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Design and assessment methodology for system resilience metrics

Mohammad Najarian and Gino Lim
Department of Industrial Engineering
University of Houston

By providing objective measures, resilience metrics (RMs) help planners, designers, and decision makers to have a grasp of the resilience status of a system. Conceptual frameworks establish a sound basis for RM development. However, a significant challenge that the existing literature has not addressed is assessing the validity of and RM by determining whether it reflects all abilities of a resilient system and whether it overrates/underrates these abilities or not. This paper covers this gap by introducing a methodology that can show the validity of an RM against its conceptual framework. This methodology combines the experimental design methods and statistical analysis techniques that provide an insight into the RM's quality. We also propose a new metric that can be used for general systems. The analysis of the proposed metric using the presented methodology shows that this metric is a better indicator of the system abilities comparing to the existing metrics.

Keywords: resilience metric; resilience quantification; resilience metric assessment; statistical analysis; experimental design; power systems

1. INTRODUCTION

Natural or human-made disasters may impose costs, disrupt routine activities, and threaten human life. From 1980 to 2011, more than 130 extreme events resulted in 881 billion dollars in damages in the United States (Smith & Katz, 2013). Hurricane Katrina caused 108 billion dollars and 1,833 fatalities in 2005 (FEMA, 2006). Hurricane Harvey in 2017 and Sandy in 2012 cost $125 (National Hurricane Center, 2018) and $70 billion, respectively (FEMA, 2017). To improve understanding of unfavorable events and alleviate the resulting consequences, researchers and practitioners have developed several concepts such as risk, robustness, stability, survivability, and reliability. Risk is the possibility of an undesired event and its sequenced loss (Corotis, 2012), robustness is the system's ability to tolerate short-term adverse conditions (Corotis, 2012), stability is the ability of a system to withstand long-term disruptions and continue its critical operations (Jen, 2003), survivability is the ability of a system to minimize the impact of a finite disturbance on value delivery to alleviate the consequences of unfavorable events (Sterbenz et al., 2010), and reliability is the ability of a system or component to function under stated conditions (operational and environmental) for a specified period of time (Kiran, 2017; Tolk, Fritts, Cantu, & Gharehyakheh, 2017). However, in the face of the extreme events, like catastrophic hurricanes or earthquakes, some aspects are not covered by these concepts which led to the development of another concept: resilience.

Resilience (or resiliency) comes from the Latin word "*resiliō*," which means "to bounce" (Alexander, 2013). Disciplines like social systems (Kwok, Doyle, Becker, Johnston, & Paton, 2016), organizational systems (Sahebjamnia, Torabi, & Mansouri, 2018), economic systems (Rose, 2004), psychology (Brown, 2015), ecology (Holling, 1973), and engineering(Heinimann & Hatfield, 2017; Yodo & Wang, 2016) have been studying resilience. However, each discipline considers it from its point of view; hence, the definitions may vary. The common elements of resilience among them are disruption and returning to the normal situation. Compared to the other fields, not only the number of resilience studies in the realm of engineering are limited(Hosseini, Barker, & Ramirez-Marquez, 2016), but also there is not unanimity on its definition. We divided the literature review into two sections: 1) resilience conceptual framework that includes the studies on the concepts and fundamentals of resilient systems, and 2) resilience quantification which reviews the studies on the RMs.

1.1. A Conceptual Framework of A Resilient System

Theoretical frameworks mainly discuss the characteristics of a resilient system and steps to enhance the system's resilience. Omer et al. (Omer, Nilchiani, & Mostashari, 2009) characterized the disaster resilience's goals to include reduced failure probabilities, reduced consequences from failures, and reduced time-to-recovery. The resilience of a network is a multidimensional, dynamic concept (Ji & Wei, 2015) that addresses its ability to absorb and recover from an external, high-impact, low-probability event (Liu, Wu, & Zhou, 2016). Both pre-disaster (preparedness) and post-disaster (recovery) activities are necessary for a resilient system (National Infrastructure Advisory Council, 2009).

Performance (Ayyub, 2014; Ouyang & Dueñas-Osorio, 2012) or functionality (Cimellaro, Reinhorn, & Bruneau, 2010; Ganin et al., 2016) of a system refers to the requirements or objectives (Ayyub, 2014) of the system under study that indicates how well the system fulfills its intended goals (Jean-Paul Watson et al., 2014). It is measured as a dimensionless (percentage) function of time (Cimellaro et al., 2010; Ouyang & Dueñas-Osorio, 2014). For example, for a natural gas network it can be the combination of the normalized gas flow rate and the total length of the network (Cimellaro G. P., Villa O., & Bruneau M., 2015). For a power system, it can be the percentage of energized transmission substations, the percentage of critical facilities with power, or the percentage of customers with power (Ouyang & Dueñas-Osorio, 2012).

Four abilities of a resilient system are anticipation, absorption, adaptation, and rapid recovery (Ayyub, 2014; Collier, Panwar, Ganin, Kott, & Linkov, 2016; Francis & Bekera, 2014; Ganin et al., 2016; J. Phillips, M. Finster, J. Pillon, F. Petit, & J. Trail, 2016; Kamalahmadi & Parast, 2016; L.Carlson et al., 2012), We merged the resilience profile from

