Time-dependent resilience assessment and improvement of urban infrastructure systems

Min Ouyang1,a) and Leonardo Dueñas-Osorio2,b)

1Department of Control Science and Engineering, Image Processing and Intelligent Control Key Laboratory of the Education Ministry of China, Huazhong University of Science and Technology, 1037 Luoyu Road, Wuhan 430074, China
2Department of Civil and Environmental Engineering, Rice University, 6100 Main Street, MS-318, Texas 77005, USA

(Received 21 November 2011; accepted 28 June 2012; published online 16 August 2012)

This paper introduces an approach to assess and improve the time-dependent resilience of urban infrastructure systems, where resilience is defined as the systems’ ability to resist various possible hazards, absorb the initial damage from hazards, and recover to normal operation one or multiple times during a time period \( T \). For different values of \( T \) and its position relative to current time, there are three forms of resilience: previous resilience, current potential resilience, and future potential resilience. This paper mainly discusses the third form that takes into account the systems’ future evolving processes. Taking the power transmission grid in Harris County, Texas, USA as an example, the time-dependent features of resilience and the effectiveness of some resilience-inspired strategies, including enhancement of situational awareness, management of consumer demand, and integration of distributed generators, are all simulated and discussed. Results show a nonlinear nature of resilience as a function of \( T \), which may exhibit a transition from an increasing function to a decreasing function at either a threshold of post-blackout improvement rate, a threshold of load profile with consumer demand management, or a threshold number of integrated distributed generators. These results are further confirmed by studying a typical benchmark system such as the IEEE RTS-96. Such common trends indicate that some resilience strategies may enhance infrastructure system resilience in the short term, but if not managed well, they may compromise practical utility system resilience in the long run. © 2012 American Institute of Physics. [http://dx.doi.org/10.1063/1.4737204]

Urban infrastructure systems are vital to the operation of modern society and its economy, yet they are unavoidably subject to different types of hazards and are vulnerable to cascading failures within and across systems. Hence, different from traditional system safety analyses using scenarios or hypothetical accidents in an attempt to understand their effects and the reasons for their occurrence, the concept of resilience has been proposed in acknowledgment of the unavoidability of hazards or accidents. A number of articles have recently assessed the resilience of systems under single and multiple hazards. However, these studies neither address the evolving features of infrastructure systems due to the steady increase of service demand and post-event improvement efforts, nor address inter-hazards interactions, as the occurrences and effects of future hazards may be affected by previous ones. Capturing these unexplored features leads to the proposal of a time-dependent resilience metric for urban infrastructure systems. This paper uses power transmission systems as examples to show the time-dependent and nonlinear features of resilience, and discusses the effectiveness of some resilience-inspired strategies, including situational awareness (SA) enhancement, consumer demand management, and distributed generators (DGs) integration, in order to emphasize the need to carefully manage emerging smart infrastructure techniques.

I. INTRODUCTION

Economic prosperity, public health and safety cannot be achieved without the normal operation of critical infrastructure systems, including electric power systems, telecommunications, natural gas and oil, banking and finance, transportation, water supply systems, government services, and emergency services.1 Most critical infrastructure is composed of networked systems and exposed to different types of hazards. The failures of some system components at the local level may result in the disruptions of other components via cascading failures, and may also affect other systems due to interdependencies. For example, communities that lack electric power, even for short periods of time, have trouble meeting basic needs for food, shelter, water, law and order.2 Hence, traditional system safety analyses focus on scenarios or hypothetical accidents in an attempt to understand their effects and the reasons for their occurrence.3 Alternatively, recent resilience analyses acknowledge that hazards or accidents are unavoidable and attempt to improve system resilience with respect to different possible hazards.
Regarding the term “resilience,” scholars or institutes from different fields have proposed different definitions. As a synthesis of the available literature, this paper defines the resilience as the joint ability of infrastructure systems to resist (prevent and withstand) different possible hazards, absorb the initial damage, and recover to normal operation. Based on different definitions of resilience, many researchers have proposed various methods or frameworks to quantify it and assess it. One of the pioneer works in the field of infrastructure systems is from the Multidisciplinary Center for Earthquake Engineering Research (MCEER), which provides a general framework to define and quantify the seismic resilience of communities or any type of physical and organizational systems. Resilience in this framework includes four properties: robustness, redundancy, resourcefulness, and rapidity, while resilience itself is quantified with four interrelated dimensions: technical, organizational, social, and economic. Based on this framework, there are many emerging studies on the resilience assessment and quantification of performance for practical utility systems to support resilience-based decisions. These studies include the comparisons of seismic resilience retrofit strategies in a water delivery system, seismic resilience assessment for acute care facilities, hurricane resilience analysis for networked infrastructure systems, quantification of disaster resilience using an analytical function which can fit both technical and organizational issues, the formulation of adjusted resilience metrics with the consideration of preferences and priorities of a decision maker, the quantification of system resilience with the consideration of recovery cost, and the proposal of a resilience assessment framework adequate for both single and multiple hazards.

The above studies can be classified as static resilience analysis because they keep the system initial parameters constant and the resilience is measured by a static quantity. But in practice, infrastructure systems are always evolving due to the steady increase of service demand and post-event improvement efforts, including enhancements of physical component capacities, implementation of improved operation standards and guidelines, focus on safety culture, and the integration of new technologies, all of which result in the system’s resistant, absorptive and restorative capacities changing as a function of time. Also, during the evolvement and improvement processes, the occurrences and effects of future hazards may be affected by previous ones so that there exist inter-hazards interactions. These aspects cannot be captured by static resilience analyses, requiring a method to quantify resilience by a time-dependent metric that enables exploration of the evolving and nonlinear features of resilience.

