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Resilience Framework, Methods, and Metrics for the Prioritization of Critical Electrical Grid Customers

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Abstract: One of the main objectives of new operating regimes, such as transactional power systems, is to make the power grid more resilient to catastrophes and disturbances, while at the same time making it possible to supply electricity to the largest number of customers. Although this is true, it is well known among power system operators that not all customers are the same. The consequence of this is that any discussion around the impact of transactional power systems on power system resilience should consider the needs of its critical users (such as control centers, fire stations, and hospitals) over other users. In assessing power system resilience, a metric is needed that gives "bonus points" to those systems that, under all circumstances, can continue to provide electricity to their critical users. In order to serve as a parameter in the assessment of power grid resilience, the research presented here discusses the proportion of critical loads existing in critical infrastructures. Once the critical loads are characterized, the next step is the inclusion of these loads in resilience metrics. This paper proposes resiliency metrics in which certain customers (those categorized as critical) are assigned a higher weight than others. One thing to keep in mind is the fact that there is no one-size-fits-all approach for all power systems, and that the assignment of such weights to customers can vary significantly from one operator to another based on their unique systems and the current and expected states of their critical customers.

Keywords: resilience metrics; critical customers; critical loads; customer prioritization

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1. Introduction

Because modern societies depend on the availability of electricity to carry out everyday tasks [1–5], electric power systems are considered one of the most critical infrastructures in developed countries [6–9]. The very high cost of power outages due to natural catastrophes, coupled with the impact on personal safety as a result of the loss of critical services [10], leads to the need to ensure a near-continuous supply of electricity to end users with few interruptions over an extended period of time [11]. In the case of a hurricane that can last for hours or days, the degradation in the performance level of the power grid worsens over time [12]. For example, by comparing the duration of electricity restoration time as a consequence of the 2017 hurricanes that took place in Texas, Florida, the British Virgin Islands, and Puerto Rico, it could be seen that such restoration times reached the values of 11 days, 13 days, 4 months, and 7 months, respectively [13]. Since it is practically impossible to prevent damage to the system under any cause, the emphasis is usually placed on minimizing the effect of the damage and prompt restoration of service [14]. In these cases of extreme emergency, "load shedding plans" are carried out to provide protection against system collapse [15] and, in this way, attempt to avoid cascading failures in the power grid [16–18]. Ideally, the amount of load to be shed should be as minimal as possible to avoid system instability [19,20]. In this sense, although the concepts of availability and quality of service are not new, there is a need to refer to the concept of resilience to maintain essential services to critical loads [21].

Due to the impossibility of preventing, at all times, all possible threats to the infrastructures associated with the electric power system [22], the resilience of critical infrastructures emerged with the aim of emphasizing their ability to continue providing goods and services even in the event of disturbances in the power grid [22]. Critical loads are considered to be those for which electric service is crucial for the protection or maintenance of public health and safety; these include hospitals, police stations, fire stations, critical water and wastewater facilities, and customers with special life-support equipment and the enterprises that support them [23]. Given the importance of these critical facilities to public safety, these facilities enjoy priority restoration (to the extent possible), additional communications, and other resources before and during outages [24].

The need to increase the resilience of critical infrastructure during emergencies caused by high-impact, low-probability events (such as extreme weather events caused by climate change) is more important than ever in today's world [21,25,26]. In this sense, the goal is be aimed at decreasing the frequency of major outages [27], reducing their impact on society [27], recovering as fast as possible [27], and better understanding the operational requirements of critical infrastructures [28].

The most widely used reliability metrics, namely, the System Average Interruption Frequency Index (SAIFI), the System Average Interruption Duration Index (SAIDI), and the Momentary Average Interruption Frequency Index (MAIFI) date back to the late 1960s and early 1970s [29]. Since then, the basic metrics and their application have not fundamentally changed [29]. Although electricity users highly value the resilience of the power system during storms (when homes and businesses are most affected by outages), reliability metrics generally exclude those days of major events [29]. In this sense, power sector resilience should be understood as the ability of the sector to anticipate, prepare for, and adapt to changes in changing conditions and to withstand, respond to, and recover quickly from power outages [30–33]. Assessing the impact of energy resilience on society remains an active area of research, suggesting that opportunities for improvement remain [32]. Although many metrics exist, there is no single metric or set of metrics for every purpose [32]. As a result, different metrics are needed to understand the resilience of energy systems [32].