Francis and Bekera (Francis & Bekera, 2014) and Ganin *et al*. (Ganin et al., 2016) to obtain four phases as seen in Figure 1. While the former does not assume separate phases for anticipation and absorption, the latter does not include the slack time (δ). *Anticipation* is the phase before anything happens ($t \leq t_o$) to the system while preparing for a hazard. This can include forecasting the adverse event, its severity, list of the components prone to failure, the plans for different scenarios, etc. In this phase, the functionality is in normal state (F_o). *Absorption* is the phase in which the system absorbs the impact of the hazard and reduces the severity of consequences when a disaster strikes the system ($t_o \leq t \leq t_d$). As a result, the system functionality drops to F_d. The value of F_d is closer to one as the system becomes more resilient. *Adaptation* is the phase after a disaster and just before the recovery phase ($t_d \leq t \leq t_r^*$). During this time, the system can utilize its current resources to improve the functionality of the system from F_d to F_r^*. This phase may include temporal repair, utilizing the redundant components, prioritizing and addressing the more critical demands. Francis and Bekera (Francis & Bekera, 2014) assumed initial recovery actions that take place at slack time (t_δ) to improve the functionality to F_r^*. These initial recovery actions are not final and are prone to change by the next phase. The final phase is *recovery* ($t_r^* \leq t \leq T$) in which the system gradually returns to its initial state, or to a stable state. These phases are not mutually exclusive. For example, the recovery phase may start in the middle of adapt phase.

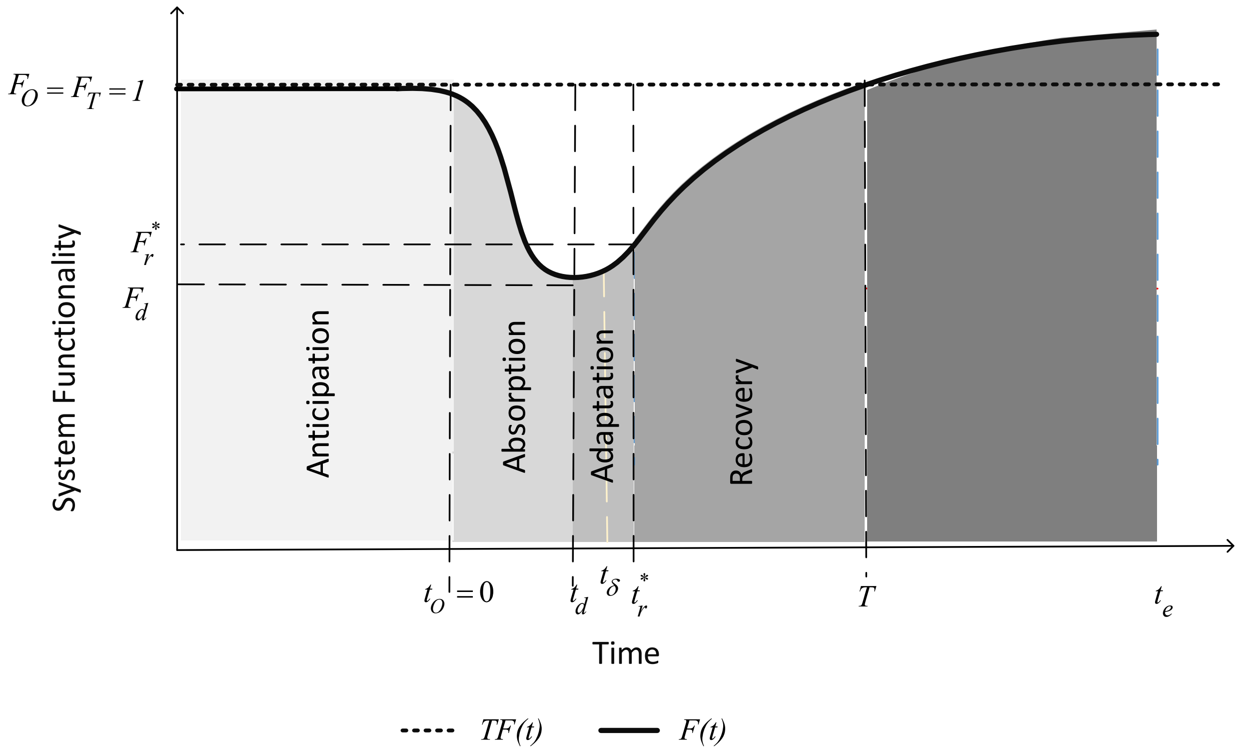

Figure 1: Phases that system undergoes in the face of an extreme event (Adopted and modified from (Francis & Bekera, 2014) and (Ganin et al., 2016)).

1.2. Resilience Quantification

The extravagant cost of disasters justifies the investment to improve the system's resilience. Quantification is an essential tool to achieve this goal. This tool can be utilized to identify, justify, and prioritize any need for improvement (*Disaster Resilience: A National Imperative*, 2012). Some other applications include monitoring changes in the resilience level, evaluating the effectiveness of the resilience strategies, or comparing the cost-effective benefits of improving resilience (*Disaster Resilience: A National Imperative*, 2012). RMs must reflect the abilities of a resilient system, and thus must serve the following goals (Goodykoontz et al., 2015; Vugrin et al., 2012):

(1) To provide objective evaluations of the system's current state of resilience.

(2) To provide a mean for identification of potential infrastructure vulnerabilities.

(3) To enable the evaluation of the changes in the resilience resulted from of the resilience enhancement activities.

There are different approaches to assess resilience. Hosseini *et al*. (Hosseini et al., 2016) categorized the quantitative measures into two groups: general and structural. General measures can be applied to any domain. They include deterministic and probabilistic, and static and dynamic models. In contrast, *structural* based measures are domain-specific representations of the components of resilience. Optimization, simulation, and fuzzy logic models are utilized in these models.