This paper introduces an approach to assess and improve the time-dependent resilience of infrastructure systems. The rest of this paper is organized as follows: Section II introduces the time-dependent metric for resilience assessment. In Section III, taking the power transmission grid in Harris County, Texas, USA as an example, the time-dependent and nonlinear features of resilience and the long-term effectiveness of some resilience strategies inspired by smart grid technologies are all simulated and discussed. Section IV discusses the contributions and robustness of the findings by exploring diverse potential system evolution forces and additionally studying a typical system such as the IEEE RTS-96. Finally, Section V provides conclusions and future research directions.

II. TIME-DEPENDENT RESILIENCE ASSESSMENT

Most research usually uses the system performance response process following the occurrence of a hazard as shown in Fig. 1 to quantify and assess resilience. The performance response process can be divided into three different stages: the disaster prevention stage \( (0 \leq t \leq t_0) \), the damage propagation stage \( (t_0 \leq t \leq t_1) \), and the recovery stage \( (t_1 \leq t \leq t_E) \). These three stages together constitute a typical response cycle, and can respectively reflect the systems’ ability to resist (prevent and withstand) possible hazards, absorb the initial damage from hazards, and recover to normal operation levels. In other words, system resilience is determined by three system capacities: the resistant capacity as the ability to prevent different possible hazards and reduce the initial damage level if a hazard occurs, the absorptive capacity as the degree to which the systems absorb the impacts of initial damage and minimize associated consequences, such as cascading failures, and the restorative capacity as the ability to be repaired quickly and effectively.

However, many infrastructure systems are continuously evolving. The occurrence rates and intensities of some hazards, and the three system capacities all change with time, leading to the unexplored time-dependent and nonlinear features of resilience. Hence, this paper introduces a time-dependent resilience metric. Within a time period from 0 to \( T \) (with cases of sufficiently large \( T \) allowing for future system evolution), denote the target performance curve by \( TP(t) \), and the real performance curve by \( P(t) \), while system resilience \( R(T) \) is quantified as the ratio of the area between \( P(t) \) and the time axis to the area between \( TP(t) \) and the time axis,

\[
R(T) = \frac{\int_0^T P(t)dt}{\int_0^T TP(t)dt}. \tag{1}
\]

![FIG. 1. Typical performance response curve of an infrastructure system following the occurrence of a hazard.](image-url)
Note that the value of $R(T)$ is bounded in the range $[0, 1]$. During $T$, system responses under different possible hazards are captured by $P(t)$, which can contain none or many $t_0$ to $T$ cycles. Hence, Eq. (1) fully captures the resistant, absorptive, and restorative capacities of infrastructure systems. In addition, if the curves $P(t)$ and $TP(t)$ are measured by different performance level metrics, the amount of flow or services delivered, the availability of critical facilities, the number of people served, or the enabling potential of economic activities, Eq. (1) corresponds to the technical, organizational, social, and economic dimensions of resilience, respectively. This paper takes the amount of flow delivered as the performance level metric, and focuses on the technical dimension of resilience. Other dimensions of resilience could be estimated as well provided adequate system and contextual data. For example, if the fraction of customers served is used as the performance level metric, the social dimension of resilience can be assessed as it is similar to a power system reliability metric used in the industry—the average service availability index (ASAI), which is the ratio of the total number of customer hours in which service is available during a given time period to the total customer hours demanded. However, even for the technical dimensions and different from reliability analyses, which usually model the hazards and the restoration processes by deterministic parameters or random variables with distribution parameters estimated from the historical data, the resilience analysis requires modeling the emergency responses and restoration efforts in detail to analyze and compare the effectiveness of improvements under different conditions. In addition, different ranges of $T$ yield different forms of resilience.

First, when the time span $0$ to $T = T_p$ represents a time period in the past, the real performance curve $P(t)$ can be plotted from the recorded historical data but the targeted performance curve $TP(t)$ during the disruptive processes may be difficult to ascertain if the selected performance metric, such as the amount of flow delivered for technical resilience, has a time-varying feature. In this case, the targeted performance curve can be determined according to the real performance curve trends, for instance, as a straight line between points $A$ and $B$ (Fig. 1). Then, system resilience can be computed from $TP(t)$ and $P(t)$ according to Eq. (1).

Second, when the time span $0$ to $T = T_c$ marks a period ending at a current point in time there is a performance process that cannot account for system evolution as the time is just passing and no actions have taken place. Hence, system parameters are all fixed, and the hazards can be modeled according to empirical data up to that point. Then, resilience can be simulated and computed from current system parameters. As these parameters are all fixed, this resilience provides an estimation of system performance at the current time point and then can be called “current potential resilience.”

Third, when the time span $0$ to $T = T_f$ marks a period ending in the future, it considers the system evolving process, and system parameters may be modified at each time and after each accident or hazard event. With the evolution and improvement models, system resilience can also be simulated and computed. Note that this resilience value depends on the improvement strategies to be adopted; hence, it can be called “future potential resilience.”

