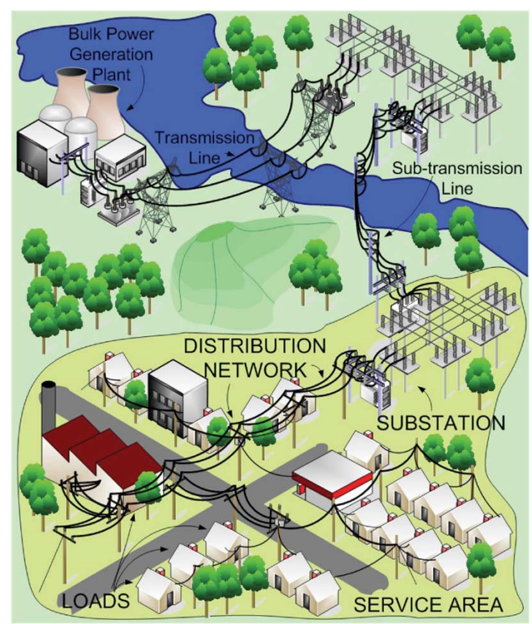

Fig. 3. TO A: electric supply from bulk power grid.

All TOs typically require some external source of energy that is delivered into the service area by one or more *primary energy supply infrastructures* (PESIs)—also called lifelines in earthquake studies nomenclature—in order to power the load. Typically, TO A systems have a substation that acts as the interface between the distribution network within the service area and the PESI formed by a sub-transmission line and the rest of the bulk power grid. The TO B, displayed in Fig. 4, adds a local power plant made of power electronic interfaces, batteries, and a diesel generator, that provides backup power when the grid looses service. This power plant acts as the interface between the local power distribution and the bulk electric grid. In addition to the power grid, the roads necessary to transport diesel fuel for the standby diesel generator are another PESI. Roads are still the PESI in TO B when backup fuel cells without reformers are used instead of diesel gensets. If natural gas gensets are used instead of diesel generators, then the natural gas distribution network is a PESI. In TO C, power is supplied primarily from local DG power sources through power electronic interfaces and supported by ancillary hardware, such as energy storage devices for short term load following. All these components form a local power generation and controlled plant that when combined with the local power distribution infrastructure and the load constitutes a *micro-grid*. The main bulk utility grid can serve as a secondary energy supply infrastructure in addition to the PESIs, such as a natural gas distribution network for microturbines, fuel cells with reformers, or some types of reciprocating engines. Some other DG technologies, such as photovoltaic (PV) modules and small wind generators, do not require any PESI. Micro-grids show promise to achieve improved power supply resiliency to critical events over TOs A and B because well designed micro-grids—i.e., micro-grids with diverse power supply from at least two distinct PESIs—eliminate the single point of failure encountered at the grid tie in TOs A and

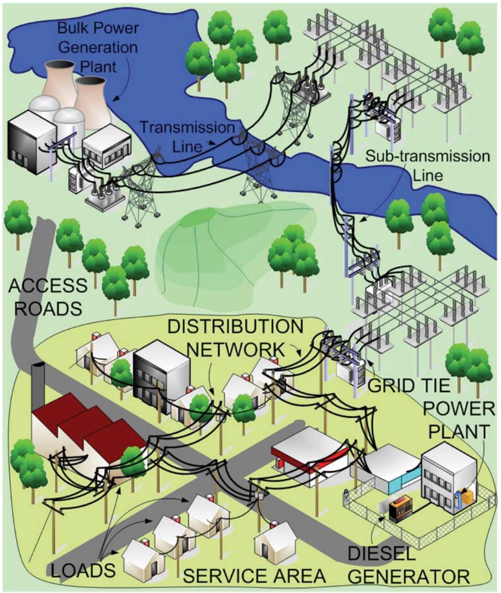

Fig. 4. TO B: electric supply from bulk electric grid with power backup from a diesel generator.

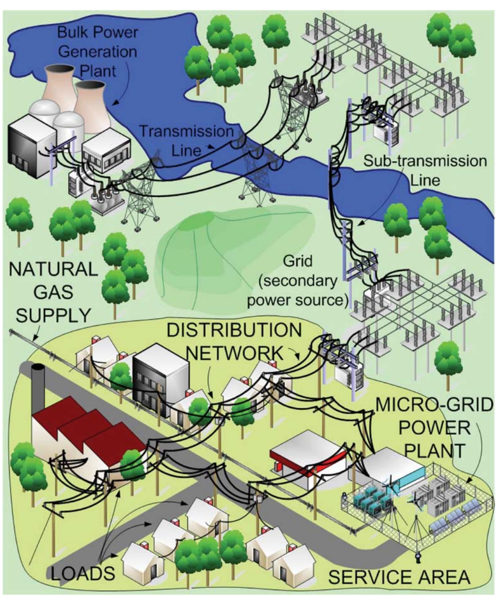

Fig. 5. TO C: micro-grid.

B [1]. Logically, in order to achieve high availability, it is desirable to select DG technologies for which their PESIs are affected by the critical event less severely than the electric grid.

B. Critical Event Timeline

The proposed framework considers that a critical event influences the power supply technology planning process in three phases shown in Fig. 6: *during the critical event, the immediate aftermath* of the extreme event, and the *long term aftermath* of the extreme event. For most critical events, Phase I—i.e., during the critical event—lasts for a relatively short time; at most for a few days. Phase II (immediate aftermath) starts when Phase I ends and is usually termed response, recovery and restoration phase. It typically lasts from a few days to several weeks, until 100% of the power infrastructure within the service area and its primary, and in some cases secondary, energy supply infrastructures have been repaired of all damage received during the critical event. At the end of Phase II power could be supplied to the loads in the same conditions that existed before the critical event occurred. However, some of this load may have disappeared due to the critical event actions. This significant effect of critical events is recognized in the last phase, the long term aftermath. It starts immediately after Phase II ends and lasts until the load is restored to the same levels existing before the critical event occurred. Hence, Phase III introduces in the planning process the fact that the service area load, and, hence, the local power supply infrastructure demand, may be severely affected by such events. Inclusion of this phase in the planning framework is an important difference from conventional critical events planning approaches that consider phases I and II but not the long term effects [16]. Yet, as Hurricane Katrina demonstrated, demand evolution plays a very important role in technology planning for critical events [17]. Phase III may last from a few weeks up to several months and even years.

III. Concept Definitions and Assumptions

The first concept that needs to be defined is that of the system under study. The system under study involves the local power supply infrastructure up to the demarcation points to the lifelines. Although these lifelines are not part of the system subject to eventual procurement decisions, their behavior when influenced by the critical event is a fundamental part of the risk analysis and planning framework. In effect, the selection of the most adequate TO, and the choice of local distributed generators technology for TO C, is heavily influenced by the PESIs availability at their demarcation point with the system under evaluation. In all TOs the system under study includes a local power distribution network. For TO A the system also includes the substation that connects the distribution network in the service area with the main power grid. For TO B the system adds a local power plant with backup generation. For TO C the system includes a local power generation and control plant, and the local power distribution infrastructure.