Willis and Loa (Willis & Loa, 2015) classified the metrics by three characteristics: resolution, type, and maturity. *Resolution* refers to the scale of the system being described; *type* refers to where the metrics fit; and *maturity* relates to the suitability, systematically collection, and organization of the metrics. Moreover, an RM should not be difficult to implement (ENISA, 2011; Kwasinski, 2016), and it must produce the same result when the assessment is repeated (ENISA, 2011).

While some papers assume that RM can be greater than 1 (Francis & Bekera, 2014; Wang, Gao, & Ip, 2010), Ayyub(Ayyub, 2014) defines the RM to be a function that maps a set of possible situations, to the interval [0,1]

$$RM : C \rightarrow [0,1], \tag{1}$$

in which C is an algebra.

The network structure and components (Abbasi, Barati, & Lim, 2017; Khayatian, Barati, & Lim, 2016; Saeedeh Abbasi, Masoud Barati, & Gino Lim, 2017a, 2017b; Whitson & Ramirez-Marquez, 2009; Zhang & Wang, 2016) can also improve the resilience of a system, and network measures can be included in an RM. Abbasi *et al.* (Abbasi et al., 2017) presented a resilience vector for a power grid which comprised of five sub-indices: load shedding cost savings, restoration cost savings, adaptability, weighted algebraic connectivity, and weighted betweenness centrality. The last two subindices are extracted from the network structure. Zhang and Wang (Zhang & Wang, 2016) introduced a network-based RM that does not consider the performance of the system. However, performance must be incorporated into a metric (Jean-Paul Watson et al., 2014) because it reflects how well the system delivers on its intended purpose during and after an event (Jean-Paul Watson et al., 2014).

Some researchers used the ratio of the area of real performance region to the area of target performance as an RM (Bruneau et al., 2003; Jin, Tang, Sun, & Lee, 2014; Shen & Tang, 2015; Zobel & Khansa, 2014). Others divided the previous metric by the recovery time to take into account the time-to-recovery (Baroud, Barker, Ramirez-Marquez, & Rocco S., 2014; Henry & Emmanuel Ramirez-Marquez, 2012; Kadri & Chaabane, 2015; Renschler et al., 2010). The metric offered by Francis and Bekera (Francis & Bekera, 2014) is based on the few data points $((t_o, F_0), (t_d, F_d), (t_{r^*}, F_{r^*}), (t_e, F_e))$ on the functionality curve (Figure 1), which does not consider the whole functionality curve that indicates how the process degrades and recovers. Kwasinski (Kwasinski, 2016) used a metric from reliability as an indicator of resilience. Ayyub (Ayyub, 2014) used a weighted sum of normalized ratio of areas in two intervals, one from t_o to t_d, and the other from t_d to T.

Definition. Valid Resilience Metric

A valid RM associated with a conceptual framework is a metric that

i) Reveals if a system has the abilities suggested by the associated conceptual framework, and

ii) Is not biased towards any of these abilities, i.e., it must not overemphasize or underemphasize the importance of any of these abilities.

Systems with different abilities' settings can have the same resilience measure against the same incident (Figure 2), but it may be different for a biased metric. For example, consider System 2 in Figure 2 with a weak absorption but a rapid recovery, and System 3 with a better absorption but a tardy recovery compared to System 2; for an unbiased RM System 2 and System 3 have the same resilience value, but for a biased metric which overemphasizes the rapid recovery, System 2 shows a better resilience.

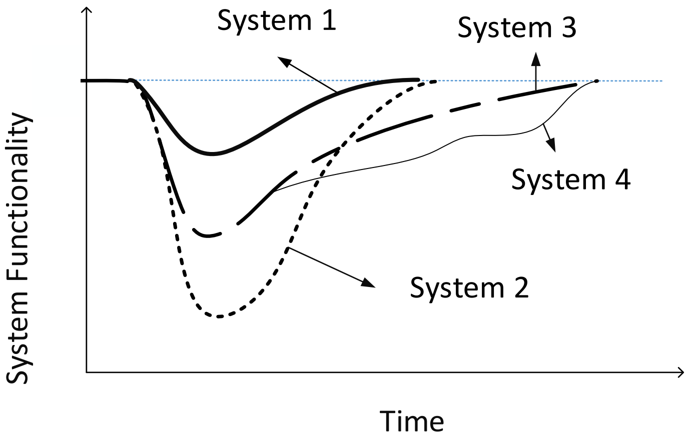

Figure 2: systems different settings of abilities: System 1 has a higher absorption and shorter recovery period comparing to other two systems. While System 2 has a shorter recovery and poorer absorption comparing to System 3, both have the same resilience measure

Now that we defined a valid RM, the question that arises is *"how can we validate an RM?"* In the subsequent sections of this study, we present our proposed RM and a methodology to examine the validity of RMs. We provide numerical results, analyze our proposed metric, and compare it to other performance-based metrics. Throughout this document, we use RM and resilience index interchangeably.

2. EXISTING RESILIENCE METRICS

So far, several RMs have been developed for the systems which are categorized as general or structural (Hosseini et al., 2016). In this section, we present the existing metrics and their limitations. We use the following notation in the rest of this document. We name the existing metrics as $Index_i, i = 1 \ldots 6$. The pair (t, F) indicate the time and functionality of the system at that time (Figure 1). The point (t_O, F_O) on the curve corresponds to the normal or initial state when an incident occurs, at (t_d, F_d) system has degraded to its lowest functionality, t_δ is the time that the initial recovery actions are started, $(t_r^*,\ F_r^*)$ is the end of adaptation, where initial recovery actions end, and $(T,\ F_T)$ corresponds to the point that recovery is achieved.