The first form of resilience is based on historical data and can be easily computed from Eq. (1). The second form of resilience has been studied already in another paper by the authors. Hence, this paper mainly considers the third form of resilience. Section III uses an example to illustrate the technical aspects of resilience assessment and improvement.

### III. EXAMPLE APPLICATION

This paper mainly uses the truncated power transmission system in Harris County, Texas, USA shown in Fig. 2 as an example to illustrate the technical resilience assessment and improvement method. The original system data are obtained from Platts. There are 417 nodes, in which 23 of them are generator nodes. The reminder is a set of substation nodes, in which the ones with degrees equal to one (57 nodes) are assumed to be load nodes; the rest are transshipment nodes. The nodes are linked by 551 lines with a total length of 2411.5 km. Due to the unavailability of power injections and line susceptance data for security reasons, this paper assumes that all lines have the same susceptance value of 1, and that all lines have the same line capacity value of 0.475 with all voltages equal to 1 in a normalized fashion. Also, for illustrative purposes, assume that all nodes have the same power injection, and their values make the maximum value of all line flows 90% × 0.475. The generator capacities are then set as 1.2 times their generation. These parameter settings and assumptions are all based on the work from Pepyne, and deemed reasonable for the focus of the paper on resilience analyses.

### A. Resilience assessment model

To obtain the $TP(t)$ and $P(t)$ functions in a period of time $0$ to $T_f$ to quantify system future potential resilience, hazards require modeling, as well as system cascading failures, restoration processes, and the long term evolution and improvement mechanisms.

Power systems are subject to different hazards types. For illustrative purposes, this paper considers random hazards and emerging internal hazards during the system

![FIG. 2. A geographical representation of the power transmission grid in Harris County, Texas.](image)
evolution process due to line overloads. The random hazards are a collective name for hazard types that may include equipment failures as well as hazards triggered by vegetation (trees), animals, and human errors. They only cause a small portion of the system components to initially fail and have the typical features of variety and uncertainty so that their occurrence can be modeled by random failures, where each component possesses a representative failure probability.

To capture the internal cascading process, several models have been proposed in the last decade, including DC based OPA models (a joint effort from the U.S. Oak Ridge National Laboratory, the Power System Engineering Research Center at the University of Wisconsin-Madison, and the University of Alaska, where “OPA” is the combination of key letters from these three organizations), AC based power flow models, hidden failure models, complex network based models, and stochastic models. Based on these existing models, this paper uses the DC power flow calculation to capture the main operation features of the power system for computational efficiency and also considers hidden failures along with operator and communication errors, which are frequent causes for blackouts in practice.

For the restoration, scholars mainly assign to each damaged component a restoration time given a damage level based on historical statistics. Finally, for the evolvement and improvement mechanisms, this paper mainly considers the load growth and the capacity improvement of overloaded lines (with details in the simulation procedures introduced later in this subsection). Other aspects such as network topology along with component aging could be added in future studies.

The above damage, restoration, and evolvement aspects lead to the nonlinear feature of power system performance responses to different hazards. Hence, building upon the introduced resilience metric, evidence from existing studies, the investigations from several major blackouts, and the common practices from the utility companies, this paper uses the following resilience assessment model, in which the time-dependent evolvement and improvement modules are mainly based on the OPA model. The output is an estimate of $P(t)$ from 0 to $T_f$ under pertinent hazards, where the amount of total delivered power flow is the performance level metric. The flow chart in Fig. 3 synthesizes the method and follows these steps:

1. Set the start time $t = 0$.
2. Initialize or update system parameters, such as power injections and line capacities. If $t = 0$, initialize the system as the traditional power system. If considering some smart infrastructure improvement strategies, as discussed in Subsections III B–III E, it requires modeling such interventions and adjusting the corresponding system parameter settings. If $t > 0$, system parameters may be further updated based on two types of mechanisms. One is based on the post-blackout improvement decisions introduced in step 17. The other is the growth of power demand. Each day the daily peak power demand for each load substation is multiplied by a fixed parameter $\lambda$ that represents the daily rate of increase in electricity demand. The parameter $\lambda$ is set as 1.00005 based on past electricity consumption in the United States, corresponding to a yearly rate of 1.8%. In addition, to represent the daily local fluctuations in power demand, all power loads are multiplied by a random number uniformly distributed in the range of $[1 - r, 1 + r]$, where $r$ is set as 0.20. Also, for each generator $i$, its capacity increases proportional to the absolute difference between its current capacity and the sum of its connected line capacities until one of the following two conditions is satisfied: (1) the sum of all generator capacities reaches 1.2 times the total power demand; (2) the capacity of generator $i$ reaches the sum of its connected line capacities. In addition, with the daily peak demands, hourly power demands can be also estimated based on the hourly load profile if required, as discussed in Subsection III D. Finally, at the current time point $t$ in a daily or hourly
scale, the values of $TP(t)$ and $P(t)$ are identical and both equal to the sum of total power loads.

3. Identify all main hazards acting upon the studied power system, and model their frequencies and impact mechanisms according to the hazard features. For illustrative purposes, this paper only considers random hazards and the emerging overload-induced hazards during the evolution process. The random hazards are modeled by random failures with a daily failure rate $p_0$. For each power line, generate a uniformly distributed random number $n_r \in [0, 1]$, if $n_r < p_0$, then the line fails; otherwise, it remains normal. The emerging internal hazards are captured in step 5. Also, for all initially damaged components, assign to each of them a restoration time $t_r$, which is the sum of a variable $\varepsilon$ describing the arrival time for dispatched resources and a variable $\eta$ denoting the time to repair the damaged components.