The service area for the system under evaluation is inside a larger region that may or may not contain other service areas served by the same power supply service operator. It is assumed that this region is subject to only one particular type of disaster to occur—e.g., hurricanes or earthquakes. If two or more type of disasters may occur, then the results of the study for each type of disaster could be compared in order to choose one of the solutions or to combine both solutions into one. Six other important definitions for the proposed framework are as follows.

1) Hazard [18]: "It is a potentially damaging physical event, phenomenon and/or human activity, which may cause loss of life or injury, property damage, social and economic disruption or environmental degradation."

Hence, the hazard is the originator of power supply disruptions to loads within the service area and not the means by which these effects are produced—as considered in [19]—which in here is called *damaging actions*. E.g., if the hazard is a hurricane, then its damaging actions are the strong winds, the storm surge, floods, torrential rains, and tornados.

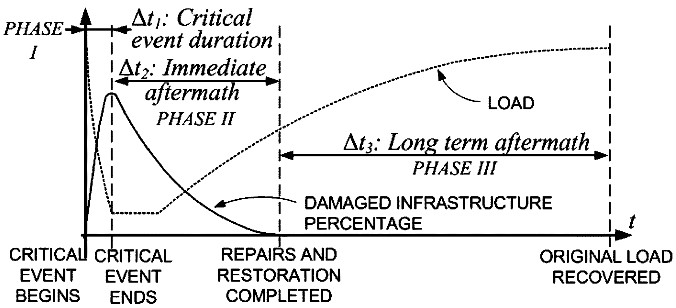

Fig. 6. Critical event timeline.

2) Hazard Probability (P_H)*:* It is the probability that a given hazard—i.e., a critical event—with a given intensity H_i will occur within some specified time interval.

Two important concepts are related with this definition: *hazard intensity*, H_i, and *time interval*. In the proposed framework, the time interval is the system under study total lifespan. Critical event intensity is a more complex concept for two reasons. One is that a given hazard may happen multiple times and with different intensities during the system lifespan. Thus, the evaluation process may involve choosing which hazard *scenario* to consider. One scenario may consider the most intense possible hazard. Another scenario may consider an expected intensity combined with its average occurrence frequency. Yet another scenario may compare different case studies each of them with a different value for H_i and corresponding return period. The second reason is that there could be different ways of characterizing H_i. In order to provide some basis for discussion and without pursuing a detailed analysis for being out of the scope of this work, let's consider that the hazard is a hurricane. The most common way of indicating hurricane intensity is with the Saffir–Simpson 5-category scale which is based on a 1-minute mean maximum sustained wind speed measured at a height of 10 m. However, this scale has been shown to be inaccurate when attempting to describe damage, as it happened with Hurricane Katrina [1], [20]. For this reason, there have been a number of publications suggesting different ways to measure hurricane intensity [20]–[22]. Yet, these measurements do not provide a clear indication of different intensities along the area affected by the storm. In order to provide an alternative way to measure hurricane intensity that can serve as a basis for the discussion, it is suggested to measure hurricane intensity with a local index, derived from the one proposed in [20], called *Local Tropical Cyclone Intensity Index (LTCII)* and defined as

$$(\text{LTCII}) = \left(\frac{h}{h_0}\right)^2 \left(\frac{V_{\max,\text{SW}}}{V_{\max,\text{SW},0}}\right)^2 \left(\frac{A_{\text{TS}}}{A_{\text{TS},0}}\right) \left(\frac{T_{\text{TS}}}{T_{\text{TS},0}}\right) \tag{1}$$

where $V_{\max,\text{SW}}$ is the maximum sustained winds at the studied location, A_{TS} is the area over land of tropical storm winds, and T_{TS} is the time period under tropical storm conditions at the studied site. For the latter, if the service area location is not likely to be under tropical storm winds, then T_{TS} is made equal to 1. The sub-index 0 indicates reference values. These reference values are $V_{\max,\text{SW},0} = 74$ mph (the lower threshold for a category 1 hurricane), $A_{\text{TS},0} = 35341$ mi^2 (the area of a semicircle with a radius of 150 mi—a typical average radius for tropical storm winds in a category 1 hurricane), and $T_{\text{TS},0} = 12$ h (the time it takes to make 150 mi at 12.5 mi/h—a typical hurricane forward speed). The ratio h/h_0 equals 1 when the storm surge height h is less than 4 ft (the minimum typical storm surge height for a Category 1 hurricane). Otherwise h is the actual storm surge height and h_0 is 4 ft. In (1) both factors related to storm surge and wind speed are squared because storm surge or wind speed forces on buildings, columns, and poles, are squared functions of the storm surge height or the wind speed, respectively. Further explanation of the LTCII is out of the scope of this paper. Yet, the LTCII can serve to explain some concepts in the risk-based planning framework.

Implicitly, H_i also considers the *exposure* of a system under analysis at a given *location*;e.g., for a hurricane, a system on the coast is more exposed to high winds and storm surges than an equal system located inland. Since it is more likely to have higher LTCII near the coast, for the same LTCII the system on the coast have a higher P_H than that of the system located inland; i.e., the former is more exposed than the latter.

3) Hazard Impact (I_H)*:* It is the expected effect in terms of additional cost that a given hazard of a given intensity produce for a system under study when it is constructed, operated, or configured in a standard way.

This definition encompasses several concepts: an effect that can be monetarily quantified, a hazard with a given intensity, and a system that is constructed, operated, or configured in a standard way. The effects of the hazard under evaluation in each of the three aforementioned phases are different but they can all be measured in terms of a monetary cost. This is true even in the case of loss of life, such as when evaluating the effect a power outage at a hospital or a E-911 communications center, because loss of life due to power outages can be translated into an estimated cost of life [23] plus financial liabilities.

In some previous works [18], [24], [25] that use risk-based analysis, the notion of impact is equivalent to that of exposure as the total number of people, buildings or infrastructure elements at risk in a given area. Although the concept of an area is relevant for both definitions of impact and exposure used in here, the definitions of exposure and impact are fundamentally different because a given hazard may not necessarily affect all elements at risk within the service area.

Typically, I_H is determined based on statistical analysis of past events similar to the one under study. Hence, I_H represents some expected outcome yielded by a combination of information from systems with varying characteristics. Thus, the impact measures the effects of a given hazard with a known H_i in an average condition. Since the system under study may or may not be planned to have this same average condition, an adjusting concept, called system combined vulnerabilities and defined next, needs to be included in the analysis in order to consider particular features of the system.

4) System Combined Vulnerabilities (V)*:* It is an indication of how much more or less susceptible the system under study is to receive the same impact than a reference standard system when both are subject to a hazard of a same given intensity.

In the past the concept of vulnerability has been the focus of controversy and varying definitions [26], [27]. Herein, V refers to some characteristics of the system under study that makes it more or less prone to being subject to an (average) expected impact from a hazard with a well identified intensity. The choice for how many of these characteristics are considered and how much detail is included in their description depends on the planning process accuracy goals and time constraints. In many practical cases the decision of how to consider V depends on a lead planner's executive decision as part of the planning scenario selection process.