A normalized metric (*Index*1) indicates the percentage of the targeted functionality (*TF*) that has been satisfied (Bruneau et al., 2003; Jin et al., 2014; Shen & Tang, 2015; Zobel & Khansa, 2014).

$$Index_1 = \frac{\int_0^T F(t)dt}{\int_0^T TFdt}$$

The area $\int_0^T TF(t)dt$ is a normalizing factor which helps to compare resilience of different systems and different performance magnitudes together. However, *Index*1 does not show the importance of rapid recovery ability as we have elaborated in the discussion section.

Kwasinski (Kwasinski, 2016) presented *Index*2 for power systems, which is similar to availability index (Calixto, 2016).

$$Index_2 = \frac{T_u}{T_u + T_d}$$

where T_u and T_d are the summations of the up and down times of the system's components. An obvious weakness of this metric is that if we have two components with huge capacity differences, and *Index*2 cannot distinguish the differences between their impacts on the resilience measure.

In *Index*3 (Barker, Ramirez-Marquez, & Rocco, 2013; Chanda & Srivastava, 2016) the minimum functionality is subtracted from the numerator and denominator of *Index*1 to focus more on the after event activities (adaptability and recovery). However, their metric still has the same flaw as *Index*1.

$$Index_3 = \frac{\int_0^T [F(t) - \min\{F(t)\}]dt}{\int_0^T [TF - \min\{F(t)\}]dt}$$

Francis and Bekera (Francis & Bekera, 2014) proposed an index that includes absorptive capacity (F_d/F_0) which shows the ability of the system to absorb shocks without recovery action, adaptive capacity (F_R/F_0) which relates to those post-disaster activities taken after the disruption, and speed of recovery S_p which is as follows:

$$S_p = \begin{cases} \frac{t_\delta}{t_r^*} e^{-a(t_r - t_r^*)} & t_r \geq t_r^* \\ \frac{t_\delta}{t_r^*} & otherwise \end{cases}$$

$$Index_4 = S_p \frac{F_R}{F_0} \frac{F_d}{F_0}$$

Although it includes sub-metrics for the abilities of the system, this metric just used few functionality points, and it cannot demonstrate how the functionality changes along the functionality curve (e.g., Systems 3 and 4 in Figure 2).

Ayyub (Ayyub, 2014) introduced $Index_5$:

$$Index_5 = \frac{t_0 + F\Delta T_d + R\Delta T_R}{t_0 + \Delta T_d + \Delta T_r}$$

Where $\Delta T_d = t_d - t_0$, F is the failure profile, $\mathrm{F} = \frac{\int_{t_i}^{t_d} F(t)dt}{\int_{t_i}^{t_d} TFdt}$, $\Delta T_R = t_R - t_d$, R is the recovery profile, $\mathrm{R} = \frac{\int_{t_d}^{t_r} F(t)dt}{\int_{t_d}^{t_{Rr}} TFdt}$, and $t_0 = 0$.

Kadri and Chaabane (Kadri & Chaabane, 2015) divided the value of $Index_1$ by T to incorporate rapid recovery into the RM.

$$Index\ 6 = \frac{\dfrac{\int_0^T F(t)dt}{\int_0^T TF(t)dt}}{T}$$

These two last indices put a high weight on the recovery time, while a valid metric must be unbiased towards any of the abilities.

3. PROPOSED RESILIENCE METRIC

As an attempt to overcome the shortcoming of the existing metrics, we develop a performance-based valid RM that can be used in a variety of areas and is more consistent with various conceptual frameworks. This metric includes parameters that should be determined by the decision makers; hence, it is flexible to any application at hand. Our proposed RM is based on three post-disaster related abilities (absorption, adaptation, and recovery) because it is commonly reported in the literature. Although adding the anticipation ability (a pre-disasters component) can help improve the system resiliency, it is beyond the scope of this paper.

The first component is *absorption* (r_1). This component measures how well the system can maintain its functionality in the face of an unfavorable event, and how much the negative effects will be prevented. The formula for r_1 is:

$$r_1 = \frac{\int_{t_o}^{t_d} F(t)dt}{\int_{t_o}^{t_d} TF(t)dt} \tag{2}$$

in which, $F(t)$ is the functionality of the system at time t, and $TF(t)$ is the required functionality or demand at time t. Since the functionality of a system cannot be negative (e.g., 0 indicates non-functional system), both functions map the time to R_+, the non-negative real numbers. Also, for $t \in [0, t_d)$, the following inequality holds true, $F(t) \leq TF(t)$; hence $0 \leq r_1 \leq 1$.

The second component is *adaptation* (r_2). This component shows how well we assigned and utilized the existing resources to mitigate the consequences of the event, which can be measured by the loss of functionality after degradation until recovery over the target functionality. The recovery actions may result in two situations for the functionality. If the system recovers to a steady state at the same level or below the initial state ($F_R \leq F_o$), then we use $T = t_R$. Otherwise $(i.e., F_R > F_o)$, we choose T to be the time that the functionality recovers to its initial state ($T = F^{-1}(F_o)$ and $T > t_o$, where F^{-1} is the inverse of functionality function). Because the goal of recovery is to bring the system back to the initial state, any efforts made beyond the initial state falls under *capacity enhancement* ("Capacity planning," 2018). Using this T, the formula for r_2 is as follows:

$$r_2 = \frac{\int_{t_d}^{T} F(t)dt}{\int_{t_d}^{T} TF(t)dt} \tag{3}$$

Where

$$T = \begin{cases} t_R & F_R \leq F_o \\ F^{-1}(F_o) & F_R > F_o \; and \; t > t_o \end{cases}$$

With a reasoning like the previous part, we will have $0 \leq r_2 \leq 1$.