In the scientific literature, it is possible to find a large number of research papers proposing novel power system resilience metrics. Among the most notable may be those carried out by Patriarca et al., who presented a simulation model combined with simple metrics that focus on a system's resilience at a technical level, represented through absorption, adaptation, and recovery [34]; those conducted by Mishra et al., who developed a framework for demonstrating resilience enhancement through the utilization of multi-microgrids and mobile energy storage in extreme operating conditions [35]; the research undertaken by Amirioun et al., who provided a quantitative framework for assessing microgrid resilience in response to high-impact, low-probability windstorms [36]; and the investigation conducted by Younesi, who assessed the resilience of a large-scale multi-microgrid-based power system to cope with the wide-area natural disasters with severe destructive effects [37].

However, quantification of the social consequences of not powering critical loads during a blackout has not received the same attention, and a study to address them is needed. Some authors, such as Mishra et al. [38], Poulin et al. [39], Umunnakwe et al. [40], Shi et al. [41], Hossain et al. [42], Plotnek et al. [43], and Wang et al. [44], provided a review on metrics and strategies for grid resilience and reliability; other authors, such as Sun et al. [45], Souto et al. [46], Gorham et al. [47], and Rocchetta [48], provided statistical analysis on resilience metrics; some modeled engineered system and infrastructure availability, such as Cheng et al. [49], Azimian et al. [50] and Senkel et al. [51]; others proposed multi-stage frameworks for resilience evaluation, such as Mahzarnia et al. [52], Wang et al. [53], Nasri et al. [54], Shandiz et al. [55], Cicilio et al. [56], Zhang et al. [57], and

Alkhaleel et al. [58]; and Younesi et al. [59] developed multi-objective resilience-economic stochastic scheduling models. such as

As a consequence, from this deeper survey of the updated literature related to the topic addressed here, it was possible to find that—even though there are plenty of different approaches—this paper contributes to the pool of existing knowledge by:

- Discussing the proportion of critical loads existing in critical infrastructures;
- Including these loads in resilience metrics;
- Proposing resiliency metrics in which certain customers (those categorized as critical) are assigned a higher weight than others;
- Providing resilience metrics to specifically facilitate the evaluation of critical customer prioritization (thus far not explicitly shown, to our knowledge, in any scientific paper).

By performing this thorough literature review, we ensured the originality of the idea and method presented here.

Finally, this study also indicates that many of the strategies that provide additional resilience in electric power systems with distributed energy resources rely on local coordination through microgrids and, where appropriate, the use of sensors [60].

This Section 1 briefly discussed the resilience metrics available in the literature; in the Section 2, a resilience metrics to facilitate the evaluation and prioritization of critical customers is presented and discussed; subsequently, in the Section 3, the results for case studies using the proposed metrics are shown. The Section 4 is reserved for conclusions, where the consequences resulting from the implementation of the proposed metrics are presented.

2. Evaluation of the Model Proposal and Discussion

To properly characterize critical loads, it is necessary to determine which redundant systems that electrically supply such critical loads would be the first to be used and which would be secondary (i.e., those that will only be used if there is a failure of the first redundant system) [61]. In addition, for some critical functions, a consumer may have means to temporarily maintain functionality without relying on the critical load [61]. These factors influence the contribution of critical loads to the risk assessment [61]. In the context of electric power systems, critical loads refer to processes, facilities, and services essential to health, safety, security, safety, or economic welfare, without which catastrophic loss of life, adverse economic effects, and significant damage to public confidence could result [62].