From the definition, V is estimated with respect to a baseline case. This case represents a mean impact yielded by averaging observed past outcomes from different locations with the same value for H_i. Then V is the ratio between the value associated with the characteristic under study for the system under evaluation, and the value of the same characteristic for the baseline case. For example, if the analysis is evaluating power supply for a neighborhood with overhead distribution lines and the historical data is based on areas with an average of x times more wooden poles than concrete poles, then V may equal y/x where y is the planned ratio of wooden poles to concrete poles in the service area under evaluation.

5) Hazard Adjusted Impact (I_{adj})*:* It is the product of the hazard impact and the system combined vulnerability, or the maximum possible impact; whichever of the two is less.

In any critical event there is a limit to the worst effects that the system can receive. In terms of impact, this limit is given for example by the cost of loosing all the loads during phases I and/or II of the critical event, or by the cost of having a totally unused system capacity during Phase III. Yet, since V could be larger than one, then it may happen that the product of I_H and V exceeds the worst possible impact. This is a practical impossibility that leads to the need of defining I_{adj} as

$$I_{\text{adj}} = \min[I_H V, M_I] \tag{2}$$

where the product $I_H V$ is the directly calculated impact, and M_I is the worst possible impact, e.g., a monetary measurement of an outage during phase I or II affecting all loads.

6) Risk (R)*:* It is the expected impact over an indicated period of time that a system at a given location, and with a given construction and configuration characteristics will suffer when subject to a hazard of a given intensity. Hence, risk is mathematically defined here as

$$R = P_H \left(\sum_{p=1}^{3} I_{\text{adj,p}} \right) \tag{3}$$

where the index p indicates the critical event phase. Hence, the definition of risk considers a ternary approach in line with previous works such as [18], [24], [28] in which vulnerability is combined with the classical definition of risk involving hazard likelihood and impact [13] in order to reflect the fact that the analyzed system may differ from the baseline design.

IV. Technology Planning Framework

The lifetime cost, C_L, includes the expected cost from having the system operating in a zone subject to some hazard—i.e., the risk R from (3)—the system capital and installation cost C_{CI}, the operational cost C_O, and the down time cost when outages occur during normal operation, C_D. Hence, C_L is

$$C_L = R + C_{\text{CI}} + C_O + C_D \tag{4}$$

which is used to compare system configurations among and within the three TOs in order to select the one with the lowest value for C_L. In (4) all costs are, actually, referred to some present value at the time when the technology is planned and selected, and they include some estimated financial cost. Analysis of financial and depreciation costs is not within the scope of this work so they will not be further discussed here.

The focus in (4) is on calculating R because $C_{\text{CI}}, C_{\ D}$, and O_C can be obtained from vendors and other sources that are not necessary to discuss here. As it was alluded before, R may change depending on how H_i and the hazard return period are considered. When the historical data imply that a hazard of a given expected intensity may occur a given number of times during the system lifetime, R can be calculated as the product of R calculated for a single occurrence of such event by the number of times the event is expected to happen during the system lifetime. In other cases, it might be desirable to consider different intensities of the critical event, each of which have an associated expected return period. Hence, R can be obtained as the sum of the individual risks obtained for each considered H_i. Another scenario could yield R by considering the worst situation in terms of H_i and/or expected return time. The decision of which of these scenarios to choose—one or more if it is desirable to compare R for different cases—depends on a number of factors including the service area power infrastructure owner practices, strategies, and goals. Since analysis of these factors is out of the scope of this paper and the presented planning framework is not limited by which approach to choose, the discussion will be based on considering a single hazard of an expected intensity so P_H in (3) is known. For example, in case of hurricanes, P_H can be calculated based on public historical statistical data [29] and the fact that P_H follows a Poison distribution [30], [31].

A. Phase I: During the Critical Event

Phase I duration is represented by $\Delta t_{\ 1}$, which is often determined from historical statistical data. Since the proposed framework is not limited to a given hazard and the focus here is not on detailing how to determine $\Delta t_{\ 1}$ and other parameters associated to each hazard, but rather utilizing them, further discussion of these parameters will be limited to particular examples to clarify some concept. In order to have a uniform basis for discussion, most of these examples consider that the hazard is a hurricane for which Δt_1 can be considered to be equal to T_{TS}.

Since it is assumed that P_H is already known, risk calculation involves determining $I_{\text{adj},1}$, which is the sum of two components, each with its respective values for vulnerability and impact: damaged hardware vulnerability and impact V_{1D} and I_{H1D}, respectively, and outage vulnerability and impact V_{1O} and I_{H1O}, respectively. The damaged hardware impact is

$$I_{H1D} = E_{\text{DI}} C_{\text{CI}} \tag{5}$$

where E_{DI} is the expected portion of damaged local power supply infrastructure depending on H_i. The outage impact is

$$I_{H1O} = E_{\mathrm{pu},1} O_{C/t} \Delta t_1 L \tag{6}$$

where $O_{C/t}$ is the cost of one outage per unit time and load, L is the total load existing before the critical event, and $E_{\mathrm{pu},1}$ is the expected portion of L that losses service if a given hazard with well specified H_i occurs. Load and $O_{C/t}$ can be specified based on two criteria: if the service area is a building, they are expressed in kW, but if the service area is a neighborhood they can be measured based on the number of customers.

The value for $E_{\mathrm{pu},1}$ depends on H_i, and its calculation depends on the choice for the TO under consideration, and on the system architecture design and configuration. Eventually, I_{H1O} is influenced by whether or not the substation (for TO A) or the power plant (for TOs B and C) survives the event. So

$$E_{\mathrm{pu},1} = P_S(1 - A_S) + (1 - P_S) = 1 - P_S A_S \tag{7}$$

where P_S is the local power supply infrastructure probability of survival—i.e., the probability as a function of H_i that the plant or substation and the local power distribution network are not destroyed obtained from historical statistical data—and A_S is the system availability. From a reliability perspective, the system is configured as a series combination of the substation or power plant and the distribution network. Thus

$$A_S = A_{\mathrm{ST/PP}}(1 - O_I) \tag{8}$$

where $A_{\mathrm{ST/PP}}$ is the availability of the substation or power plant while operating subject to the critical event and O_I is the expected portion of outages, by now, in the distribution network. In principle, when the service area is a building it can be considered that $O_I = 0$. When the service area is a residential neighborhood, O_I can be estimated based on statistical data from past events. But, in the particular case of TO A, O_I also factors in the critical event effect on the PESI, i.e., the grid. Thus, O_I should be considered in (8) regardless of the service area characteristics. As it is explained next, O_I is also considered—although implicitly—regardless of the service area characteristic as part of the power plant availability calculation for TO B through the grid's power supply availability.