The third component is time-to-recovery (r_3). Each system has a favorite time-to-recovery (T_0) which can be determined in several ways, such as expert opinion. Having T_0 we calculate r_3 using formula (4).

$$r_3 = f(T) = \begin{cases} 1 & T \leq T_0 \\ \frac{T_0}{T} & ow \end{cases} \quad (4)$$

When $r_3 = 1$, it tells us that the time-to-recovery is shorter than the favorable time and if the recovery time is terrible ($T \to \infty$) then the corresponding component is very small ($r_3 \to 0$). The function $f(T)$ can be replaced by the function that best suits the system. Also, it holds that $0 \leq r_3 \leq 1$.

Our proposed RM is a convex combination of the three components.

$$r = \lambda_1 r_1 + \lambda_2 r_2 + \lambda_3 r_3, \quad (5)$$

$$\sum_{i=1}^{3} \lambda_i = 1 \textit{ and } \lambda_i \geq 0 \textit{ for i=1,2,3,}$$

where r_1, r_2, and r_3 are values of absorption, adaptation, and recovery components, respectively. The weight parameters ($\lambda_1, \lambda_2, \lambda_3$) can be obtained using any priority ranking method among those three abilities such as analytic hierarchical process (AHP) (Brink, 1994).

4. A RESILIENCE METRIC ASSESSMENT METHODOLOGY

When we talk about a valid RM, the question arises: "how can we assess its validity". In this section, we introduce a methodology that can be used for this purpose. This methodology is not just for a particular case or domain and can be applied to any performance-based RM. Our methodology utilizes experimental design (Montgomery, 1991) and statistical analysis.

"An experiment is a test or a series of tests in which purposeful changes are made to the input variables of a process or a system so that we may observe and identify the reasons for changes that may be noticed in the output response" (Montgomery, 1991). Experimental design is an efficient procedure for planning experiments so that the data obtained can be analyzed to yield valid and objective conclusions. It is used to choose between alternatives, select the key factors affecting a response, model a process, "fine tune" a process, and optimize a process output.

We use the experimental design method to assess the validity of a metric. The steps of the proposed methodology are as follows.

Step 1: Select factors and their levels. We must have a factor for each of the items we want to study, which in our case they are abilities of the system. Each factor can be a function of sub-factors. Combinations of factor levels are called treatments. The **response** variable is the RM value.

Step 2: Obtain the performance measure for each treatment. The probability of occurrence of extreme events is minimal, and it is not feasible to get the real data for experiments. Hence, we use simulation to obtain the data. The output of a simulation is the functionality of the system which will be used in calculating the resilience.

Step 3: Calculate RM. In this step, we use the performance data in the previous step to calculate the resilience for each treatment.

Step 4: Analyze the results. Now use analysis of variance (ANOVA) to test the statistical significance of factors' effects on the resilience of the system. The output of ANOVA includes the *p*-values for the factors. In statistics, we compare this *p*-value with a significance level. The smaller the *p*-value, the more significant it is. If *p*-value for a factor is significant, it signals that changing the value or level of that factor (ability) will not change the resilience; hence we can say that that metric is not valid. For example, if a factor associated with absorption has a p-value of 0.1, then it shows that this factor is not significant, and that means that absorption has no significant effect on the resilience of the system. However, from the conceptual framework, we know that it is one of the key abilities of a resilient system.

5. NUMERICAL STUDIES

In this section, we will examine our proposed RM by the methodology that we presented in Section 4. For this, we need a system to simulate the events (i.e., feed input factors for each treatment and extract response and calculate the output of the proposed RM). We adopted security constrained unit commitment (SCUC) which models electrical power systems (Bertsimas, Litvinov, Sun, Zhao, & Zheng, 2013; Khodaei & Shahidehpour, 2010). The SUSC model and description can be found in Appendix A.

For simplicity, without loss of generality, we assumed that the disruption just affects the nodes (generators), however, it can be extended to include links and other components as well. We applied SCUC on a 57-bus test case which consists of 57 buses, seven units, and 80 lines. The data can be found in Appendix B. Now we go through the steps of our methodology for metric assessment.

5.1.METRIC ASSESSMENT

The following steps are followed to assess the proposed resilience metric and check if it is a valid RM for the power system example.

Step 1: Select factors and levels. Let labels A, B, and C stand for the three design factors (absorption, adaptation, and recovery, respectively). The factors should be extracted from the primary items that influence the resiliency of the power system units. These items are time-to-recovery, generation capacity, ramp up, ramp down (Khodaei & Shahidehpour, 2010), and severity, where severity is the number of generators that are inoperable. In 57-bus test case data, there is a high correlation among the generation capacity, ramp up, and ramp down. Due to this correlation we arbiterarily choose one of them, e.g. generation capacity. During an adverse event, a better absorption can result in fewer inoperable generators. Hence we use severity as a measure of A. Generation capacity can be used for B. This is because, after an adverse event, the high capacity generators can inject more spinning and non-spinning reserves into the system and satisfy more demand (Ahmadian, Vahidi, Jahanipour, Hoseinian, & Rastegar, 2016; Matos, Bessa, Botterud, & Zhou, 2017). Factor C is time-to-recovery.