4. If there are damaged components, remove them from the system. Run the DC optimum power flow (OPF) model to get the new line flows from real power demand.\textsuperscript{22}

5. Verify whether there are overloaded lines whose flows exceed their capacities; if yes go to step 6, otherwise go to step 7.

6. When there are overloaded lines in the physical systems, and due to insufficient situational awareness (e.g., communication interruptions, failures of the emergency management system, EMS), the dispatch center may fail to make a DC OPF re-dispatch;\textsuperscript{26} this failure probability is denoted by $1 - \delta$. If failed to make a DC OPF-dispatch, then record all overloaded lines and go to step 7, or directly go to step 7 if there is a successful re-dispatch. The DC OPF re-dispatch is used to minimize the change in generation or load shed subject to the system constraints, denoted by the following cost function:\textsuperscript{22}

$$\sum_{i \in S_p} |p_i - P_i| + \sum_{j \in L_p} W|p_j - P_j|,$$

where $P_i$ ($P_j$) is the power injection for node $i$ ($j$) before re-dispatch and $p_i$ ($p_j$) is the new power injection. $S_p$ is the set of generators and $L_p$ is the set of demand nodes. All generators are assumed to run at the same cost and all loads have the same priority to be served. However, the load shed is assigned a penalty factor $W = 100$ to reflect power management practices. The minimization of the cost function is done with the following constraints:\textsuperscript{22} (1) total power generated and consumed should be identical: $\sum_{k \in V_p}(p_k - P_k) = 0$, where $V_p$ is the set for all nodes; (2) power flow through each line $ij$ should be less than its capacity $|f_{ij}| \leq F_{ij}^\text{max}$, $ij \in E_p$, where $E_p$ is the set of all power lines; (3) power produced by each generator $i$ should be less than its capacity: $0 \leq p_i \leq P_i^\text{max}$, $i \in S_p$; and (4) ensure load shedding ($p_j - P_j$) is positive and less than the absolute value of initial load $P_j$ so that: $P_j \leq p_j \leq 0$, $j \in L_p$. This optimization problem can be transformed into a standard linear programming (LP) problem. The solutions are the new power injections of the nodes and the power flows through transmission lines.

7. For each line connected to the end of the failed lines and exposed to hidden failures for the first time, test its failure with probability $hp$.\textsuperscript{24} If failed, assign to the line a repair time, which is the sum of $\varepsilon$ and $\eta$. Also, overloaded lines are assumed to be all tripped due to various reasons. If the lines are tripped by normal relay operations, they can be reconnected without dispatching repair crews, and their repair time is zero; if the lines are tripped with damage, such as contact with trees, some repair efforts are required, and each damaged line is assigned a repair time, which is the sum of $\varepsilon$ and $\eta$. The probability of overloaded lines failed with damage is denoted by $fd$.\textsuperscript{22} The probability variables $hp$ and $fd$ are informed by historical data or previous studies and their values are set at the end of this subsection.

8. Verify whether there were failed lines; if yes, remove them from the system and go to step 4 to keep simulating the cascading failure; or go to the step 9.

9. Record the current simulation time, with the value of $P(t)$ as the current total power delivered, and the value of $TP(t)$ the same as its value assigned in step 2.

10. Verify whether there are damaged lines, if yes, go to step 11 to start the restoration process, otherwise, go to step 16 to judge whether there is load shedding.

11. Move to time $t = t + t_e$, where $t_e$ refers to the emergency response time for failure detections and restoration decisions.

12. Restore the damaged and unrestored components with the minimum restoration time $\min\{t_r\}$. Move to $t = t + \min\{t_r\}$.

13. Reconnect all restored components, and then make a DC OPF re-dispatch. If it reduces the current total power supply, cancel the reconnection and go to step 12; otherwise, keep the reconnection and then go to step 14.

14. Record the simulation time, the value of $P(t)$ as the current total power delivered, and the value of $TP(t)$ as its value assigned in step 2.

15. Verify whether all components have been restored. If yes, go to step 16; otherwise, go to step 12 to keep restoring the remaining damaged components.

16. Verify whether there is load shedding, if so, determine the time $t_s$ to restore the shed loads and then move the time $t = t + t_s$. Restore all loads, record the time. The values of $P(t)$ and $TP(t)$ are identical and both equal to the total power delivered or the value of $TP(t)$ set in step 2, Then, go to step 17. If there is no load shedding, go directly to step 17.

17. Verify whether the simulation time reaches the value $T_f$, if yes, go to step 18 to end. Otherwise, make improvement decisions, move the time to a new day (or the next hour if the simulation runs at a hourly scale) and go to step 2. Here, similar to the OPA model,\textsuperscript{21,22} engineering post-blackout improvement is simplified into a parameter of post-blackout improvement rate $u$, which takes effect after the blackout events. This means the capacities of all overloaded lines during the last blackout are multiplied by the constant parameter $u$. Also, note that in practice there is a day-ahead market which can affect the next-day load allocations, especially when the demand is
higher than the total supply and then it needs to shed load for balance. This feature is simply modeled in step 2 by daily local fluctuations while step 6 can capture the load shed if necessary.