In this sense, critical loads refer to the minimum load necessary for any critical infrastructure to carry out its essential functions during a natural disaster or state of emergency [63]. The collateral damage resulting from not feeding critical loads depends on the type of critical infrastructure evaluated. As a consequence, not all the loads of a critical infrastructure should be considered as critical loads; instead, only the percentage of loads necessary to keep critical services operational should be considered. By definition, a component is critical if the effects of its failure are intolerable for the installation [64]. Because of this, and according to a “ranking” of the load priority, power should be ensured to critical loads by disconnecting non-critical loads [65].

Taking into account [66–68], the research presented here considers that, depending on the system configuration, a disturbance of a system component may or may not cause a service interruption to customers and may affect the power quality even if the service is not interrupted. Following [41], this article considers infrastructure resilience as the ability of a system to withstand, respond to, and recover from disruptions. This capability can be described in terms of both time and system performance [41]. A resilience curve, as shown in Figure 1, represents, within a specific scenario, the evolution over time of a measure of system performance [41]. A curve typically starts at a nominal level, decreases due to a disturbance, and then recovers (ideally returns to the nominal level) [41]. Metrics are used to compare curves by quantifying key dimensions of the curves [41]. In Figure 1, residual performance metrics describe the system performance following the disruption, generally after cascading failures [41], whereas the disruption duration is defined as the duration during which the network performance was below 99% [69].

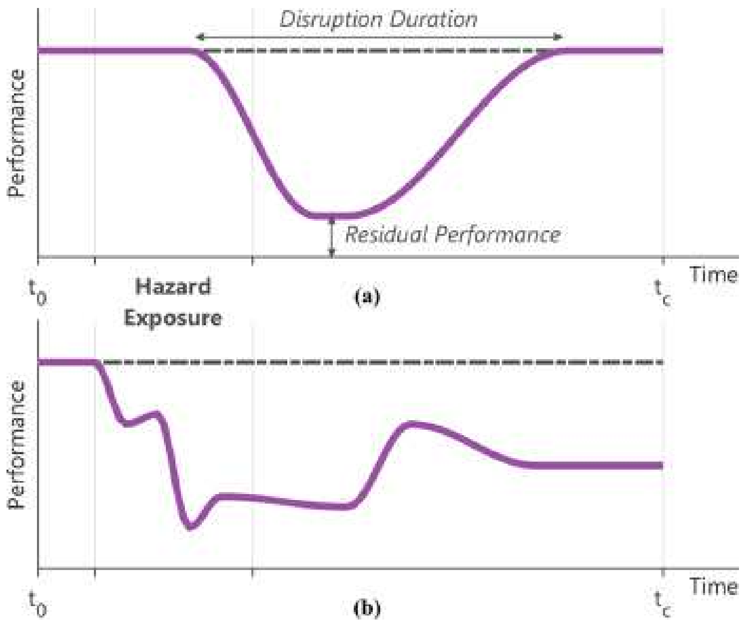

Figure 1. (**a**) Typical resilience representation with two possible summary metrics; (**b**) resilience representation curve showing non-idealized system behavior. Source: [39].

The performance measure (vertical axis in Figure 1) can quantify system availability, system productivity, or service quality [39]. In the abscissa axis, t_0 means the initial instant of the global control duration [39], and t_c is the expected or mean recovery time [39].

As shown in Figure 1, an electric power system can have various performance states when subjected to unforeseen internal or external disturbances. Through any quantifiable metric (such as reliability, availability, etc.), system resilience can be quantified [70]. A quantifiable metric can help to study, adapt, and mitigate high-impact, low-probability events [71] and, as a consequence, improve system resilience [72]. Due to the above, a model based on a quantifiable metric is proposed in the research presented here. In particular, a quantitative model and metrics of electrical grids' resilience evaluated at a power distribution level, developed at the University of Pittsburgh [73], is adapted. Based on the definition of resilience, the framework presented in [73] proposes a resilience metric that is based on a measure analogous to availability. In [73], individual resilience (R_I) for a single load is defined as:

$$R_I = \frac{T_U}{T} = \frac{T_U}{(T_U + T_D)} \tag{1}$$

which establishes an appropriate measure of resilience through the dependence of the rise and fall times, T_U and T_D, respectively.

