A Quantitative Method for Assessing the Resilience of Infrastructure Systems

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Abstract: Resilience is a dynamic multi-faceted term and complements other terms commonly used in risk analysis, e.g. reliability, availability, vulnerability, etc. The importance of fully understanding system resilience and identifying ways to enhance it, especially for infrastructure systems our daily life depends on, has been recognized not only by researchers, but also by the public. During recent years, several methods and frameworks have been proposed and developed to explore applicable ways to assess and analyse system resilience. However, they are tailored to specific disruptive hazards/events mainly for other than technological systems, or fail to properly include all the phases, e.g., mitigation, adaptation and recovery. In this paper, after defining the term, a generic quantitative method for the assessment of the system resilience is proposed, which consists of two components: a hybrid modelling approach and an integrated metric for resilience quantification. The feasibility and applicability of the proposed method is tested using an electric power supply system as the exemplary system.

Keywords: Resilience, Critical Infrastructure, Agent-based Modeling, Reliability

1. INTRODUCTION

Engineered infrastructure systems have always been "complicated", but in recent years, they have witnessed growing integration and interconnectedness, which have turned them into complex systems [1, 2]. To better understand the performance of these systems, especially their behaviors during and after the occurrence of disturbances (e.g., natural hazards or technical failures), a great effort has been devoted by researchers with emphasis on different phases and aspects, e.g. availability assessment during the initial loss phase, evaluation of restoration efforts during recovery phase, etc. However, these assessments are challenged by the diversity of the physical flow in the infrastructure systems, by the lack of comparable indexes for quantifying system performances, and by the multiplicity of loss scenarios. A unifying method to analyze and strengthen system performance as responses to disturbances is still missing. To this aim, resilience analysis [3-6] is a proactive approach to enhance the ability of the infrastructure systems to prevent/avoid damage before disturbance events, mitigate losses during the events and improve recover capability after the events.

2. RESEARCH STREAMS AND PROPOSED METHOD

The term resilience is still evolving and has been developing in various fields. The first definition is given by an ecologist, C. S. Holling, who described resilience as "*a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables*" [7]. Since then, others have put forward domain-specific resilience definitions [8, 9]. The concept of resilience is also introduced to engineered technical systems. From an engineering perspective, resilience can be defined as "*the ability of the system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable time and costs*" [10]. In recent years, assessing and engineering resilience of infrastructure systems has emerged as a fundamental concern for researchers [11, 12]. Up to now, resilience still lacks a comprehensive description, calling for further developments to frame its definition. A broader definition for this term is then proposed in this paper, which describes resilience as "the ability of a system or a so-called 'System of Systems' (SoS) to resist effects of a disruptive internal or external event/force, either shocking or creeping, and the ability to reduce both magnitude and duration of deviation of the system performance level between original (or target) state and new steady state due to internal and external efficient efforts".

The proposed definition can be further interpreted as the ability of the system or SoS to withstand a change or a disruptive event by reducing the initial negative impacts (absorptive capability), by adapting itself to them (adaptive capability) and by recovering from them (restorative capability). These capabilities can be regarded as three essential resilience features: enhancing any of them will enhance system resilience. They focus on the system response during and after the occurrence of disruptive events. It is important to further understand and find ways to quantify them that contribute to characterization of the system performance [13]. **Absorptive capability** refers to an endogenous ability of the system to reduce the negative impacts caused by disruptive events and minimize consequences. In order to quantify this capability, *robustness* can be used, defined as strength of the system to resist initial impacts [14]. An example of enhancing it is to improve system redundancy, which provides an alternative way for system to operate. **Adaptive capability** refers to an endogenous ability of the system to adapt to disruptive events through its self-organization capabilities in order to minimize consequences. It is the dynamic ability of the system to adjust itself throughout the recovery period. Emergency systems can be used to enhance it. **Restorative capability** refers to an exogenous ability of the system to be repaired by external actions throughout the recovery period. For example, installing real-time monitoring systems (e.g., SCADA (Supervisory Control and Data Acquisition system) for most infrastructure systems) enhances the system restorative capability because it allows the automatic detection or even prediction of disruptive events and, therefore, shortening the total disruption period. Both adaptive and restorative capabilities describe the system's ability during the recovery phase, and it is not straightforward to distinguish their effects on system performance, which can be improved by enhancing the restorative capability during recovery phase after the deployment of repair actions and by enhancing adaptive capability before and after repair actions. Therefore, the simultaneous quantification of both capabilities is given same indicators, i.e. *rapidity* (*RAPI*) and *performance loss* (PL).