Since substations do not usually have redundant configurations, for TO A the availability of the substation equals the product of the substation components availability. For TO B the power plant availability is obtained from [15]

$$A_{\mathrm{PP}} = \left(1 - \frac{(\lambda_{\mathrm{GS}} + \rho_{\mathrm{GS}}\mu_{\mathrm{MP}})\,\lambda_{\mathrm{MP}}}{\mu_{\mathrm{MP}}(\mu_{\mathrm{MP}} + \mu_{\mathrm{GS}})}\right) A_T A_I \tag{9}$$

where A_T is the transfer-switch availability, A_I is the power electronics interfaces availability that depends on the design of the individual interfaces and the power plant configuration—e.g., redundancy strategy—λ_{GS} is the failure rate of the series combination of the generator set and diesel circuit, μ_{GS} is the genset and fuel repair rate, ρ_{GS} is the genset failure-to-start probability, λ_{MP} is the mains power failure rate, and μ_{MP} is the mains power repair rate. These two last values are considered with the grid operating under the effects of the hazard of a given intensity, and can be estimated based on

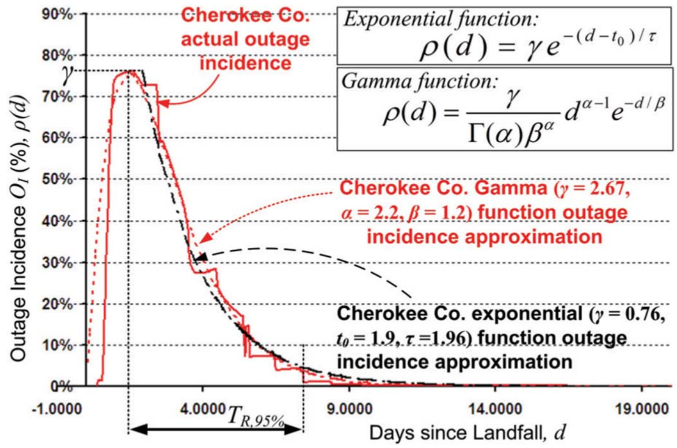

Fig. 7. Outage profile for Cherokee County after Hurricane Ike. and two possible curve approximations. $T_{R,95\%}$ and γ, are also are indicated.

statistical data from past events, such as the curves indicated in Fig. 7. Since, usually, genset autonomy is much longer than Δt_1, access roads reliability characteristics are not a factor for Phase I. If batteries are used, their contribution to power plant availability can be considered with the approach discussed in [32]. However, if other backup technologies that do not include locally stored energy, such as natural gas generators, are used, then, the availability of these other infrastructures needs to be considered as discussed next with the TO C.

Micro-grids do not necessarily rely on locally stored energy to achieve higher availability. Instead, high availability is achieved with a diverse power supply. Hence, PESI behavior is more relevant than for TO B systems. Thus, similarly to TO A systems, but contrary to TO B systems, critical event effects on the region surrounding the service area may be as relevant as the effects on the service area itself. Since local power sources in TO C are assumed to be in hot-standby, A_{PP} can be estimated using availability success diagrams, such as the one exemplified in Fig. 8 for a micro-grid primarily powered by natural gas microturbines, and complemented by the grid as a secondary supply to provide diversity. Then

$$\begin{aligned} A_{\mathrm{PP}} &= 1 - Q_{\mathrm{MTS}} Q_{\mathrm{EG}} \\ &= 1 - (1 - A_{\mathrm{NGs}} A_{\mathrm{MT}} A_{\mathrm{MTi}}) \\ &\quad \times (1 - A_{\mathrm{EG}} A_{\mathrm{EGi}}) \end{aligned} \tag{10}$$

where A indicates availability, Q indicates unavailability, and the subindices *MTS*, *EG*, *NGs*, *MT*, *MTi*, and *EGi* refer to the microturbine system, electric grid, natural gas supply, microturbine, microturbine interfaces, and electric grid interfaces. The availability of the power electronic interfaces, A_{MTi} and A_{EGi}, and the microturbines, A_{MT}, depend on how they are configured. For example, if there are $n+1$ microturbines in a redundant configuration ($m = 1$ in Fig. 8), then

$$A_{\mathrm{MT}} = (n+1) a_{\mathrm{MT}}^n (1 - a_{\mathrm{MT}}) + a_{\mathrm{MT}}^{n+1} \tag{11}$$

where a_{MT} is the availability of each microturbine unit. Once A_{MTi}, A_{EGi}, and A_{MT} are known, A_{NGs} and A_{EG} can be estimated from past events statistical data. For hurricanes, A_{EG} can be known based on the expected percentage of outages in a given area for a given LTCII. For example, A_{EG} for a micro-grid in

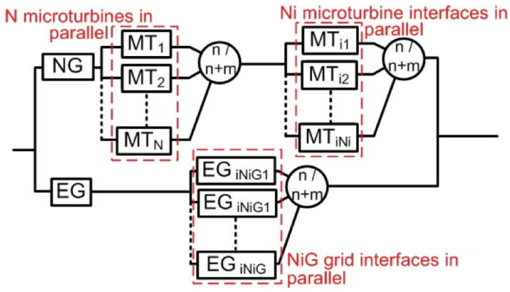

Fig. 8. Reliability success diagram of a micro-grid powered primarily by microturbines and secondarily by the electric grid.

Fig. 9. Gilchrist, TX, after Hurricane Ike.

Fig. 10. Galveston, TX, after Hurricane Ike.

Cherokee County in Texas for an LTCII of 0.55 can be estimated based on Hurricane Ike data (Fig. 7) at $1-\gamma = 0.24$, where γ is the peak value for O_I. Natural gas supply availability, A_{NGs}, is less dependent on the LTCII and from [33] it can be estimated at almost 5-nines. Hence, even when the grid is severely affected, from (7) and considering a building service area or a buried distribution network, $E_{\mathrm{pu},1}$ is close to 0 because P_S in such area is almost 1, O_I is close to zero, and (10) indicates that A_{PP} is close to 1. Thus, unless micro-grids are severely damaged, a good choice of power supply technologies yields a very low impact in Phase I. This study is also useful in order to select the suitable local DG sources in micro-grids; e.g., during earthquakes both A_{NGs} and A_{EG} may be close to 0, leading to A_{PP} being near 0, too, which implies that some other power supply option needs to be selected. Since PV modules and small wind generators with enough locally stored energy do not need any PESI, they are usually excellent choices if there is enough space for the required capacity.

During Phase I, both V_{1D} and V_{1O} can be related with fragility characteristics. For this reason, it is important to distinguish whether the service area is confined to some building, as it occurs in a hospital or telephony central office (CO), or to some open area which includes a few blocks of a residential neighborhood. For a building, if the hazard is a hurricane, V_{1D} decreases as the facility is built higher to avoid storm surge or flood waters, but if the hazard is an earthquake, higher constructions and more batteries lead to higher values for V_{1D}. Soil characteristics at the building planned location also affect V_{1D} both for hurricanes and earthquakes. For a residential neighborhood service area and in case of a hurricane, outage chances are typically higher in zones where more trees or other constructions, such as billboards may affect the distribution network [5]. Thus, this vulnerability may be related to the number of line spans that have vegetation or billboards within a minimum distance. Similarly, another vulnerability can be considered based on the ratio of overhead distribution lines length with respect to buried distribution lines length.