For factors A and B, we selected two levels using the Pareto rule in a way that the distance between two levels is 80% of the range of data. In a severe situation, the number of inoperable generators will increase. In the 57-bus test case, there are seven generators with generation capacities of 20, 30, 50, and 80 Megawatts. Since we have seven generators, at its lowest level, B assumes 1, which means that only one generator will become inoperable and the rest of generators will continue their regular production. At its highest level, four generators will become inoperable. For factor C, which is the time-to-recovery, we used the time-to-repair (TTR). Researchers use lognormal and exponential probability distributions for TTR (O'Connor, 2002). We collected the mean time-to-repair (MTTR) of each generator (unit) (Janusz Buchta, Andrzej Oziemski, & Maciej Pawlik, 2014; Lee C. Cadwallader, 2012; Oyedepo, Fagbenle, & Adefila, 2015; Podofillini, L., Sudret, B., Stojadinovic, B., Zio, E., & Kröger, W., 2015) and we fit an exponential probability distribution for the TTR. We assume that generator is operable after this TTR. The time horizon for usual SCUC is 24 hours, however, since the MTTR for some generators was more than 24, we considered a 96 hours horizon. Let *g(t)* be the exponential probability distribution function of time-to-repair, *t*, and $G(t)$ is its cumulative distributin function. Therefore, the TTR corresponding to a probability

p is calcuated as $G^{-1}(p)$. We expect a complicated relationship between time-to-recovery and the RM value. Hence, five levels(says, 2014) are selected to reflect the actual effect of recovery time on the RM. The first four levels are $G^{-1}(0.25)$, $G^{-1}(0.5)$, $G^{-1}(0.63)$, and $G^{-1}(0.75)$. The last level (T) is the minimum of the time horizon (96) and $G^{-1}(0.99)$ for the selected generator.

Table I. Factor and levels. For recovery time f is the exponential probability density function

Factor Name	**Factor ID**	**Levels**
Generating capacity (MW)	A	Low (-) = 20, High (+) = 80
Severity (#of inoperable generators)	B	Low (-) = 1, High (+) = 4
Time-to-recovery (Hours)	C	$G^{-1}(0.25)$, $G^{-1}(0.5)$, $G^{-1}(0.63)$, $G^{-1}(0.75)$, T

Figure 3 shows the treatments resulted from experimental design. The name of each treatment consists of the AB treatment label (i.e., *1, a, b, ab*), an underscore, and probability of factor C. For example, case a_0.25 corresponds to the TTR for the probability of 0.25 and AB at *a* (i.e., factors A is at its high level (+) with a value of 80 and B is at its low level (–) with a value of 1.) For each treatment, we generated the data for inoperable generators.

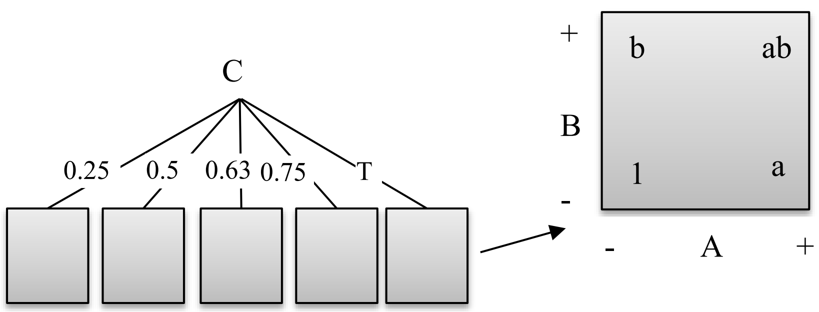

Figure 3: design of the experiment for analysis of metrics

Step 2: Obtain the performance measures. For this step, we coded the SCUC in Java and used Java API of IBM CPLEX Studio 12.6 for optimization("IBM Knowledge Center - Java tutorial," 2018). For each of the treatments, we fed the input data into the SCUC, extracted load shedding, and calculated the demand served (demand served equals actual demand minus load shedding). Figure 4 plots the demand served and actual demand.

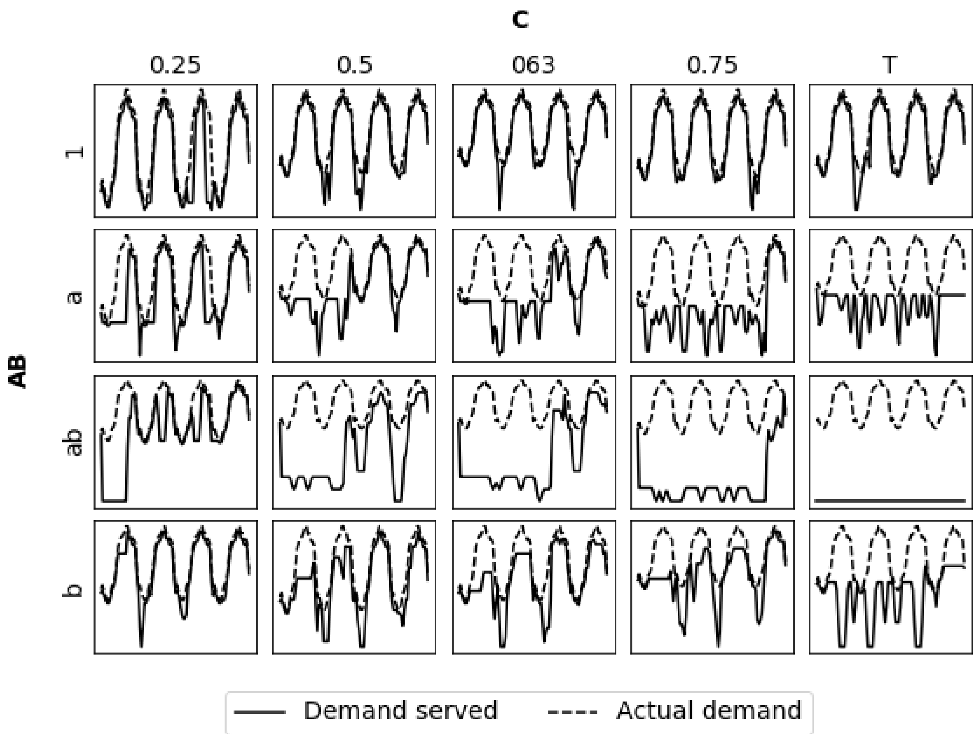

Figure 4: Demand vs. supply for each treatment. The columns correspond to levels of factor C, and the rows correspond to level combinations of AB.