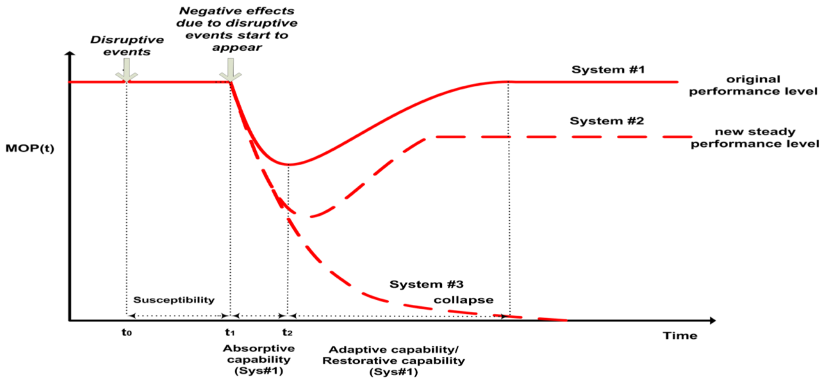

Figure 1 Illustration of essential resilience capabilities

Figure 1 provides a general illustration of these essential resilience capabilities. The y-axis represents the measurement of performance (*MOP*). Examples of MOP include availability of critical facilities, the number of customers served, connectivity of a network, the level of economic activities, etc. The selection of the appropriate MOP depends on the specific service provided by the infrastructure system under analysis. For generality, in the following we assume that the value of MOP is normalized between 0 and 1 where 0 is total loss of operation and 1 is the target MOP value in the steady phase. It is assumed that the disruptive event occurs at t_0, and that the *MOP* values starts dropping at t_1. It should be noted that in many cases t_0 might not be equal to t_1 and the t_1 - t_0 delay depends on the selection of the *MOP* and on the disruptive event. For instance, it could take several hours for customers to lose electricity services due to maintenance mistakes, while it might only takes seconds for same customers to lose services due to natural hazards such as earthquake, hurricane, etc. System susceptibility can be used to characterize the system performance during the time between t_0 and t_1. The focus of this paper is related to resilience quantification after the appearance of the negative effects, and therefore, susceptibility will not be considered. The system capabilities that have an effect on system resilience can be exemplified with respect to system performance variations following a disruptive event. As seen in Figure 1, system#1 performance returns to its original steady level after recovering from the lowest level at t_2. System#2 performance reaches a new steady level, which is lower than its original steady level. It should be noted that the new steady performance level could also be higher than its original steady level. System#3 performance drops significantly and finally collapses to zero. System#1 and system#2 outperform system#3 with respect to the three essential resilience capabilities. Therefore, system#3 can be considered the least resilient system. On the other hand, system#1 seems more robust against the disruptive event than system#2, i.e. the lowest performance level is higher for system#1 than for system#2. However, it takes more time for system#1 to reach the new steady level. Therefore, system#2 is more adaptive and restorative than system#1. The qualitative assessment and comparison among resilience capabilities call for the development of an approach that can be used to quantify them and integrate them into one system resilience index.

During last decade, researchers have proposed different methods and frameworks to quantify/assess system resilience. In 2003, the first conceptual framework is proposed by Bruneau et al. in [14]. The purpose of this framework is to measure the seismic resilience of a community to an earthquake by estimating the expected degradation regarding the quality of community infrastructure. In this pioneering research work, the concept of *Resilience Loss* (RL), later also refereed as so called "resilience triangle", is introduced, which has been widely used afterwards as a fundamental guidance for system resilience assessment. Based on this framework, more research works have been carried out from different aspects using various approaches. In 2004, Chang and Shinozuka propose a probabilistic approach for measuring seismic resilience after earthquake events [15]. In 2007, Rose at al., develop static and dynamic metrics based on the resilience loss concept to measure economic resilience. In recent years, the importance of improving the resilience of interdependent infrastructure systems or at least minimizing negative impacts caused by unexpected disruptive events has been recognized and accepted by the public. Therefore, a variety of research works have been developed targeting interdependent systems. In 2008, McDaniels et al. develop a knowledge-based approach using decision flow diagrams to improve the understanding of the resilience of infrastructure systems [16]. Similar approach is also proposed by Argonne National Lab [5, 17]. This type of knowledge-based approach is straightforward and easy to understand. However, it is a pure data-driven approach and the quality of the collected information could have significant effects on the accuracy of final results. To overcome these limitations, more comprehensive analytical approaches have been developed with the help of the advanced modeling techniques. In [18], System Dynamic (SD) is applied to assess the degree of socio-ecological system resilience. This approach combined with Complex Network Theory (CNT) is later applied by Filippini and Silva as part of the framework of qualitative resilience analysis of infrastructure systems [19].

Resilience is a dynamic multi-faceted term and its assessment should cover all the phases, e.g., disruption and recovery phase, and include all the essential resilience capabilities using an integrated metric. Most of existing methods for resilience quantification lack the ability to cover all the phases, and to include all resilience capabilities within all integrated metric and even overlap with other concepts such as robustness, vulnerability, fragility etc [20, 21]. Some quantitative methods for resilience measurement are not consistent with the concept of resilience [22]. Furthermore, these methods rely on the modeling approaches that partially capture the complex behavior of infrastructure systems. All this makes clear that there is a pressing need to develop a quantitative method for the assessment of the resilience of different infrastructure systems subjected to various hazards, which is built on the aforementioned challenges and should be able to provide an over-arching and cross disciplinary vision of integrated risk management. Therefore, a generic quantitative method targeting the holistic analysis of today's infrastructure systems is proposed and presented in this paper. The method consists of two components: 1) a hybrid modelling approach to achieve a close representation of the system and analyze its dynamics during and after the occurrence of the disruptive events. 2) an integrated metric for resilience quantification which can incorporate all essential resilience capabilities and characterizing resilience as the system ability. The focus of this paper is mainly related to the second component of the method.