Vulnerabilities also vary depending on particular characteristics of each TO. If the hazard under consideration is a hurricane, important vulnerabilities in TO A are the substation construction characteristics and the length of the service area feeder. Other characteristics that are important for TO B in addition to those for TO A are the height of the diesel fuel tank access points. In TO C vulnerabilities depend on the choice of local power generators. For PV modules and small wind generators vulnerabilities can be estimated for different LTCII values based on manufacturers and scientific studies on structures resistance and anchoring. In case of sources requiring natural gas, such as fuel cells with reformers and microturbines, V equals 1 for hurricanes but it may increase depending on the portion of the pipeline length running on the shore.

The relationship between P_H, and both I_{H1D} and I_{H1O} during Phase I can be examined with Hurricane Ike as a case study. As mentioned, service area exposure is considered only as part of P_H. Thus, for the same H_i a more exposed site has likely a higher P_H value. Conversely, for the same P_H, less exposed sites likely have lower LTCII. For example, consider two sites in Texas where the expected hazard is what was observed with Hurricane Ike—since the reference event is the same, P_H is the same in both sites: Gilchrist (Fig. 9) with an LTCII of 76 and where all infrastructure disappeared, and downtown Galveston (Fig. 10) with an LTCII of 3.22, and where the impact was less severe because the seawall made downtown Galveston to be less exposed than Gilchrist. Yet, I_{adj} for Galveston still equaled M_I because of Galveston's electric supply intrinsic vulnerabilities originated in the fact that it is on an island powered from the mainland. Away from the coast, likely values for LTCII for the same P_H typically decrease rapidly. With Hurricane Ike, the LTCII in Cherokee County was 0.55. Yet, although damage in such inland areas is significantly less severe (Fig. 2), impact on TO A systems may still be extreme because of the grid's weaknesses, such as predominant aerial wired infrastructure, centralized generation and control, and lack of redundancy in subtransmission feeders.

For many hazards, sensitivity to H_i varies depending on the TO. The previous discussion indicates that for hurricanes, full grid outages are observed for a wide range of LTCIIs, which suggests that TO A systems tend to have high risk values. In TO B systems, LTCII variations play a more influential role on $E_{\mathrm{pu},1}$ through the estimated value for P_S, because locally stored diesel

Fig. 11. Near Point a La Hache, LA, after Hurricane Katrina.

Fig. 12. AT&T's Sherwood CO after Hurricane Ike.

energy makes the situation within the service area to be more important than that of the surrounding PESIs—i.e., mains grid and fuel delivery roads. For example, it can be predicted that P_S for an expected LTCII such as those observed in Gilchrist after Hurricane Ike, or near Point a La Hache, Louisiana after Hurricane Katrina (LTCII $=81$) and shown in Figs. 9 and 11, respectively, to be so low that $E_{\mathrm{pu},1}$ equals nearly 1. On the contrary, relatively low LTCII such as that found in Cherokee County after Hurricane Ike likely lead to values of $E_{\mathrm{pu},1}$ close to $1-A_{\mathrm{PP}}$ because P_S is approximately 1. Intermediate values for LTCII, such as 20 found where AT&T's Sherwood CO is located (about 3 miles SE from of the site in Fig. 10) likely imply P_S values between 0 and 1. Although I_{H1O} for this LTCII may not represent a complete outage, particular vulnerabilities such as a building almost at ground level (Fig. 12), makes V_{1D} to drive $I_{\mathrm{adj},1}$ for such LTCII to M_I, as it occurred with Hurricane Ike.

B. Phase II: Extreme Event Immediate Aftermath

Phase II duration is indicated by Δt_2. Calculation of Δt_2 needs to consider both the case in which the local power supply infrastructure survives (with a probability P_S of such event to happen) and the case in which it does not (with a probability $1-P_S$). If for a given hazard and H_i value the expected repair time for the destroyed system is Δt_{2S}, and the expected restoration time for all relevant PESIs is Δt_{2i}, then

$$\Delta t_2 = P_S \Delta t_{2i} + (1-P_S)\mathrm{Max}(\Delta t_{2i}, \Delta t_{2S}). \quad (12)$$

Δt_{2S} has two components: $\Delta t_{2\mathrm{PP/ST}}$ related to the power plant or substation repair time, and Δt_{2D}, related with the service

Fig. 13. AT&T's Lake CO in New Orleans and its surroundings.

area distribution repair time. Since the service area distribution network has a limited extension, in almost all applications $\Delta t_{2D} \ll \Delta t_{2\mathrm{PP/ST}}$. If $P_{\mathrm{DPP/ST}}$ is the probability that the power plant or substation is destroyed then

$$\Delta t_{2S} = P_{D,\mathrm{PP/ST}} \Delta t_{2\mathrm{PP/ST}} + (1-P_{D,\mathrm{PP/ST}})\Delta t_{2D}. \quad (13)$$

If it is assumed that adequate circuit protections are used, damage to the power plant or substation is independent to damage to the service area distribution, and probability for those events only depends on the hazard characteristics and on the attributes of each of those system parts. Thus, if P_{Ds} is the probability that the system does not survive and $P_{D,D}$ is the probability that the service area distribution is destroyed, then

$$P_{\mathrm{Ds}} = 1 - P_S = P_{D,\mathrm{PP/ST}} + P_{D,D} - P_{D,\mathrm{PP/ST}} P_{D,D}. \quad (14)$$

Another difference between phases I and II is that $E_{\mathrm{pu},2}$ is typically a function of time. If the power plant or the substation is destroyed, then $E_{\mathrm{pu},2}$ is 1 until those components have been repaired. Then, for the rest of Δt_2, $E_{\mathrm{pu},2}$ is the system unavailability Q_S which equals $1-A_S$ given by (8). Otherwise, $E_{\mathrm{pu},2}$ equals $1-A_S$ from (8) for the entire Δt_2, as shown in (15) at the bottom of the page. In some cases—e.g., TO A systems or TO B and C systems when the service area is a neighborhood—$E_{\mathrm{pu},2}$ also depends on time because O_I is a function of time as suggested by Fig. 7. Once $E_{\mathrm{pu},2}$ is known, I_{H2} is calculated from

$$I_{H2} = O_{C/t} L \int_0^{\Delta t_2} E_{\mathrm{pu},2}(t)dt. \quad (16)$$

It can be expected that in Phase II failure and repair rates and, thus, availabilities, such as A_{PP}, change according to the new operational conditions. For simplicity, failure and repair rates affecting $A_{\mathrm{PP/ST}}$ may be considered constant during Phase II. Yet, this framework does not limit this assumption, so a more detailed evaluation may consider them a function of time.