18. End.

Note that the target performance curve $TP(t)$ is simply fixed as a constant line during each blackout event, which does not affect the following discussions in this paper. However, given a daily and hourly load profile, a time-dependent $TP(t)$ can be also easily simulated to compute the resilience based on the above procedures.

For the same time period from 0 to $T_f$, repeating the above steps yields different realizations of the evolving process, which corresponds to different resilience values to capture uncertainties. Random hazards are modeled by random failures with a daily failure rate $p_0 = 0.00015$ from historical data. For other parameters, based on reality and common practices, their values are set as follows: for restoration time $t_r = \varepsilon + \eta$, where the variable $\varepsilon$ is assumed satisfying the uniform distribution $[0, 3h]$ and the variable $\eta$ satisfying the exponential distribution with mean value 5h. During the cascading failures, the hidden failure probability $hp = 0.005$, the probability of overloaded lines failed with damage $fd = 0.3$, the time required to restore shed load $t_s = 8h$, the probability of OPF dispatch $\delta$ is first set as 0.95; the emergency response time is first set as $t_e = 3h$; and finally, the post-blackout improvement rate is first set as $u = 1.01$.

Some parts of the assessment model are based on previous models, while the impacts of some parameters settings have already been discussed in the existing literature, such as small $hp$ and $fd$ which can reduce the cascading failure sizes. Thus, this paper does not emphasize parameter sensitivity analyses to mainly study the time-dependent features of resilience (Subsection III B) and the impacts of some improvement techniques, feasible for emerging smart infrastructures, including situational awareness enhancement (Subsection III C), consumer demand management (Subsection III D), and distributed generation integration (Subsection III E).

### B. Time-dependent features of resilience

The resilience metric $R(T_f)$ has a time-dependent feature, depending on the time span 0 to $T_f$ under consideration. During the system evolution process, an influential parameter is the post-blackout improvement rate $u$ (step 17). For large $u$, there should be less frequent blackouts as well as small cascading failure sizes. To illustrate the impacts of $T_f$ and $u$, this paper simulates the $TP(t)$ and $P(t)$ functions for the next ten years 500 times, and then calculates the resilience values under different $T_f$ from 1 yr to 10 yr with a step of 1 yr (a period of 10 yr is short enough for the system to evolve without major topological changes and long enough to evolve to new steady states).

As the reliability of the power system is very high (99.97%), the resilience $R(T_f)$ also has a high value. To clearly differentiate among resilience values, this paper presents the resilience value through a logarithmic transformation $-\log_{10}(1 - R(T_f))$, which is an increasing function with respect to $R(T_f)$. Specifically, if the value of $R(T_f)$ includes $n$’s in its decimal portion, the value of $-\log_{10}(1 - R(T_f))$ is in the range $[n, n + 1)$. For example, if $R(T_f) = 0.9997$, then $3 \leq -\log_{10}(1 - R(T_f)) = 3.52 < 4$. Fig. 4(a) shows the logarithmic form of resilience $-\log_{10}(1 - R(T_f))$ as a function of $T_f$ under several typical values of $u$, while Fig. 4(b) presents the resilience variation at $T_f = 1$ and 10 under different post-blackout improvement rates. The error bars with 98% confidence intervals are also displayed.

The figures display two significant features. First, with the increase of $u$, system resilience $R(T_f)$ at a given $T_f$ increases (because of the identical variation tendency for $R(T_f)$ and $-\log_{10}(1 - R(T_f))$, results also illustrate the variation of the resilience $R(T_f)$). Trends are consistent with practical expectations. For large $u$, the system will always have enough capacity to absorb the disturbances and there will be less frequent blackouts as well as smaller cascading sizes, so the system is more resilient. For small $u$, the system has insufficient absorptive capacity and the system can collapse with constant blackouts, and the system resilience is compromised. Second, and less intuitive, with the increase of $u$ the resilience as a function of $T_f$ changes from a decreasing

![Fig. 4. (a) The logarithmic transformation of resilience $-\log_{10}(1 - R(T_f))$ under several typical values of post-blackout improvement rate, $u$. The error bars with 98% confidence intervals are also displayed. (b) Resilience with $T_f = 1$ and 10 under different post-blackout improvement rates, $u$.](image-url)
function to a constant line to an increasing function. This nonlinear phenomenon is because increasing $u$ from 1.001 to 1.1 changes the system from a state dominated by power demand growth (more frequent blackouts and larger cascading sizes) to a state dominated by post-blackout improvement efforts (less blackouts and smaller cascading sizes). Specially, if $u > 1.1$, the system can quickly evolve to new resilience levels.

C. Impact of situational awareness enhancement

Lacking adequate SA may lead to serious consequences and has been identified as one of the primary factors in previous blackouts. In the future smart grids, situational awareness can be improved in many aspects relative to today’s SA systems, as with the deployment of advanced monitoring sensors, and the installation of advanced visualization tools in control rooms.

In the proposed resilience model, the impact of SA can be reflected in each of the three resilience stages. In the disaster prevention stage, SA can facilitate early warnings, so that the daily failure rate $p_0$ decreases. In the cascading failure stage, SA can help operators in the control room make fast and accurate emergency decisions when facing the appearance of overloaded lines while minimizing the possible load shedding, which can be partially reflected by the OPF dispatch probability $\delta$. In the restoration stage, SA can accelerate the restoration decisions and lead to efficient restoration procedures, which can be partially mirrored by the emergency restoration time $t_e$. To study the effect of SA, this paper simulates resilience variations under different values of $p_0$, $\delta$, and $t_e$. The simulation results are presented in Fig. 5. The error bars with 98% confidence intervals are also displayed. The error bars are wider for $T_f = 1$ relative to $T_f = 10$, which is mainly because $T_f = 10$ is long enough for the system to evolve in to a new equilibrium level and display superior resilience for different SA parameter settings. However, the error bars, even for $T_f = 1$, are still small in practical terms under different values of $p_0$, $\delta$, and $t_e$, which indicates strong robustness for the resilience estimation.