3. METHOD PART 1-A HYBRID MODELLING APPROACH

Developing a comprehensive modeling framework with the capabilities of achieving a closer representation of infrastructure systems and gaining insights into interactions within and among them is vital for improving our understanding of these systems. Currently, a broad scale of modeling approaches have been developed, e.g., Input-output Inoperability Modeling (IIM), Complex Network Theory (CNT), Agent-based Modeling (ABM), System Dynamic (SD), Petri-Net (PN), etc (see [23] and [24] for details about these approaches). The lack of coherent modeling approaches hinders the possibilities of analyzing dynamic system behaviors in a sufficient way. Therefore, it is essential to develop a comprehensive modeling approach with the capabilities of achieving in-depth insights of infrastructure system behaviors. In practice, there is still no "silver bullet approach". Instead, it has proven necessary to integrate different types of modeling approaches into one simulation tool in order to fully utilize the advantages of each approach and optimize the efficiency of the overall simulation. In [25], the PN approach is integrated with the ABM approach to model interdependent infrastructure systems. In [26], authors combine the CNT with SD approach in order to develop a resilience indicator. However, all of these hybrid approaches are not capable to solve one of key challenges for developing such type of simulation tool: the required ability to create multiple-domain models, and effectively exchange data among them [27]. One solution for handling these technical difficulties and meeting these challenges is to distribute different simulation components by adopting the concept of modular design [28]. Through this approach, the overall simulation tool is divided into different simulation modules, which are domain-specific or sector-specific simulation components. The modules are then combined in a distributed simulation platform [24, 29].

4. METHOD PART 2-AN INTEGRATED RESILIENCE METRIC

Resilience is a complex concept that can not to be adequately addressed considering one single system capability[16]. One solution is to develop corresponding measures assessing various essential resilience capabilities in different phases, and then integrate them into a unique resilience metric.

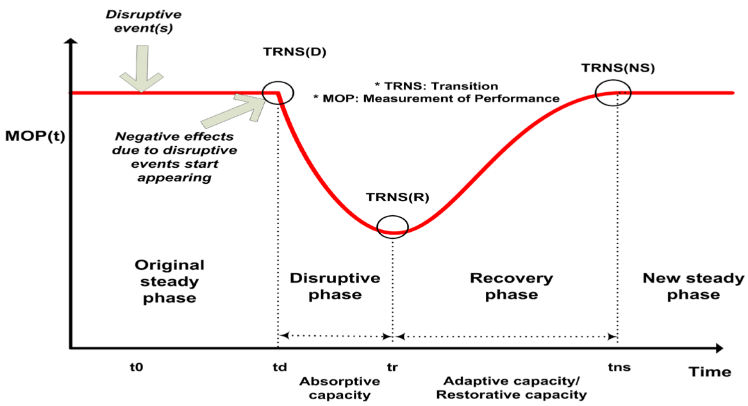

Figure 2 System resilience transitions and phases

The performance of the system#1 shown in Figure 1 is further illustrated in Figure 2, and it can be characterized by four phases and three transitions. The first phase is the original steady phase ($t<t_d$), in which the system performance assumes its target value. The second phase is the disruptive phase ($t_d \leq t<t_r$), in which the system performance starts dropping until reaching the lowest level at time t_r. During this phase, the system absorptive capability can be assessed by developing appropriate measures. As discussed in Section 1, *Robustness* (R) is one measure to assess this capability, which represents the minimum *MOP* value. This measure is able to identify the maximum impact caused by

disruptive events; however, it is not sufficient to reflect the ability of the system to absorb the impact. Two additional complementary measures are further developed: *Rapidity* ($RAPI_{DP}$) and *Performance Loss* (PL_{DP}) during disruptive phase. In [30], the term rapidity is referred as "the capability to meet priority and achieve goals in a timely manner in order to contain losses and avoid future disruption". This term can be quantified mathematically as the slope of performance level. To improve the accuracy of the estimation of the measure rapidity, the method of ramp detection can be adopted. In general, a ramp is a change with a large enough amplitude and over a relatively short period [31]. According to [32], a ramp is assumed to occur if the difference between the measured value at the initial and final points of a time interval Δt is greater than a predefined ramping threshold value. The system rapidity can then be calculated as the average of slope of each ramp. Compared to the calculation of average the rapidity, this method is more comprehensive in term of capturing the system performance during different phases. The performance loss, using the system illustrated in Figure 2 as an example, can be interpreted can be quantified as the area of the region bounded by the graph of the measurement of performance before and after occurrence of negative effects caused by disruptive events, which can also be referred as the system impact area. A new measure, i.e. the time averaged performance loss (*TAPL*), is introduced. Compared to the measure PL, it encompasses the time of appearance of negative effects due to disruptive events up to full system recovery and provides a time-independent indication of both adaptive and restorative capabilities as responses to the disruptive events. A system that experiences less performance loss has larger resilience. The third phase is the recovery phase ($t_r \leq t < t_{ns}$), in which the system performance starts increasing until the new steady level. During this phase, the system adaptive and restorative capability can be assessed by developing appropriate measures: *Rapidity* ($RAPI_{RP}$) and *Performance Loss* (PL_{RP}). As shown in Figure 2, the newly attained steady level may equal to the previous steady level. But it may also reach a lower level. In order to take these situations into consideration, a simple quantitative measure *Recovery Ability* (RA) is also developed. Different system phases and related system capabilities are summarized in Table 1.