While in (6) Δt_1 depends on the hazard type and its intensity, as shown by its equivalence to T_{TS} in (1), it may seem that Δt_2 could also depend on the service operator management and

$$E_{\mathrm{pu},2}(t) = \begin{cases} P_{D,\mathrm{PP/ST}} + (1-P_{D,\mathrm{PP/ST}})Q_S, & \text{for } 0 \le t \le P_{D,\mathrm{PP/ST}} \Delta t_{2,\mathrm{PP/ST}} \\ Q_S, & \text{for } P_{D,\mathrm{PP/ST}} \Delta t_{2,\mathrm{PP/ST}} \le t \le \Delta t_2. \end{cases} \quad (15)$$

maintenance procedures and strategies, and on external factors affecting repairs and service restoration speed. For example, the restoration time of the grid feeding the service area for TO A or B systems depends on the restoration process of the utility owning the local grid, e.g., the number of crews involved in restoring the grid service. Another example of these external factors is manufacturing lead times for replacement parts. However, since Δt_2 is obtained from a mean value representing a baseline case yielded by past events data, particular characteristics affecting Δt_2 for a given site are considered as part of Phase II vulnerabilities. As a result, repairs and logistic operations necessary to restore service and/or keep loads powered influence $I_{\mathrm{adj},2}$ through V but not I_{H2}.

In Phase I, V was mostly related with infrastructure weaknesses affecting both the service area and the PESIs. In Phase II, V also relates to logistical needs associated with the repair process and the service continuity strategies. For example, since TO B systems rely on diesel backup generators to power the load after a hurricane, then V depends on the service area access roads characteristics, and on a number of logistical aspects affecting fuel delivery, including refueling operation effectiveness and timing, diesel availability and contracting strategies, and number of sites owned by the same service operator that can compete for the same resources than the studied service area. For TO C, use of DG technologies, such as PV modules, that do not have logistical needs contribute to make V smaller. However, in many cases these DG technologies are not enough to power large loads. On the other hand, availability of other DG technologies depends on technical and logistical characteristics of infrastructures out of the service area. Thus, a good strategy for TO C is to choose a diverse pool of DG technologies that for a given hazard may reduce V by balancing logistical and external repairs influences with technical limitations. In any case, parameters for this phase are heavily influenced by the critical event effects both inside and outside the service area under study. Since logistical organization and operations are so important in this phase, decisions taken during pre-Phase I preparedness activities—in case the hazard allows for preparation, as it occurs with hurricanes—influence the outcome of this second phase. Thus, effects of pre-Phase I preparations, and logistical planning and actions are implicitly included in this Phase II.

C. Phase III: Extreme Event Long-Term Aftermath

Once infrastructures are repaired and service is restored there is still an often overlooked but potentially significant impact: capital costs of unused infrastructure caused by lower demand than the existing pre-Phase I. This is a typical situation for very intense hazards, such as in the area around Lake CO in New Orleans (Fig. 13), where the number of electric users three years after Hurricane Katrina was 50% of those existing before the storm. This demand shortage creates a financial cost associated with underutilized infrastructure due to differences between system capacity—planned, engineered, purchased, and installed before the critical event—and the post-event demand. The problem of unused capacity is aggravated by difficulties in estimating demand evolution after a critical event, which may lead during Phase II to repair the system to demand levels existing before the critical event. Hence, unused capacity costs have to be considered as part of C_L for of the system being planned. Thus, Phase III duration Δt_3 starts when Phase II ends, and lasts as long as there is idle capacity being depreciated. In Phase III, impact can be calculated with

$$I_{H3} = C_{I/t} \int_0^{\Delta t_3} U_{\mathrm{pu},3}(t)dt \qquad (17)$$

where $C_{I/t}$ is the cost of the idle capacity per unit time and $U_{\mathrm{pu},3}\ (t)$ is the expected unused portion of the system capacity. The cost $C_{I//t}$ can be calculated by dividing the sum of the system's capital and installed costs by the system's design lifetime. Since it is expected that the load does not instantaneously recover its original level, $U_{\mathrm{pu},3}$ is a function of time. For most critical events with a low to moderate intensity, both $U_{\mathrm{pu},3}$ and Δt_3 are relatively simple to model because service areas are repopulated to the original load levels relatively quickly once the evacuation orders are lifted and the restoration process is completed. Even more, for low hazard intensities, $\Delta t_3 = 0$. Yet, for locations where hazards are intense, $U_{\mathrm{pu},3}$ and Δt_3 are difficult to determine because of the little existent consistent restoration data. For example, although there is some information about New Orleans and the Mississippi River delta repopulation after Hurricane Katrina [34], data is still insufficient. In these cases, the combined experience of service area operator's personnel and local officials may provide enough information to estimate these two parameters during the planning process. For extreme cases when the load never recovers its original level, an upper bound on Δt_3 can be set equal to the equipment total capital depreciation time. For example, for TO B, Δt_3 can be made to last at most ten years because this is the typical life of most commonly used lead-acid batteries. In practice, when the load never recovers Δt_3 spans from the time when the disaster is expected to happen to the time when the idle capacity has fully depreciated.

During Phase III, V relates to inflexibility or un-scalability, because underused infrastructure costs are more severe if the system under study cannot be modified in order to adapt to a reduced and uncertain demand. Although it may initially seem that systems with design based on the TO A may be less vulnerable in Phase III because it does not include a local power plant, their vulnerability may, actually be higher, because substations do not have modular components (e.g., transformers) and design. Designs based on TO B and C may, actually, be less vulnerable to this effect if power plants with modular-scalable and flexible designs are used because components associated with excess capacity can be relocated to other sites without affecting system functionalities.

D. Significance of Estimation Errors in Risk Calculation

In order to evaluate the effect of the parameter estimation errors, let's consider the relative error sensitivity

$$S_r = \left| \frac{x}{F(x)} \frac{dF(x)}{dx} \right| \qquad (18)$$

where $F(x)$ is a function whose value depends on x, and dF is the error observed in $F(x)$ yielded by a small error dx in estimating x. Error estimation significance for R can be evaluated by calculating S_r with $F(x) = C_L$ and $x = R$. From (4) and (18),

$$S_r = \frac{1}{1 + (C_{\rm CI} + C_O + C_D)/R} = \frac{1}{1 + C_S/R}. \quad (19)$$

Thus, TOs in which C_S—sum of $C_{\rm CI}$, C_D, and C_O—is low with respect to R, as it typically happen with TO A when the load is not critical, are more susceptible to errors in R than those TOs, such as TO C, in which R is reduced through a higher $C_{\rm CI}$. Yet, since the ratio of C_S to R depends on many variables a definite answer depends on a case-by-case evaluation.