Base resilience refers to the level of resilience of the electric power system based solely on its functional properties (such as capacity, cost, and modes of operation) [74]. In other words, it represents the efficiency of the power grid without applying any management techniques to resource optimization [74]. In a more specific sense, it is also possible to define the base resilience R_B for N loads as [73]:

$$R_B = \frac{\sum_{i=1}^{N} T_{U,i}}{NT} = \frac{\sum_{i=1}^{N} T_{U,i}}{\sum_{i=1}^{N}(T_{U,i} + T_{D,i})} \tag{2}$$

where T is the time period considered; $T_{U,i}$ is the part of T in which a load i can receive electrical energy, i.e., the "rise" time; and $T_{D,i}$ is the remaining part of T in which the load i cannot receive electrical energy, i.e., the "fall" time.

Something to take into account would be the fact that it is not imperative that all N loads in a given zone suffer an interruption [73]. Outage incidence, θ, indicates the percentage of customers who suffer a power outage with respect to the total number of customers [75,76]. Therefore, θ is calculated as [73]:

$$\theta = \frac{n_o}{N} \tag{3}$$

where n_o is the number of customers experiencing an outage. The maximum incidence of outages θ_{max} is observed when n_o is equal to the maximum number of outages observed during T.

During a power system disturbance, the main objective is the proper accounting of critical loads. In this regard, only a few customers are identified as critical. This is because not all customers require the same levels of reliability of electric power supply. The formulation proposed below aims to include information regarding critical loads in a systematic way, so that these loads are properly reflected in the assessment metrics.

Suppose that TC is the set of customer types of a given electric power system. For an electricity supply company, the categorization of its customers is of high importance. During a power system disturbance, it is common for some of these customer groups to temporarily lose their power supply. In this regard, it is imperative to include the concept of weight for each type of customer, so that the system tries to "favor" the more critical loads during an emergency condition. With this consideration in mind, the base resilience metric shown in Equation (2) is modified by including weights for the different customer types. In this way, the proposed metric defines, with a weighted concept, the base resilience for N loads.

Let P_{tc} be the weighting of a customer type $tc \epsilon TC$. The prioritized base resilience metric is shown in Equation (4). This metric first evaluates the base resilience of each customer type and combines them with the assigned weights. Note that the total sum of weights is kept at one to keep the value of the resilience metric in the range of 0 and 1.

$$R_B^{prior} = \sum_{tc \, \epsilon \, TC} P_{tc} \cdot \frac{\sum_{i=1}^{N_{tc}} T_{U,i}}{\sum_{i=1}^{N_{tc}} (T_{U,i} + T_{D,i})} \tag{4}$$

In Equation (4), $\sum\limits_{tc \, \epsilon \, TC} N_{tc} = N$ is the total number of customers within the evaluated system. Since the availability of critical customers is defined using the rise $(T_{U,i})$ and fall $(T_{D,i})$ times of the critical portion of their loads, the metric defined above only improves if the critical loads are continuously energized. Because of this, it is considered important to include the priority of the loads. Consequently, and in order to improve the evaluation of electric power systems, it is imperative to modify the base resilience metric defined in Equation (2) through the inclusion of a weighting of customers.

The percentage of customers experiencing an outage in an area, relative to all customers in the area at a given time, is defined as outage incidence (see mathematical representation of Equation (3)). Because the loads are weighted, the metrics not only reflect the number of customers when quantifying the outage, but also include factors that give an indication of the loss of critical loads during an outage. Mathematically, this is expressed in Equation (5):

$$\theta_t = \frac{1}{N} \cdot \sum_{tc \, \epsilon \, TC} P_{tc} \cdot \sum_{i=1}^{N_{tc}} (1 - u_{tl}) \tag{5}$$

where, following [76], u_{tl} is the status of load l to determine in period t. $u_{tl} = 1$ if load l is restored in period t; otherwise, $u_{tl} = 0$. The maximum incidence of outages occurs when $\sum_{i=1}^{N_{tc}} (1 - u_{tl})$ equals the maximum number of outages observed before recovery begins.