Table 1 Summary of different resilience phases

Phases	Time Scope	Transition Point	Capacities (features)	Measurements
Original steady phase	$t < t_d$		Susceptibility	Susceptibility
Disruptive phase	$t_d \leq t < t_r$	TRNS(D)	Absorptive capacity	Robustness (R) Rapidity in disruptive phase ($RAPI_{DP}$) Performance Loss in disruptive phase (PL_{DP})
Recovery phase	$t_r \leq t < t_{ns}$	TRNS(R)	Adaptive capacity Restorative capacity	Rapidity in recovery phase ($RAPI_{RP}$) Performance Loss in recovery phase (PL_{RP})
New steady phase	$t \geq t_{ns}$	TRNS(NS)	Recovery ability	Recovery ability (RA)

Although the measurements introduced above are useful in assessing system behavior during and after disruptive events, an integrated metric with the ability of combining these capabilities is needed in order to assess the system resilience with an overall perspective and to allow comparisons among different systems and system configurations. Therefore, a general resilience metric is further developed. This metric differs from existing ones in that it is time-dependent and able to incorporate all three essential capabilities. Furthermore, it is not system-specific. The resilience metric builds on the quantification of the system capabilities and is calculated as:

$$GR = R \times \left(\frac{RAPI_{RP}}{RAPI_{DP}}\right) \times (TAPL)^{-1} \times RA$$

$$= R \times \left(\frac{\frac{\left|\sum_{i=1}^{K_{RP}} \frac{MOP(t_i)-MOP(t_i-\Delta t)}{\Delta t}\right|}{K_{RP}}}{\frac{\left|\sum_{i=1}^{K_{DP}} \frac{MOP(t_i)-MOP(t_i-\Delta t)}{\Delta t}\right|}{K_{DP}}}\right) \times \left(\frac{\int_{t_d}^{t_{ns}}[MOP(t_0)-MOP(t)]dt}{t_{ns}-t_d}\right)^{-1} \times \left|\frac{MOP(t_{ns})-MOP(t_r)}{MOP(t_0)-MOP(t_r)}\right| \qquad (1)$$

Where TAPL represents time average performance loss; K_{DP} and K_{RP} represent number of detected ramps in disruptive phase and recovery phase; $MOP(t_0)$ represents performance level at original steady phase. The GR provides an integrated way to measure the system resilience by considering all essential capabilities, which is consistent with original definition of the term of resilience. This approach of measuring system resilience is neither model nor domain specific. For instance, historical data can also be used for the resilience analysis. It only requires the time series data that represents system output during whole time period, making the selection of the MOP very important. The GR is a non-negative metric and its value equals to zero if 1) the performance level drops to zero after the disturbance (R=0), 2) after the disturbance events, the system performance immediately drops to its lowest level ($RAPI_{DP} \rightarrow \infty$, i.e. no absorptive capability), 3) the system performance maintains at the lowest level, R, which is the new steady state ($RAPI_{DP}$=0, i.e. no adaptive and restorative capability). Furthermore, the GR value is dimensionless and is most useful in a comparative manner. For instance, it can be used to compare the resilience of various systems to the same disruptive event. More resilient system results in higher GR value. It can also be used to compare resilience of same system under different disruptive events. Higher GR value indicates that the system is more resilient to certain disruptive events. Furthermore, the GR value can be used to compare resilience of a system to a specific disturbance under different improvement strategies. A more effective improvement strategy should increase the GR value.

5. CASE STUDY

Electric power systems are among most prominent representatives of engineered infrastructure systems and the need for their reliable and resilient performance during disruptive events becomes essential [33, 34]. In this paper, the high voltage Swiss electric power supply system (EPSS) is selected as an exemplary application to demonstrate the feasibility and applicability of the proposed quantitative method for resilience assessment.

5.1. Modelling Exemplary System

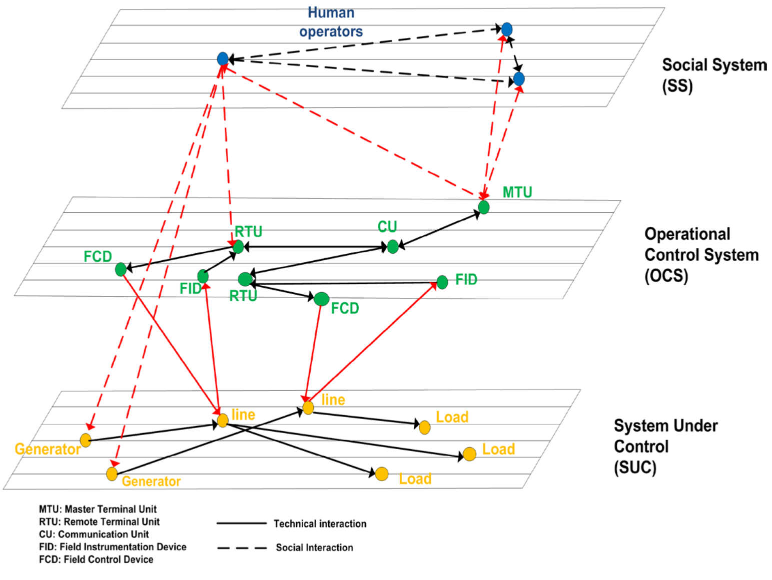

Figure 3 Representing EPSS in three subsystems (layers)

The modelling of CI is a whole research field by itself. Modelling entire infrastructure system as a whole is usually impractical [35-37]. Choosing relevant subsystems and modelling them efficiently for the intended purposes seem more promising. For each subsystem, appropriate modelling approaches/methods can be determined to fully represent its behaviour and functionalities. This type of modelling approach can also be referred as an example of the hybrid modelling approach, introduced in Section 2. Using this approach, the EPSS can be viewed as three interrelated subsystems in corresponding layers, i.e., system under control (SUC), operational control system (OCS), and social system (SS). Both SUC and OCS can be regarded as technical systems, while the SS is regarded as non-technical systems. The SUC represents technical systems that are mainly time-based. In order to fully model this type of systems, both functionality (physical laws) and structure (topology) need to be considered. The OCS represents technical systems that are mainly responsible to control and monitor corresponding SUC, e.g., SCADA system. In general this type of systems is event-driven / service-oriented. The developed model needs to be able to process messages among components efficiently and functionality of the system needs to be represented in detail. The SS represents non-technical systems that are mainly related to social factors. e.g., human performance, etc, that intend to have influences on the overall system performance. The developed model representing this subsystem need to be able to evaluate and quantify the effects of these social factors. The approach of HRA (Human Reliability Analysis) seems adequate. Figure 3 shows a simplified multi-layer representation of the EPSS with three interacting subsystems and associated elements (components): parallel planes represent different subsystems in corresponding layers while nodes represent various elements together with some of interconnections among them. The elements of the various layers depend on each other, depicted by various horizontal (inside a layer) and vertical (between layers) links.