Step 3: Calculate RM. For our proposed metric, we first calculated the metric components (Figure 5). Then, to study the effect of the choice of λ_is on the resilience, we devised different combinations of λ_is (Appendix C). The name of each combination is derived from the values of the λ_is (e.g., m145 is for $\lambda_1 = 0.1, \lambda_2 = 0.4, \text{and } \lambda_3 = 0.5$; and m25255 is for $\lambda_1 = 0.25, \lambda_2 = 0.25, \text{and } \lambda_3 = 0.5$). Finally, we calculated the resilience for each treatment and each combination of λ_is.

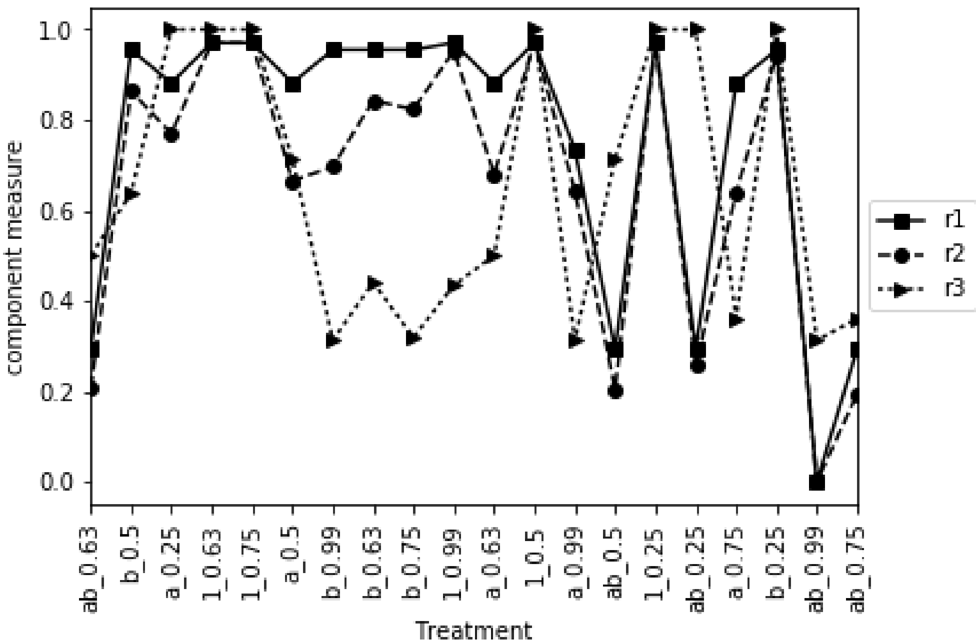

Figure 5: resilience metric components

Step 4: Analyze the results: First we determined the effect model using the experimental design techniques, and then calculated the ANOVA table. To see if there are interactions among the factors we drew interaction plots (Appendix D). Since there were no interactions (interaction lines does not cross each other) we used the following linear model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon \tag{6}$$

in which the variables $X_1,\ X_2, and\ X_3$ correspond to the factors A, B, and C. β_i are parameters and ϵ is the error term. Table II contains the ANOVA table for the metric corresponding to vector $\lambda = (0.25,0.25,0.5)$

Table II. ANOVA table for $\lambda = (0.25,0.25,0.5)$

	df	sum_sq	mean_sq	F	PR(>F)
A	1	0.4258	0.4258	75.75	1.57054E-06
B	1	0.3008	0.3008	54	8.87232E-06
C	4	0.3501	0.3501	15.75	0.000101334
Residual	12	0.0668	0.0042	nan	nan

We calculated ANOVA for all λ vectors (Table III). Among these combinations, for cases m451 and m541 the factor A is not significant at 0.01 significance level. Thus, we will exclude these two from the possible $\lambda_i s$. All other combinations are validated through our model. For application, one can choose one of these λ_i combinations using AHP.

Table III. P-values extracted from ANOVA for some combinations of λ_is

	m145	**m235**	**m25255**	**m325**	**m415**	**m154**	**m253**	**m25525**
A	1.0E-06	1.3E-06	1.5E-06	1.9E-06	3.3E-06	2.3E-07	5.6E-07	1.3E-06
B	7.9E-06	8.2E-06	9.0E-06	1.0E-05	1.4E-05	3.2E-06	9.7E-06	2.4E-05
C	7.7E-05	8.9E-05	1.0E-04	1.2E-04	2.0E-04	2.2E-04	4.1E-03	2.0E-02

	m352	**m451**	**m514**	**m523**	**m52525**	**m532**	**m541**
A	3.2E-06	1.7E-05	4.7E-06	7.1E-06	1.0E-05	1.5E-05	3.2E-05
B	6.1E-05	3.1E-04	2.8E-05	6.8E-05	1.1E-04	1.9E-04	4.9E-04
C	7.9E-02	4.5E-01	2.5E-03	2.5E-02	7.2E-02	1.7E-01	5.2E-01

6. DISCUSSION

The presented methodology enables us to study various resilience metrics quantitatively. Since we are looking for a general metric to quantify the system resilience, all metrics are compared based on the conceptual framework of a resilient system (Section 1.1). If two out of three resilience abilities are fixed as constant and leave the other one to change, we must be able to identify the change in a resilient metric. If it does not show that the altered ability have a significant effect on the metric, and the resulting metric is not valid.