Figure 1 showed the trajectory of system performance in the event of a power outage. The area defined by the trajectory curve is equivalent to the loss of system performance.

With the inclusion of a weighting in the formulation, the objective is the minimization of the load outage duration, taking into account the priority of the loads. To increase the weighted availability of critical loads, it is necessary to decrease the area under the resilience curve, presented in Figure 2. This is achieved by (i) prioritizing critical customers and critical loads; (ii) bringing them into service more quickly; or (iii), while reacting to an event, providing uninterrupted supply to critical loads such that their overall downtime is decreased.

(i) If the event is completely avoided or if the probability of its occurrence is decreased, then the mean time between events increases.
(ii) If the system can respond more quickly to the occurrence of an event and the event is reacted to more quickly, then the depth of the event may decrease, so that the curve in Figure 2 becomes shallower.
(iii) Similarly, if system improvements make the system able to recover from events more quickly, the final part of the curve in Figure 2 is advanced in time so that the duration of the event is shortened, the rate of recovery increases, and the area can be reduced again.

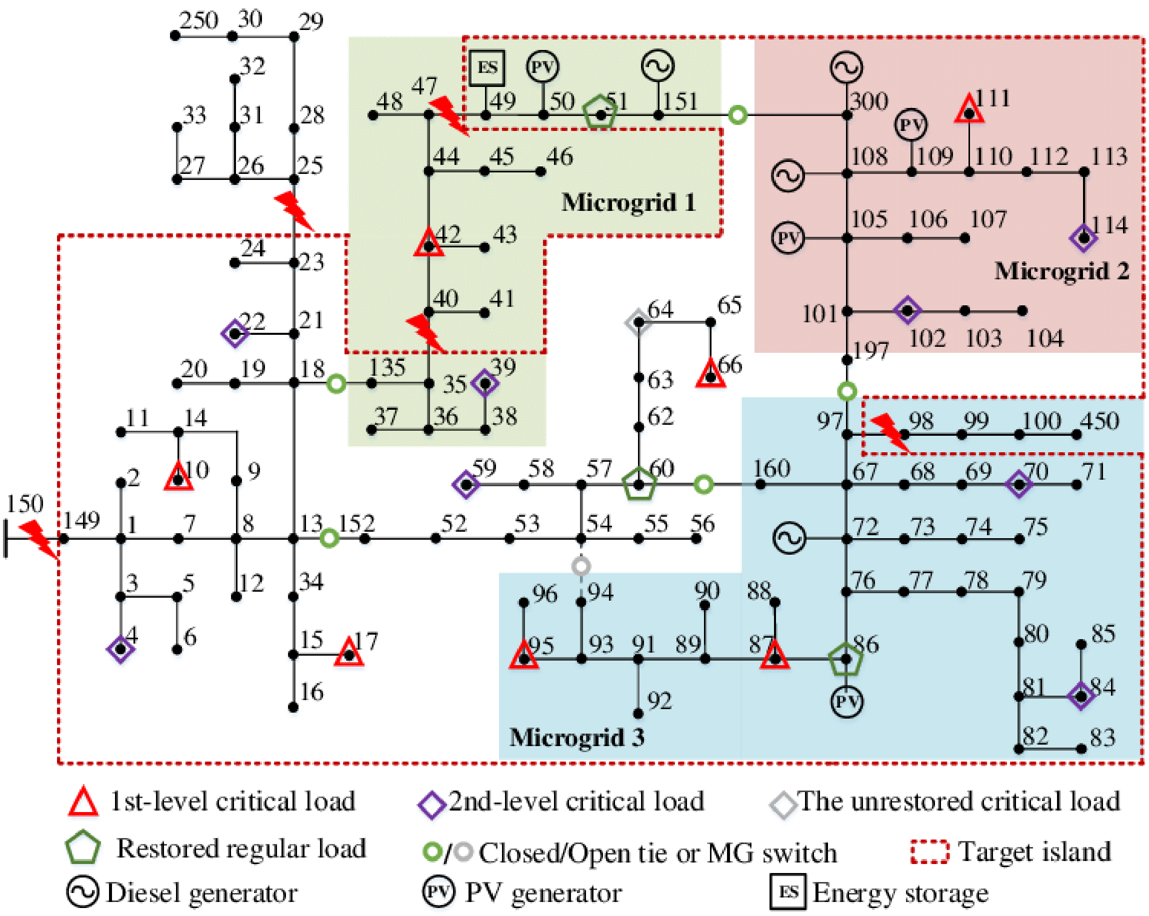

Figure 2. IEEE 123-node test system with three microgrids. Source: [77].

In summary, the availability of critical loads can increase if a system can (1) avoid or postpone the event, (2) respond or react to the event, or (3) recover from the event quickly.

3. Results

Section 2 suggested the need to improve the existing metrics for critical load prioritization. To this end, a modification to one of the existing metrics in the literature [73] was proposed to include the concept of weighting. This section further clarifies the application of the proposed concept through a case study. The first step is to know and understand the system that is supporting a disturbance. For this purpose, the power network topology proposed in [78] and shown in Figure 2 is used.

One thing to keep in mind is the fact that there is no one-size-fits-all approach for all power systems, and that the assignment of such weights to customers can vary significantly from one operator to another based on their unique systems and the current and expected states of their critical customers. It should also be mentioned that, although the factors influencing the electrical resilience of modern electric power systems are numerous and constantly changing [79], the viability of power flow is the most influential factor in the resilience of electric power systems [40]. Following the definition provided by Raoufi et al., the research presented here assumes that the power system resilience is "the ability of this system to withstand disasters (low-frequency high-impact incidents) efficiently while ensuring the least possible interruption in the supply of electricity, sustain critical social services, and enabling a quick recovery and restoration to the normal operation state" [80].