A two-layer ABM-based modelling approach has been developed for purpose of integrating stochastic time-dependent factors into the resilience assessment of the EPSS [38]. Within the two-layer concept, the lower layer represents the separate modelling of the physical components by means of conventional, deterministic techniques such as power flow calculations, whereas the upper layer represents the abstraction of the electric power system with all its components as individual agents. Based on this approach, a time-stepped and agent-based model is developed to simulate the SUC. In total, 585 agents are created to model corresponding components, i.e., transmission lines, generators and loads. Similar to the modelling approach used to model the SUC, a failure-oriented two-layer ABM-based modelling approach is also used to model the SCADA system. In total, 587 agents are created to corresponding components, i.e., FCDs, FIDs, and RTUs [24]. In order to model SS, i.e. human operator performance in this case, the CREAM method combined with the ABM and Fuzzy logic is implemented [24]. It is the first effort to implement a human operator performance model capable assessing Performance Shaping Factors (PSFs) dynamically using the ABM approach. During the simulation, if there is a request for the operator take actions (e.g., handle an alarm), the PSFs will be assessed based on current simulation environment, e.g., time of day, simultaneous goals, etc, and corresponding Human Error Probability (HEP) ([0,1]) will then be calculated. The lower HEP value indicates better performance by human operators. To decide whether or not there is an error by human operators, it is necessary to set a threshold value (HEP_A) representing the maximum acceptable HEP value. If a calculated HEP is more than HEP_A, then it is assumed that a human error occurs (the human action fails to perform). The higher HEP_A indicates less human errors. All the developed models of three subsystems are integrated in a High Level Architecture (HLA)-compliant experimental simulation platform.

5.2. Design of Experiment

Although little damages caused by natural hazards have been observed throughout last century in Switzerland, historical records reveal that hazards such as earthquakes and winter storms were the cause of significant damage in at least 9 events over the past 1000 years [39]. According to [40], the estimated frequency of natural hazards, i.e., winter storms, which have the potential to result in the simultaneous disconnection of 20 transmission lines is about $6E^{-4}$ to $7E^{-4}$ per year. The impact of this disruptive event will result in large negative effects, and should not be underestimated even if the frequency of its occurrence is relatively low (low frequency, high consequence event). Therefore, in this paper, it is assumed that a natural hazard, e.g., winter storm, impacts central region of Switzerland, where power transmission lines are located; as a result of this event, 17 transmission lines are disconnected. This region is selected for the system resilience experiment based on the Lothar winter storm occurred in 1999 [41]. To simulate the performance response of the infrastructure under study (EPSS) subjected to the disruptive event, all three models (SUC, SCADA, SS) are included in the experiment. The number of available transmission lines is selected as the MOP. The simulation starts at the t = 0 h. It is assumed that the disruptive event occurs at time 3 h. Before this time, all the modeled systems are in the original steady state and operate under normal conditions. At the t = 3 h, the failure generator triggers the disconnection of 17 predefined transmission lines within region affected by the storm. In order to model the quasi-simultaneous disconnection of the affected lines, it is assumed that the interval between disconnections of two lines follows a normal distribution N(35,3) seconds. The sudden disconnection of a transmission line will be first detected by the corresponding RTU (Remote Terminal Unit) component of the SCADA system and an alarm will be sent to the control center (MTU), which is referred as the *abnormal line disconnection alarm*. After receiving the alarm, repair actions will be determined by the operators in the control center in order to restore the disconnected lines. It is assumed that the general response time (Response_G) for this type of alarm follows a normal distribution N(80,5) seconds. The sudden disconnections of many transmission lines may overwhelm the operators in control center, possibly resulting in the delay of response and repair actions. In order to simulate this situation, the formula below is used to calculate actual response time (Response_A):

$$\text{Response}_A = \text{delay factor} * \text{Response}_G$$

$$\text{Delay factor} = \begin{cases} \text{weighting factor} * (\text{HEP} - \text{HEPA}) + 1 & (\text{HEP} \geq \text{HEPA}) \\ 1 & (\text{HEP} < HEPA) \end{cases} \quad (2)$$

The actual response time (Response_A) determined by the delay factor should close to reality and therefore, need to remain in a rational range. In this experiment, weighting factor is set to 100 based on results from after several trial runs. It is assumed that repair actions for the abnormal disconnected lines are always performed successfully and the repair time is assumed to follow exponential distribution with the mean value equal to MTTR (mean time to repair). The sudden disconnections of transmission lines could also overload other transmission lines, especially their neighboring ones [42], and have the potential for knock-on effects with cascading consequences. If a transmission line is overloaded, an overload alarm will be generated and sent to the operator in the control center (MTU) by the corresponding RTU component. If the operator recognizes this alarm and handles it successfully ($\text{HEP}<\text{HEP}_A$), the corrective actions will be performed, i.e., power load re-dispatch. However, if no action is taken after a certain time past the overload alarm, it is considered that the operator has failed to react to the overload alarm ($\text{HEP}\geq\text{HEP}_A$), and the protection devices, e.g., circuit breakers, will automatically disconnect the overloaded line to prevent permanent damages to the infrastructure. In general, abnormal line disconnection alarms are triggered when the system is in disruptive phase ($t_d \leq t < t_r$) and the handling of this alarm completes when the system is in recovery phase ($t_r < t < t_{ns}$). Conversely, overload alarms can be triggered either at the disruptive or recovery phase because overloads. The simulation stops when the systems reach the final steady state. Then, the performance measures, including the GR, are evaluated. Furthermore, a reliability metric is also calculated, i.e. ASSAI (Average Substation Service Availability Index), which is the ratio of the total number of hours that service is provided by all available substations during a given time period to the total demanded hours (Eq 2).