Also, from the figures, when SA is improved, i.e., decreasing the daily failure rate $p_0$, increasing the OPF dispatch probability $\delta$, and reducing the response time $t_e$, the resilience values at any given $T_f$ all increase. For a base case with $p_0 = 0.00015$, $\delta = 0.95$, and $t_e = 3$ h, the logarithm form of resilience $-\log_{10}(1 - R(1))$ is 3.848 at $T_f = 1$. If the cost of different improvement actions is known, the best strategy for resilience improvement can be found through comparing the ratio of resilience enhancement magnitude to the strategy’s cost. As a particular case, the cost for the following strategies is identical: $p_0$ reduces to 0.00005, $\delta$ increases to 1, and the emergency response time $t_e$ reduces to 2 h; hence, the corresponding logarithmic form of resilience $-\log_{10}(1 - R(1))$ changes to 3.963, 3.851, and 3.967, respectively. Then, it

FIG. 5. Resilience variation for $T_f = 1$ and 10 under different SA parameter settings, with $u = 1.01$: (a) initial failure probability $p_0$, (b) OPF dispatch probability $\delta$, and (c) emergency response time $t_e$. The error bars with 98% confidence intervals are also displayed.
As the smart grid deployment unfolds, “smart appliances” and “intelligent equipment” will be installed in homes and businesses, interconnecting with energy management systems in “smart buildings.” These technological advancements will enable consumers to better manage energy use and reduce energy costs, leading to likely flattened hourly consumer load profiles. To analyze the effect of consumer demand management, the simulation is run in an hourly scale. In step 2 of the simulation procedures, after getting substation daily peak power demand, this paper assumes that hourly power demands are normalized by the peak power demand following the “traditional” curve in Fig. 6. For illustrative purposes, if considering demand management, the hourly load profile is assumed to change from the traditional curve to the smart grid curve 1 in Fig. 6. These two traditional and smart grid 1 curves keep the power consumption constant, i.e., the integral of the traditional curve in the range [1 h, 24 h] has an identical value relative to the smart grid curve 1. The smart grid curve 1 can be marked by the normalized average load demand \( \langle L \rangle = 0.745 \). Also, as utility owners usually seek to maximize line utilization, \( \langle L \rangle \) may evolve to the smart grid curve 2 in the long run. This section simulates resilience under the traditional curve and the smart grid curve 1, and also analyzes the resilience variations during the evolving process from the smart grid curve 1 to the smart grid curve 2. Fig. 7(a) presents the resilience results under a traditional load profile and several typical load profiles with demand management, including the levels for smart grids 1 and 2, and Fig. 7(b) shows the resilience variations at \( T_f = 1 \) and 10 under demand management with distinct \( \langle L \rangle \).

From the figures, two interesting results can be found. First, if the demand profile changes from the traditional curve to the smart grid curve 1 (\( \langle L \rangle = 0.745 \)), resilience increases. Also, when \( \langle L \rangle \) increases from 0.745 to 1, the resilience at any given \( T_f \) is compromised. Typically, at \( T_f = 1 \), the resilience reaches the traditional resilience level 99.991% (4.05 for \( -\log_{10}(1-R(1)) \)), under the traditional load profile when \( \langle L \rangle \) is at around 98%. This indicates that demand management can largely improve the utilization of the line capacities, and \( \langle L \rangle \) can increase from 0.745 to 0.98 with the expectation that the resilience level is not lower than the traditional resilience.

Second, with the demand management and the increase of \( \langle L \rangle \), the resilience curve \( R(T_f) \) experiences a transition from a decreasing function to an increasing function at critical \( \langle L \rangle = 0.975 \) (also shown at the intersection of the two curves in Fig. 7(b)). This nonlinear phenomenon is mainly because small \( \langle L \rangle \) not only reduces the grid congestion and blackout frequency, but also cuts down the post-blackout improvement actions. The former can initially increase resilience, while the latter makes the demand growth exceed the post-blackout improvement efforts and the network becomes more and more congested in the evolution process, leading to more blackouts until the demand growth and post-blackout improvement efforts can balance again. But a small \( \langle L \rangle \) also makes the system have a strong absorptive capacity, which requires a long time to reach the new equilibrium state. So, the resilience levels at \( T_f = 1 \) and 10 are close for small \( \langle L \rangle \) but depart significantly as \( \langle L \rangle \) increases, giving advantage to the large \( T_f \) at the maximum \( \langle L \rangle \).