The increasing pressure around environment protection [81], the issue of renewable energy accommodation [82], and the need for better and faster event detection and identification [83] suggests the need to improve the existing metrics for critical load prioritization, as proposed in the research presented here.

In the representative system presented in Figure 2, there are three types of customers:

- First-level critical loads (human life/safety-related loads);
- Second-level critical loads (public operation management institutions, necessary city operation loads, and industrial customers);
- Regular loads (residential loads).

Additionally, there are three different types of resources:

- Diesel generators;
- Distributed generators (PV, fuel cells, etc.);
- Energy storage.

For these case studies, a grid disturbance event was considered that caused a major grid outage that was remedied within the same day. Table 1 summarizes the different types of customers and their assigned weights. These values were randomly selected for demonstration purposes and may not reflect the actual values used in practice.

Table 1. Type of customers and their assigned weighting. Source: own elaboration.

Customers	Number of Loads for a Set of Customer Types (N_{tc})	Weighting of Customer Type (P_{tc})
First-level critical loads (human life/safety-related loads)	7	0.6
Second-level critical loads (public operation management institutions, necessary city operation loads, and industrial customers)	9	0.3
Regular loads (residential loads)	300	0.1
Total	316	1

Next, some case studies were conducted to see the performance of critical loads on the proposed resilience metric. In the case studies, it is shown how the new resilience metric in (4) captured the concept of the critical load, whereas the original base resilience metric defined in (2) did not.

A one-day lead time was considered. Three different case studies showed different individual customer availabilities. It is possible to observe how the value of the resilience metric increased with increasing customer availability. The uptime and downtime of each customer were taken and entered into the equations to evaluate the metric. For example, in Case I, of the seven first-level critical loads, six of them were always on and never lost power supply throughout the day, whereas one first-level critical load was without supply

80% of the time (i.e., it was only in service 20% of the time in a day). Therefore, in this particular case, its total uptime was 7.2 (i.e., 1 + 1 + 1 + 1 + 1 + 1 + 1 + 1 + 0.2). Doing similar calculations, the metric for Case I was evaluated using (2). Similar calculations were performed for calculating the metric when the uptime and downtime of a customer changed for different case studies.