$$\text{ASSAI} = \frac{N_S \times (\text{number of hours}) - \sum_{i=1}^{N_S} \text{Res}_i}{N_S \times (\text{number of hours})} \quad (2)$$

where Res_i represents the restoration time for ith substation if service interruption exists and N_S represents the total number of substations.

Two hypothetical strategies are considered in order to compare system's resilience to the same disruptive event, i.e. improvement of the human operator performance (increasing HEP_A) and efficiency of line reparation (decreasing MTTR). In total, 18 experiments are set: $\text{HEP}_A \in \{0.03,0.3,1\}$ and $\text{MTTR(h)} \in \{0.5,1,1.5,2,2.5,3\}$. The number of simulation runs (N) for each experiment is determined by the coefficient of variation (CV) of the resilience measure of the corresponding target system. In this simulation, $CV_{GR} \leq 0.13$ is the criteria to determine the number of runs for each computer experiment which are needed to estimate system resilience.

5.3. Simulation Results

Figure 4 shows the system performance following the disruptive event under various simulation scenarios, in which the MTTR varies from 0.5 h to 3 h and HEP_A is set to 0.3. In Figure 4, the y-axis denotes the MOP (the number of available transmission lines) and the x-axis denotes the simulation time. At time t = 3 h, the disruptive event is triggered. The negative effects caused by this event start to appear immediately, i.e. the MOP value starts dropping. After about 12 minutes, the MOP value reaches its lowest level, i.e. 92.1%. The MOP value then begins to increase as the result of the repair actions. Similar results are observed in Figure 5, in which HEP_A value varies from 0.03 to 1 and MTTR value is set to 2.5 h. Compared to the results shown in Figure 4, human operator performance has influence not only on the system adaptive and restorability capability during recovery phase, but also on the absorbability capability during disruptive phase, although the effects on the latter are less significant. It can be seen that system robustness is enhanced by improving human operator performance.

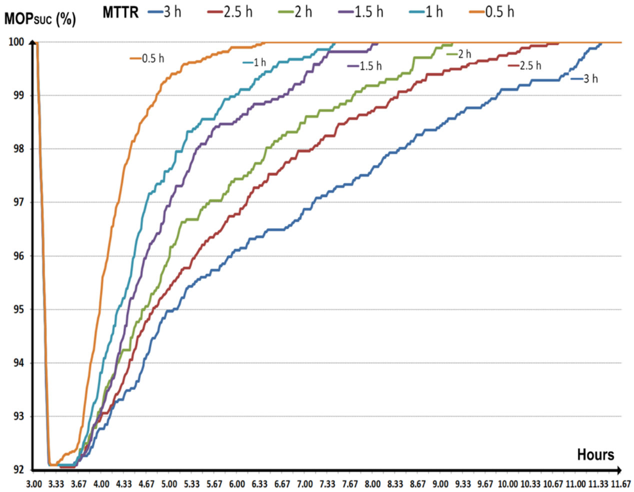

Figure 4 The system performance under different experiments with varying MTTR (HEP_A=0.3, N={18,10,11,10,13,11} for MTTR from 0.5 h to 3 h)

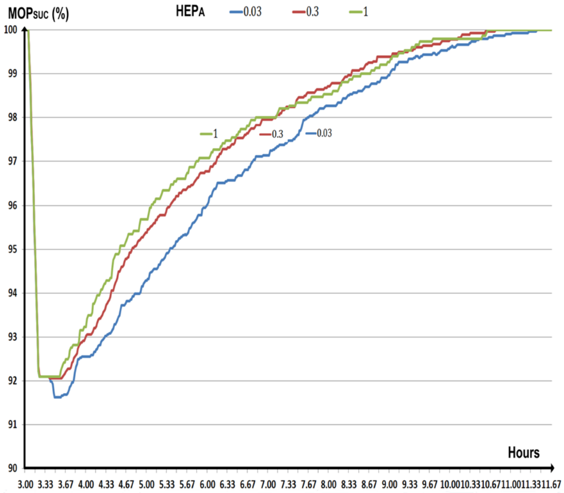

Figure 5 The system performance under different experiments with varying HEP_A (MTTR=2.5 h, N={14,13,10} for HEP_A from 0.03 to 1)

Figure 4 and 5 provide parts of simulation results demonstrating the feasibility of the developed method for the system resilience analysis. The overall simulation results are summarized in Table 2, including the coefficient of variation for each measure. It should be noted that the CV value for R varies very little for each case and is not included in Table 2. The strategy of improving the repair efficiency has little effects on the absorptive capability of the infrastructure. As seen from the Table 2, all the measures related to this capability, i.e., R, PL_{DP}, $RAPI_{DP}$, vary not significantly if comparing results from case studies with same HEP_A value but different MTTR value.