E. Impact of distributed generation integration

The future smart grids can easily integrate many types of distribution generation into the systems, leading to two-
way power flows. This integration can reduce power grid congestion and improve system efficiency, reliability, and flexibility. Recent studies have shown that a local generator can be connected into the power systems as a constant load, source or zero loads to the grid. To deploy DGs, two types of strategies are considered. In strategy S1, the DGs are randomly deployed at the load substations. In strategy S2, the DGs are deployed at the load substations which have the minimum network efficiency from the central generators (the original generators). The network efficiency $E(j)$ for a load substation $j \in L_p$ is defined as follows:

$$E(j) = \frac{1}{N_c} \sum_{i \in S_p} \frac{1}{d_{ij}}, \quad j \in L_p,$$

(3)

where $N_c$ is the number of central generators, and $d_{ij}$ is the shortest path length from central generator $i$ to load substation $j$. When a DG is deployed, its capacity is assumed to be 1.2 times the initial demand of the corresponding load substation, and the capacity keeps fixed in the future evolution process. Based on these assumptions, for each deployment strategy, the resilience is simulated and computed under different number $ndg$ of DGs. Fig. 8(a) shows the logarithmic form of resilience under several typical $ndg$ numbers of distributed generators with the random deployment strategy $S_1$ and minimum network efficiency strategy $S_2$ with different numbers of distributed generators, $ndg$.

From the figures, it can be found that for the random deployment strategy $S_1$, with the increase of $ndg$, the system resilience increases for a given $T_f$ while the resilience $R(T_f)$ transits from an increasing function to a decreasing function over entire ranges of $T_f$ values. The threshold $ndg$ for trend transition is at around 15, accounting for 26% of the total number of load substations Fig. 8(b). The transition is mainly because the larger the $ndg$, the less congestion in the power grid; consequently, there are less frequent blackouts and less post-blackout improvement actions on the power system, so the system is more resilient in the first years of operation after intervention. But with the daily increase of power demand, insufficient post-blackout improvement actions make the system become congested again, leading to more blackouts until the post-blackout improvement actions can catch up the demand increase. Finally for large $T_f$, the system reaches another resilient level, which is worse than the initial resilient state with DGs, but still better than the resilient state without DGs.

A similar nonlinear phenomenon to the one described above also occurs to the minimum network efficiency based deployment strategy $S_2$, as shown in Fig. 8(b), but the threshold value of $ndg$ is reached at around 5 (8.8%). Also, the strategy $S_2$ is more effective than the strategy $S_1$ at any given $ndg$. This is because if a load substation has small network efficiency, it is far from the central generators and then it is easy to disconnect from the network under cascading processes. Deploying DGs to these low efficiency substations can effectively bring more system capacity to absorb the disturbances and get less cascading sizes relative to the random deployment. Particularly, when deploying only 5 DGs, at $T_f = 1$, the strategy $S_2$ can bring a resilience value of 99.9995% ($4.34$ for $–\log_{10}(1 – R(T_f))$) compared to the resilience value 99.990% ($4.02$ for $–\log_{10}(1 – R(T_f))$) under strategy $S_1$.

However, this paper only shows that different deployment strategies bring different resilience. Whether there are better strategies and how to find the optimum strategy is outside the scope of this study but it will be a future research direction.

IV. DISCUSSIONS

The findings in Sec. III, despite using artificial power system parameters for resilience analysis, still provide suggestions for long-term resilience management. Also, note that the results shown in Figs. 4–8 may vary for different power systems due to the various topological, geographical, and operational parameters, so this paper mainly focuses on the introduction of the time-dependent resilience concept and shows the need for careful management of smart grid techniques. These two contributions are further discussed as follows:

1. Time-dependent resilience analyses are more helpful for decision support on long-term resilience management than static resilience analyses. The static resilience analysis mainly models the hazard frequencies and intensities, the cascading failures and restoration processes, and then
produces a multiplicity of performance curves $TP(t)$ and $P(t)$ during $[t_0, t_3]$ for resilience assessment under specific disruptive events (or scenarios), single hazards or multiple hazards. This static resilience is usually measured by a static quantity, which can be used to find optimum strategies to improve system resilience. In addition, despite some recent proposed resilience metrics with certain time-dependent features, which are aimed at specific disruptive events to measure system resilience in time $t \in [t_0, t_3]$ as a function of the performance drop at time $t$ and the maximum performance drop after time $t_0$, they can still be regarded as static resilience because like other static studies the system initial parameters are kept constant. This paper proposes the concept of time-dependent resilience with the additional modeling of system evolvement and improvement mechanisms. This proposed resilience analysis approach can also capture possible inter-hazard interactions during system evolving processes, such as the occurrences and effects of future hazards which are affected by previous hazards, and cannot be addressed by static resilience analysis. Hence, this approach can better assess the long-term effectiveness of resilience-inspired intervention strategies to support decision making from a long-term perspective.