$$R_{B.CI} = \frac{7.2 + 8.4 + 270}{316 \cdot 1} = \frac{285.6}{316} = 0.904$$

Table 2 shows the value of the resilience metric using (2) for three different case studies (Case I is considered as the reference case). In Case II, it can be seen that the resilience metric increased from 0.904 to 0.951 when the availability of regular loads was increased from 270 to 285. On the other hand, for Case III, the resilience metric increased to a value of 0.906 with the increase in the availability of the first-level and second-level critical loads (see Table 2). Considering the numerical values, it is plausible to conclude that resilience is higher for Case II because this method evaluates the base resilience without a proper distinction between customers.

Table 2. Value of the resilience metric for different cases using (2).

Customers	Case I	Case II	Case III
First-level critical loads (human life/safety-related loads)	7.2	7.2	7.6
Second-level critical loads (public operation management institutions, necessary city operation loads, and industrial customers)	8.4	8.4	8.7
Regular loads (residential loads)	270	285	270
R_B	0.904	0.951	0.906

Table 3 shows the value of the resilience metric using (4) for case studies equivalent to those shown in Table 2. In this evaluation, it was observed that the resilience metric was higher in Case III than in Case II. This is because the proposed metric also takes into account a weighting of critical loads. In this case, a significant improvement in resilience can be observed, and it is observed that critical loads receive energy almost continuously.

Table 3. Value of the resilience metric for different cases using (4).

Customers	Case I	Case II	Case III
First-level critical loads (human life/safety-related loads)	$0.6 \cdot (7.2/8) = 0.54$	$0.6 \cdot (7.2/8) = 0.54$	$0.6 \cdot (7.6/8) = 0.57$
Second-level critical loads (public operation management institutions, necessary city operation loads, and industrial customers)	$0.3 \cdot (8.4/9) = 0.28$	$0.3 \cdot (8.4/9) = 0.28$	$0.3 \cdot (8.7/9) = 0.29$
Regular loads (residential loads)	$0.1 \cdot (270/300) = 0.090$	$0.1 \cdot (285/300) = 0.095$	$0.1 \cdot (270/300) = 0.090$
R_B^{prior}	0.910	0.915	0.950

From the case studies presented above, it is clear that once a prioritized metric is available, it can be used to assess the resilience of the power grid to any situation in which a disturbance occurs, and thus, guide the response of the power grid to the disturbance.

4. Conclusions

The objective of this paper was to introduce an approach based on metrics focused on the weighting of critical loads to evaluate the performance of the power grid when a disturbance is experienced. For this purpose, a structure was proposed to rank the critical parts of the infrastructure that are identified as critical based on historical disasters. A weighting-based approach was also proposed to quantify the positive impacts of prioritizing critical loads. In addition, it was shown how the proposed weighting-based formulation can be implemented to augment and improve the current metrics already in use. Although most of the literature in the field of power system resilience and reliability agrees that there should be some level of prioritization for critical customers, almost none of it provides any metrics that can facilitate the evaluation of critical customer prioritization. This paper provides a characterization of critical customers and critical loads by proposing a modification of existing resilience metrics in order to weight the impact of critical customer prioritization on those metrics.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

MAIFI	Momentary Average Interruption Frequency Index
N	Number of loads
N_{tc}	Total number of customers within the evaluated system
n_o	Number of customers experiencing an outage
P_{tc}	Weighting of a customer type
R_B	Base resilience
R_B^{prior}	Prioritized base resilience metric
R_I	Individual resilience for a single load
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
T	Time period considered
t_0	Initial instant of the global control duration
t_C	Expected or mean recovery time
TC	Set of customer types of a given electric power system
T_D	Fall time
$T_{D,i}$	Remaining part of T in which the load i cannot receive electrical energy, i.e., a "fall" time
T_U	Rise time
$T_{U,i}$	Part of T in which a load i can receive electrical energy, i.e., the rise time
u_{tl}	Status of load l to determine in period t
θ	Outage incidence
θ_{max}	Maximum incidence of outages

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