Table 2 Summary of the overall simulation results

MTTR (h)	HEP_A	GR	*CV*	ASSAI	*CV*	Disruptive Phase					Recovery Phase			
						R	PL_{DP}	*CV*	$RAPI_{DP}$ (/h)	*CV*	PL_{RP}	*CV*	$RAPI_{RP}$ (/h)	*CV*
0.5	0.03	16.33	*0.13*	0.993	*0.0015*	0.916	0.026	*0.053*	0.443	*0.04*	0.09	*0.16*	0.292	*0.068*
	0.3	19.15	*0.13*	0.995	*0.0018*	0.921	0.0076	*0.097*	0.446	*0.062*	0.079	*0.13*	0.315	*0.057*
	1	20.82	*0.13*	0.995	*0.0012*	0.921	0.0075	*0.093*	0.451	*0.063*	0.079	*0.14*	0.323	*0.089*
1	0.03	15.90	*0.13*	0.986	*0.0032*	0.916	0.027	*0.042*	0.437	*0.051*	0.14	*0.17*	0.273	*0.082*
	0.3	18.67	*0.12*	0.990	*0.0022*	0.921	0.0073	*0.07*	0.458	*0.049*	0.12	*0.13*	0.299	*0.06*
	1	20.40	*0.13*	0.991	*0.0024*	0.921	0.0073	*0.065*	0.457	*0.047*	0.12	*0.16*	0.296	*0.056*
1.5	0.03	14.98	*0.12*	0.982	*0.0039*	0.916	0.026	*0.05*	0.446	*0.037*	0.18	*0.17*	0.278	*0.066*
	0.3	16.29	*0.087*	0.984	*0.004*	0.921	0.0072	*0.053*	0.467	*0.037*	0.15	*0.19*	0.293	*0.043*
	1	19.26	*0.12*	0.985	*0.0044*	0.921	0.0072	*0.075*	0.453	*0.043*	0.16	*0.18*	0.292	*0.048*
2	0.03	14.04	*0.12*	0.977	*0.0042*	0.916	0.026	*0.079*	0.441	*0.042*	0.22	*0.17*	0.260	*0.12*
	0.3	15.98	*0.097*	0.984	*0.0036*	0.921	0.0072	*0.051*	0.466	*0.075*	0.18	*0.15*	0.295	*0.075*
	1	18.03	*0.12*	0.985	*0.0033*	0.921	0.0072	*0.028*	0.473	*0.002*	0.17	*0.11*	0.291	*0.055*
2.5	0.03	13.76	*0.12*	0.976	*0.0036*	0.916	0.026	*0.07*	0.447	*0.036*	0.24	*0.19*	0.272	*0.12*
	0.3	15.74	*0.055*	0.980	*0.0039*	0.921	0.0075	*0.077*	0.457	*0.047*	0.20	*0.15*	0.282	*0.022*
	1	17.16	*0.10*	0.981	*0.0032*	0.921	0.0072	*0.061*	0.466	*0.037*	0.23	*0.19*	0.282	*0.024*
3	0.03	13.73	*0.08*	0.973	*0.0057*	0.916	0.026	*0.062*	0.448	*0.039*	0.27	*0.18*	0.25	*0.058*
	0.3	14.86	*0.089*	0.975	*0.0038*	0.921	0.0072	*0.065*	0.466	*0.039*	0.28	*0.16*	0.266	*0.028*
	1	16.38	*0.088*	0.975	*0.0058*	0.921	0.0075	*0.069*	0.449	*0.046*	0.28	*0.12*	0.267	*0.042*

MTTR: Mean Time to Repair **HEP_A:** Maximum acceptable Human Error Probability **GR:** General Resilience **CV:** Coefficient of Variation
ASSAI: Average Substation Service Availability Index **R:** Robustness **PL_{DP}:** Performance Loss in disruptive phase **PL_{RP}:** Performance Loss in recovery phase
$RAPI_{DP}$: Rapidity in disruptive phase **$RAPI_{RP}$:** Rapidity in recovery phase

The R value remains unchanged, while the difference among values of PL_{DP} and $RAPI_{DP}$ is relatively low. For example, if HEP_A is set to 0.03, i.e. the human performance is poor, PL_{DP} value remains at the range of [0.026, 0.027] and $RAPI_{DP}$ value remains at the range of [0.437, 0.439] even if the repair efficiency is improved. Compared to the improvement of the repair efficiency, improving the human operator performance (higher HEP_A value) is able to enhance the absorptive capability more significantly. For example, if HEP_A is set to 0.3, i.e. the human performance is average/acceptable, the PL_{DS} value drops to the range [0.0072, 0.0076]. This indicates that system performance is less impacted during disruptive phase if the human operator performance is improved. A similar trend is also observed for the measure of R, which increases from 91.6% to 92.1% when the HEP_A value is increased from 0.03 to 0.3. However, both R and PL_{DP} do not vary significantly if the HEP_A value is increased from 0.3 to 1, indicating that this strategy becomes inefficient when the operator performance is at an average/acceptable level. Compared to effects on the enhancement of absorptive capability, the strategy of improving the repair efficiency is able to enhance system adaptive and restorative capability more significantly. The PL_{RP} value rises from 0.09 to 0.27 when MTTR value is increased from 0.5 to 3 h and the HEP_A value is set to 0.03. This indicates that the system performance is less impacted during recovery phase if the efficiency of the repair actions is improved. A similar trend can also be observed in other cases (HEP_A = 0.3 and 1). Improving the repair efficiency also has positive effects on the value of $RAPI_{RP}$, which increases from 0.25 to 0.292 (1/h), when MTTR value is increased from 0.5 to 3 h and the HEP_A value is set to 0.03, indicating that more time is needed to recover to a new steady state. Compared to improving repair efficiency, improving the human operator performance has little effects enhancing the adaptive and restorative capability. For example, the PL_{DP} value remains within the range [0.08, 0.09] when HEP_A value is increased from 0.03 to 1 and the MTTR value is set to 0.5 h.