2. Simulation results from other practical power systems with more realistic system parameters also show similar trends of smart grid intervention effects on resilience, emphasizing the need of careful management of smart grid techniques. Although this paper uses artificial power system parameters to study the time-dependent features of resilience and the long-term effectiveness of some resilience-inspired strategies, the results are not sensitive to such parameter details because the initial system parameters only change the resilience level at low $T_f$ levels, while the long-term resilience variations observed in Sec. III are mainly driven by two potential forces during system evolvement and improvement processes. One is the slow service demand growth in time, which increases system congestion and compromises resilience; the other is the post-blackout improvement efforts after each blackout, which decreases system congestion and enhances resilience. If fixing the magnitude of demand growth $\lambda$ and without smart grid upgrades, there exists a threshold value of the post-blackout improvement factor $u_t$, around which the two forces balance and the resilience remains constant with little fluctuation around the average resilience $[u_t = 1.002$ in Fig. 4(a)]. Above such a threshold, the resilience is an increasing function of $T_f$ while below it $R(T_f)$ is a decreasing function of $T_f$. However, the threshold value $u_t$ is not constant and it is affected by the system initial state, where smaller initial congestion levels correspond to larger values of $u_t$. The smart grid techniques, such as demand management and distributed generator integration, can assuage system initial congestion levels and lead to larger values of $u_t$ for smaller $(L)$ or larger $ndg$. When $u$ is set less than $u_t$ in the traditional system, the adoption of smart grid techniques, which increase the value of $u_t$, causes the value of $u$ to always be below $u_t$ and then only produce a set of decreasing curves of $R(T_f)$ for different values of $(L)$ or $ndg$ (results not shown in the paper); when $u$ is set larger than $u_t$ in the traditional system, the adoption of smart grid techniques can cause the transition from the case $u > u_t$ to the case $u < u_t$, which results in the transition of $R(T_f)$ from an increasing function to a decreasing function at a threshold value of $(L)$ or $ndg$, as shown in Figs. 7(a) and 8(a) for decreasing levels of $(L)$ or increasing levels of $ndg$. To further support these results, this paper also analyzes the time-dependent resilience of the single-area IEEE Reliability Test System RTS-96 (Ref. 35) with the consideration of demand growth and post-blackout improvement efforts. This system is specified with realistic operational parameters, although simulation results and associated figures are not shown in this paper, except for some synthesized comments.

Overall, the IEEE RTS-96 example is not congested initially and each line has power flow far from its capacity limitation. Hence, this system has a high resilience level in the first year with a logarithmic value of $-\log 10(1 - R(1)) = 5.21$, and the threshold value $u_t$ to balance the two forces is 1.2, around which the resilience $R(T_f)$ keeps a constant line and below which the resilience decreases as a function of the time period. To explore the effects of different $u$ and smart grid interventions, at any $u < 1.2$, more flattened daily load profile and more deployment of distributed generators do not change the monotonicity of the resilience function, i.e., $R(T_f)$ is still a decreasing function when increasing $(L)$ or increasing $ndg$. At any $u > 1.2$, the resilience function $R(T_f)$ is an increasing function of $T_f$ before adopting the resilience strategies considered in Sec. III, but then non-linear transitions from an increasing function to a decreasing function occur at a threshold value of the average daily load profile $(L)$ or a critical value of the number of distributed generators $ndg$. Specially, at $u = 2.0$, $(L)$ has the threshold value at around 0.949, and $ndg$ has the threshold value of 3, accounting for 17.65% of the total number of load substations, and highlighting that additional interventions can become counterproductive in the long term. The test system is also used, to confirm the robustness of resilience evolution trends to initial system parameters by running the IEEE RTS-96 system with parameter settings as suggested in Sec. III in lieu of the realistic parameters of the systems, and similar trends for the time-dependent evolution resilience are also obtained. These simulation results show that different initial system parameter settings and different levels of post-blackout improvement efforts (modeled by $u_t$), there always exist the possibility of the resilience function $R(T_f)$ to become a decreasing function when adopting smart grid techniques, which indicates that these techniques may improve system resilience in the short term, but if not managed well, they may compromise future resilience in the long run.

V. CONCLUSIONS

Different from the static resilience analysis which assumes system initial parameters constant and measures resilience by a static quantity, the time-dependent resilience
analysis additionally models system evolution and improvement processes and captures possible inter-hazards interactions. Taking the power transmission grid in Harris County, Texas, USA and the IEEE RTS 96 system as examples, this paper explores the features of resilience under different post-blackout improvement factors, and different resilience strategies, including situational awareness enhancement, demand management, and distributed generators integration. The results show that when the post-blackout improvement factors are small, the resilience curves are always decreasing functions at different levels of integration of smart grid techniques; when the post-blackout improvement factors are large, the resilience curves exhibit a transition from an increasing function to a decreasing function at either a threshold load profile with demand management, or a threshold number of distributed generators. These results indicate that the adoption of some strategies may be effective in the short term, but if not managed well, they may compromise resilience in the long run or may consume limited resources unnecessarily.

This paper only considers a few resilience improvement strategies and evolution mechanisms, while some other strategies and evolvement mechanisms, such as topological adjustments, the acknowledgment of interdependencies, the addition of new generators, substations and lines, and the retirement of some components due to economic reasons, failures, or environmental regulations, are all required to support a network-based life-cycle resilience analysis and discuss the associated nonlinear features (with $T_f = \text{several decades}$). Also, besides the random hazards and the emerging hazards due to line overloads, the addition of other types of hazards, such as earthquakes and hurricanes, as well their interaction of effects due to the allocation of improvement resources, enables a more comprehensive resilience analysis. In sum, this paper paves the way to develop a mature tool to design and improve evolving infrastructure systems and their resilience by accounting for their nonlinear nature in the short and long run.

ACKNOWLEDGMENTS

This material is based upon work supported in part by the U.S. National Science Foundation under Grant CMMI-0748231, the National Science Foundation of China under Grants 90924301 and 91024032, and the Independent Innovation Foundation of Huazhong University of Science and Technology under Grant 2012QN088. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the sponsors. The authors also wish to thank Rice University and the Office of Public Safety and Homeland Security of the City of Houston for their support.

17C. W. Zobel, Decision Support Syst. 50, 394–403 (2010).