Calculation of S_r of R with respect to P_H, V, or I_H yields each the same result: $S_r = 1$. Hence, high (low) relative errors in the estimation of any of these 3 parameters lead to a high (low) relative error in R. There are extensive studies on disasters evaluating relative errors in estimating P_H [30] and since analyzing meteorological or geophysics values is not the focus of this paper, further discussion on errors in estimating P_H will not be discussed here. Nevertheless, in most cases P_H can be estimated with sufficient accuracy to avoid significant impacts on R. Vulnerability estimation errors are not discussed in detail here either because its evaluation is site and application specific. Indeed, since V is evaluated with respect to a baseline case, there are almost endless options to consider. Moreover, inclusion of V in the planning process is often dependent on the lead planner decision based on the desired analysis complexity level, so in those cases when V has a relative large error, part of the lead planner decision involves evaluating tradeoffs between acceptable error levels and planning process complexity.

Within the context of this work, it is more relevant to discuss errors in estimating parameters affecting I_H. The main parameters being estimated that affect the calculations of impacts are the durations of the phases (Δt_1 to Δt_3), infrastructure hardware-related parameters ($E_{\rm DI}$ and $U_{\rm pu,3}$ (t)), and load-related parameter (O_I affecting both $E_{\rm pu,1}$ and $E_{\rm pu,2}$). Errors in $E_{\rm DI}, U_{\rm pu,3}(t)$, and Δt_3 tend to affect more those TOs with higher $C_{\rm CI}$—i.e., TO C—whereas errors in $E_{\rm pu,1}$ and $E_{\rm pu,2}$, and in Δt_1 and Δt_2 tend to affect less reliable systems, such as TO A ones. Estimation errors for TO B systems represent cases somewhat in between TO A and TO C systems because TO B systems have higher $C_{\rm CI}$ and availability than TO A systems but lower $C_{\rm CI}$ and availability than TO C systems.

In Phase I, I_{H1D} and I_{H1O} are directly proportional to $E_{\rm DI}$, and Δt_1, respectively. Hence, S_r for I_{H1D} or I_{H1O} with respect to $E_{\rm DI}$ and Δt_1, respectively, is 1. The other parameter that affects I_{H1} is O_I through $E_{\rm pu,1}$, as indicated by (7) and (8). Except for TO C when the service area is a building, I_{H1O} depends implicitly or explicitly on $1 - O_I$. The resulting S_r increases from 0 when $O_I = 0$ to a positive value $\xi < 1$ when $O_I = 1$. Since $\xi < 1$, the relative error in I_{H1O} is less than that for O_I. Yet, since Δt_1 is almost always much shorter than Δt_2 or Δt_3, usually I_{H1O} does not have a significant weight over total risk calculation. Other estimated parameters in Phase I are those related with $A_{\rm ST/PP}$. Yet, these parameters can almost always be estimated with a negligible error because of industry's long experience in building databases for reliability studies. Survival probability P_S is another parameter often with a negligible error because for a given H_i and disaster complete destruction is relatively simple to model and anticipate, as Figs. 9 and 11 exemplify.

Estimation of most parameters in Phase II leads to similar observation than those in Phase I, except for the effects of that the time dependence of O_I has on Δt_2 and $E_{\rm pu,2}$. For simplicity, let's assume that electric service restoration follows an exponentially decaying form, as indicated in Fig. 7 through $\rho_e(t)$, with γ being the maximum value for O_I reached at the end of Phase I, and τ the time constant—obtained empirically based on the 95% restoration time, $T_{R,95\%}$ trough $\tau = T_{R,95\%}/3$. Since Δt_2 is related to τ—e.g., Δt_2 can be defined as equal to 5 τ or equal to $T_{R,95\%} = 3\tau$—then only τ needs to be estimated. For TO A it can be shown from (16) that if $\Delta t_2 = T_{\rm R,95\%}, I_{H2}$ is

$$I_{H2} = O_{C/t}L((1 - A_{\rm ST/PP})\Delta t_2 + 0.95 A_{\rm ST/PP}\gamma\Delta T_2/3) \quad (20)$$

then, the relative error in I_{H2} increases with increasing values of γ and Δt_2. Hence, special attention needs to be placed in studying these parameters in order to reduce errors in estimating I_{H2}. A similar relationship is observed for TO B or TO C when the service area is a neighborhood. However, when the service area is a building, $E_{\rm pu,2}$ for both TO B and C equals $(1 - A_S)$. Hence, S_r of I_{H2} with respect to Δt_2 is 1.

In Phase III, if load restoration is assumed to follow a bounded exponentially increasing curve (Fig. 6), then $U_{\rm pu,3}$ (t) has an exponentially decreasing form. The two parameters that need to be estimated are the initial idle capacity $U_{\rm pu,0}$ and Δt_3. Since Δt_3 is related to the time constant of $U_{\rm pu,3}$ (t), then S_r for I_{H3} with respect to either $U_{\rm pu,0}$ or Δt_3 equals 1 for all TOs, so relative significant errors in I_{H3} could be made when $U_{\rm pu,0}$ or Δt_3 are large. However, both $U_{\rm pu,0}$ and Δt_3 have deterministic upper boundaries—total system capacity for $U_{\rm pu,0}$ and equipment capital depreciation time for Δt_3. Hence, in their maximum values, when their effect on the error in calculating I_{H3} would be highest, there are no estimation errors.

In order to support this discussion, consider that in 2005, a few weeks after Hurricane Rita, a study is performed in order to evaluate power options for a data center to be located in Cherokee County, Texas, that will process banking data from 100 offices. The downtime cost for each bank is \$30 K/hour. For such a data center with a total power consumption of about 700 kW, $C_{\rm CI}$ for TO A is \$200K, for TO B is \$2.4M (includes 4 h of battery backup), and for TO C is \$2.8M (powered by natural gas microturbines and diesel reciprocating engines). For simplicity, C_O for all cases is \$613 K/year and total depreciation time is ten years. The potential hazard affecting the site is a strong category 2 hurricane striking the Texas northern Gulf Coast, which translates into an LTCII of 0.55. The return period for such hurricane is 19 years. Thus, P_H for a ten-year span is 0.31, and if the hurricane occurs it is more likely to happen at the 5.82 year mark. It is expected that such a hurricane will close 30% of the 100 banks for 30 days and another 20% of them will close permanently. Only for TO C it is possible to relocate half of the idle capacity. It is assumed that all vulnerabilities are 1 and that $P_S = 1$. Planners use data from the 2004 and 2005 hurricane seasons in order to characterize the hazard. From these data, it can be shown that γ follows a logistical regression curve