Both strategies have positive effects on the enhancement of resilience capabilities. Improving repair efficiency is a more efficient strategy to enhance the system adaptive and restorative capability during the recovery phase. On the other hand, improving human operator performance is a more efficient strategy to enhance the system absorptive capability during the disruptive state. In order to assess that whether these strategies are able to enhance the overall resilience capability, the integrated GR metric must be used. Figure 6 illustrates the value of GR, i.e. the system resilience to the disruptive event, with respect to the two improvement strategies using the 3D surface diagram. When both improving strategies are performed simultaneously, the system resilience can be enhanced significantly. Figure 6 indicates 51.6% increase of GR value from 13.73 to 20.82 when MTTR value decreases from 3 hours to 0.5 h and HEP_A increases from 0.03 to 1.

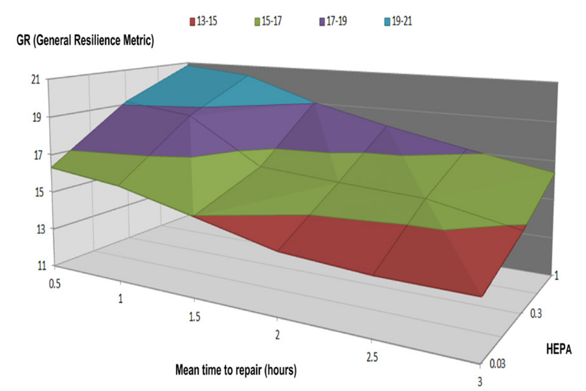

Figure 6 The GR value under different simulation scenarios

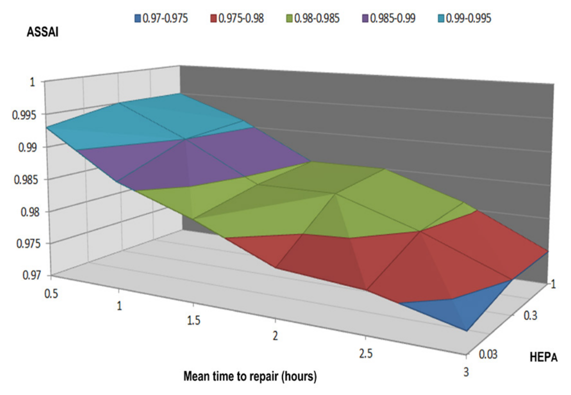

Figure 7 The ASSAI value under different simulation scenarios

Figure 7 illustrates the ASSAI value, i.e. system reliability after the disruptive event, with respect to the two improvement strategies using the 3D surface diagram. Reliability and resilience are correlated, although they characterize system performances from different aspects. Reliability is a property of the system; conversely, resilience is an ability of the system. The reliability metric shows a trend which is similar to the trend of resilience, indicating that both improvement strategies have non-negative effects on system reliability and resilience. Nonetheless, according to the Figure 6 and 7, the implementation of both improving strategies improves significantly the system's ability to withstand the negative effects caused by the disruptive event (GR_{SUC} increases 51.6% from 13.73 to 20.82); but on the other hand, it is not capable of improving the system's safety property significantly (ASSAI value only increases 2.3% from 0.973 to 0.995 under same scenario). The comparison between these two metrics exemplifies the advantage of the proposed resilience metric, which is capable of quantifying the behavior of systems in a more comprehensive way by integrating the information related to the system performance in various phases of system loss, adaptive, and recovery.

6. CONCLUSION

Research work on modern infrastructure systems is of great importance for our societies and protection of their assets. In recent years, the infrastructure system evaluation and analysis have broadened to the development of systemic approaches to analyse and understand their behaviours in a holistic way. This paper presents a quantitative method including a novel hybrid modeling approach and the time dependent quantifiable metric for resilience measurement in the context of engineered infrastructure systems. Within this method, three resilience capabilities as well as different measurements and phases related to these capabilities are identified. In order to demonstrate the feasibility and applicability of the proposed quantitative method, it is applied to evaluate behaviors of an electric power supply system (EPSS) after the occurring of a natural hazard, e.g., a winter storm, using two hypothetical improvement strategies (i.e., improvement of the repair efficiency an improvement of human operator performance). The results show that although both strategies are able improve the system resilience significantly, their effects on different resilience capabilities vary. These results also indicate that besides its capability of providing the final outcome quantifying the system behaviors, the resilience metric is also capable of gaining insights into different phases by evaluating corresponding system capabilities, providing a more flexible and comprehensive way to analyze system behaviors compared to the reliability metric (e.g., ASSAI) by gaining insights into system performance in different phases and highlights the limits of reliability indicators in capturing resilience. The ultimate goal is to apply the proposed method in order to develop efficient mitigation and protection strategies by decision makers to maintain and retrofit resilience of infrastructure systems in the long run. Future research work will intend to explore possibilities of expanding the capabilities of this method in other domains, e.g., organizational and social domain. Furthermore, the concept of resilience costs, e.g., service lost cost due to disruptive events and recovery costs, will also be considered in order to improve the applicability and usefulness of the resilience metric. Systems that are resilient to a disruptive event will have lower costs than systems that are less resilient to same event.

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