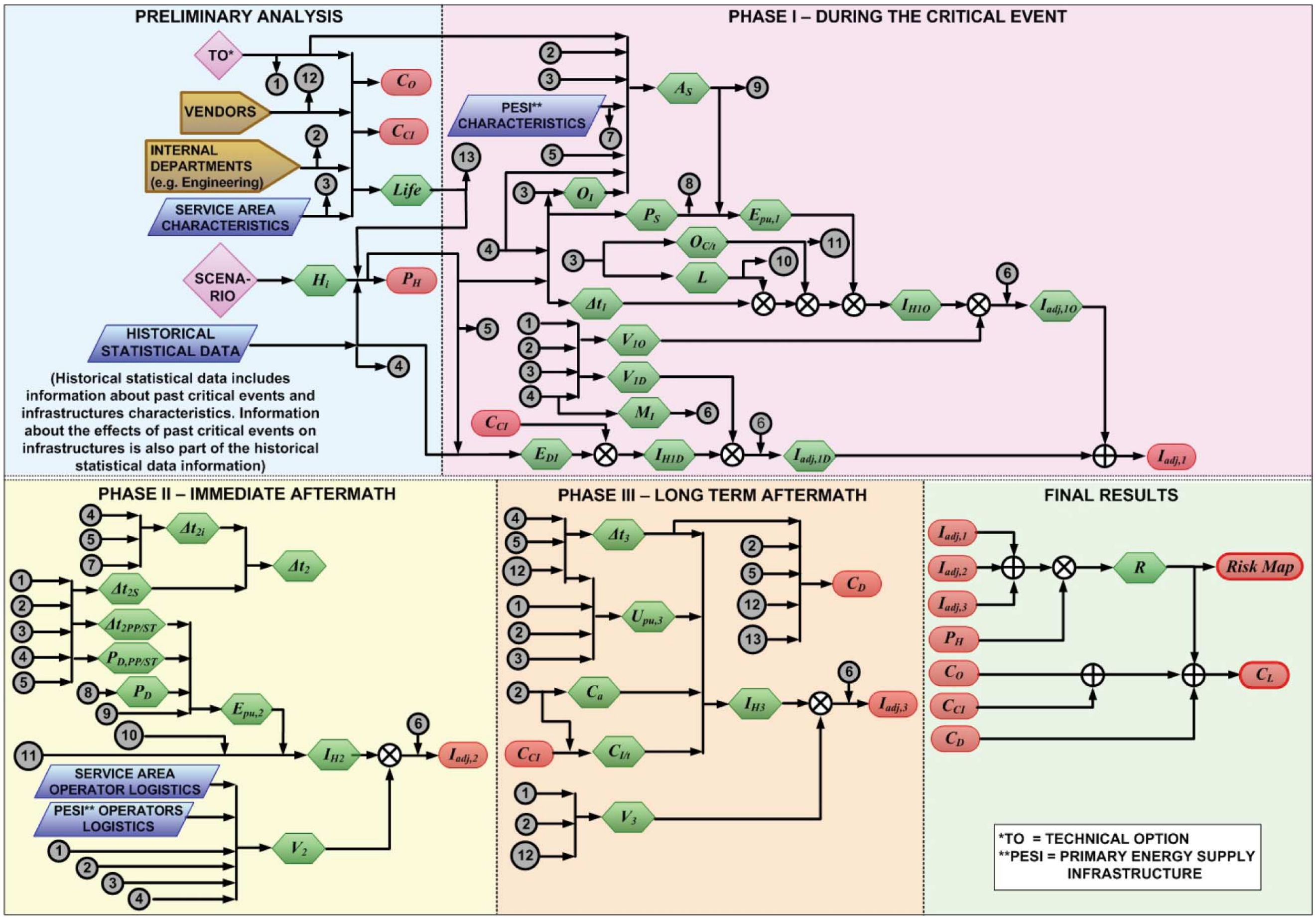

Fig. 14. Graphical flow chart representation of the described risk analysis-based planning framework process.

TABLE I
LIFETIME COSTS AND ITS COMPONENTS IN MILLIONS OF DOLLARS

TO	Values	C_{CI}	C_O	C_D	R	C_L	Largest $I_{adj,i}$
A	Estimated	\$0.2	\$6.1	\$240.8	\$38	**\$285.1**	$I_{adj,2}$ = \$104.22
B	Estimated	\$2.4	\$6.1	\$2.4	\$0.69	**\$11.6**	$I_{adj,2}$ = \$1.93
C	Estimated	\$2.8	\$6.1	\$0.24	\$0.066	**\$9.2**	$I_{adj,3}$ = \$0.21
A	From Ike	\$0.2	\$6.1	\$226	\$38.07	**\$270.4**	$I_{adj,2}$ = \$102.24
B	From Ike	\$2.4	\$6.1	\$2.26	\$0.41	**\$11.2**	$I_{adj,2}$ = \$0.93
C	From Ike	\$2.8	\$6.1	\$0.23	\$0.11	**\$9.23**	$I_{adj,3}$ = \$0.35

with respect to Log(LTCII) in which there is a 75% chance that the actual value for γ falls within $\pm 10\%$ of the value given by the regression curve, implying a correlation of almost 0.85. For $T_{R,95\%}$ the regression curve is a 6th degree polynomial with a similar correlation. The values estimated from these curves were $\gamma = 0.68$, and $T_{R,95\%} = 6.71$ days. An additional value of interest is A_S which equals 3-nines for TO A in normal operation, 0.996 for TO B during the expected hurricane and 5-nines in normal operation, and 6-nines for TO C [15]. Table I summarizes the results of the estimated calculations, and for comparison adds actual data from Hurricane Ike which affected the studied area three years after Rita causing at the data center site a $\gamma = 0.76$, and a $T_{R,95\%} = 5.89$. In both calculations TO C is the best choice with a minimal risk. Downtime cost leads to higher C_L for TO A. Outages in Phase II are the highest risk factor for TOs A and B. Errors between estimated and actual values for C_L are small enough to validate the proposed evaluation framework.

V. SUMMARY AND CONCLUSIONS

This paper presents a risk analysis-based framework—summarized in Fig. 14—to plan power procurement decisions for service areas that could be subject to a critical event. The planning process involves comparing three different TOs based on their lifetime cost obtained from adding the capital and installation cost, the operation cost, the downtime cost under normal conditions, and the risk associated with losses related with service outages, equipment damages, and unused hardware capacity that may result from a critical event. The three TOs are: direct power from the grid, grid supported by a backup power plant, and a micro-grid with local DG. For the last TO, the planning framework allows identifying the most suitable DG technologies to be used at the evaluated site.

The analysis divides the risk related with a given hazard in 3 phases: during the critical event, the immediate aftermath, and the long term aftermath. For each of these phases risk is calculated as the combined monetary effect of the hazard impact and the system vulnerability. Although hurricanes are the main hazard used to exemplify some of the concepts, the same framework can be used to a wide variety of critical events, both of nature and human origin. In practice, it is expected that the planning framework will be implemented with a computer. The systematic method represented in Fig. 14 and the use of a quantitative risk analysis approach (as opposed to a qualitative approach) facilitate computer implementation of the planning process and comparison of the relative value of each TO. It also allows for a simple mapping of risk levels that may affect a system when located at different sites. Although the described calculations rely primarily on using expected mean values from a random variable, the framework allows for more detailed evaluation using more elaborate distributions. Yet, in most practical problems, these more elaborate methods do not yield a significant difference over the expected mean value approach and likely demand more time. Future work will be dedicated to study historical statistical data from past hurricanes and earthquakes in order to support practical implementation of the planning framework.

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