We now examine the performance of the existing resilience metrics using the proposed assessment methodology for the power network system discussed in Section 5. For this specific example, the results of Step 1 and Step 2 are the same as those presented in Section 5. Hence, we will perform the remaining two steps for each of the metrics in this section. The result of Step 3 is summarized in Figure 6. As we expected, $Index_2$ is less sensitive to the generation capacity in a way that when we have four high capacity inoperable generators (case ab_0.99), the rest of the indices are close to 0. $Index_6$ has the least correlation with other metrics, and it shows less variability compared to other RMs. One can see that when we have a long time-to-recovery and more significant severity (cases ab_0.99 and case b_0.99), $Index_3$ drops dramatically. Also for case 1_0.25 which is the least severe case, $Index_3$ has an unfavorable result, and we have weaker resilience than case 1_0.63, which has the same treatment setting except for time-to-recovery.

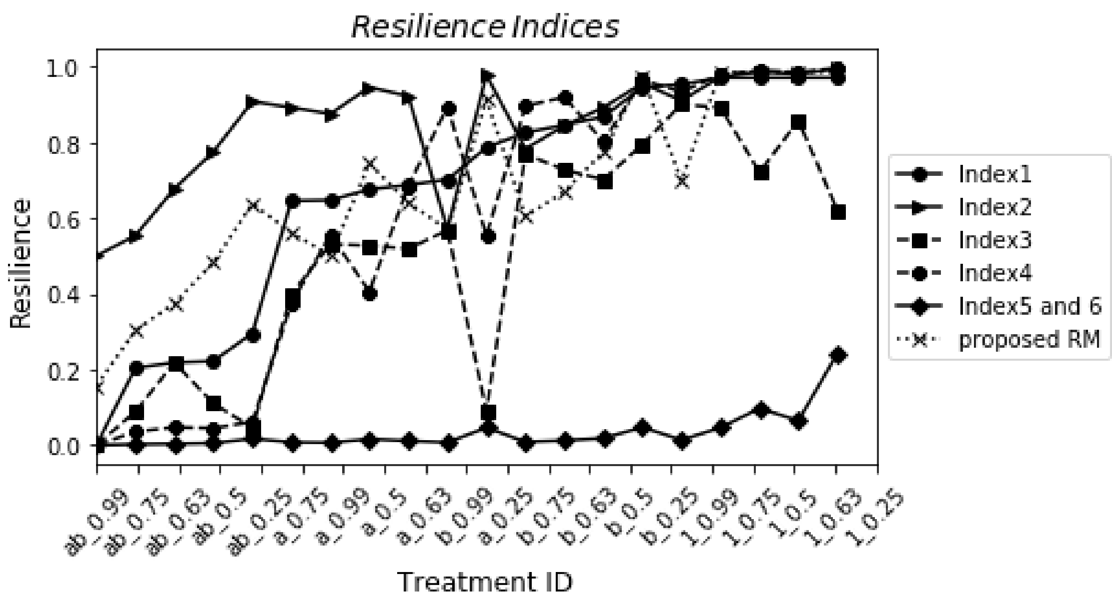

Figure 6: Chart of RM values for experimental design treatments

Analysis of variance will demonstrate which factors have a significant effect on the metrics. The *p*-values from ANOVA tables for these metrics are summarized in *Table IV*.

Table IV. The p-values extracted from ANOVA analysis

	$Index_1$	$Index_2$	$Index_3$	$Index_4$	$Index_5$	$Index_6$	**Our proposed Metric***
A	4.24E-06	3.23E-02	1.29E-05	4.67E-07	5.18E-02	1.57E-06	1.49E-06
B	1.71E-04	1.17E-04	1.41E-02	1.40E-03	5.67E-02	1.31E-05	1.49E-06
C	5.15E-01	9.75E-03	8.93E-01	9.97E-01	2.20E-01	1.72E-02	3.85E-05

*Results are based on $\lambda = (0.25, 0.25, 0.5)$

The p-value is a good way to assess statistical significance of a factor on resilience. $Index_1$ shows that at a significance level of 1%, recovery time is not a statistically significant factor for resilience, while the other two factors are significant. Resilience frameworks emphasize that time-to-recovery is one of the important abilities of a resilient system. Based on this perspective, $Index_1$ is not valid. Likewise, $Index_2$ underrates the effect of factor A. $Index_3$, $Index_4$, $Index_5$, and $Index_6$ do not show the significance of time-to-recovery (their p-value is larger than 0.01). Table V summarizes the pros and cons of the existing metrics.

Table V. Pros and cons of the current RMs derived from the ANOVA analysis

	Pros	**Cons**
$Index_1$	Considers the absorption and adaptation	Does not reflect recovery time
$Index_2$	Considers adaptation and time-to-recovery	Undervalues the significance of absorption
$Index_3$	it better shows the significance of absorption	Does not reflect adaption and recovery time
$Index_4$	Considers absorption and adaptation	It is more sensitive to the absorption than to the time to rcovery.
$Index_5$	A absorption and adaptation have significance (by adjusting significance level)	underrates the effect of the time to recovery.
$Index_6$	Considers the absorption and adaptation	Time to recovery is not important.

Overall, the p-values of all factors in our proposed metric are close to 0 as seen in Table VI; hence, they are all significant. Furthermore, the proposed metric is not biased toward any of the three factors. Therefore, our proposed metric is a valid resilience metric.

7. CONCLUSION

Building a resilient system or community cannot be overemphasized against disasters. There have been several approaches reported in the literature to quantify resilience of a system. However, they were often designed to work for a specific application and there is a large variability on the performance of resilient metrics. Therefore, we have developed a statistical assessment method for a resilient metric to be valid according to the concept of resilience. The design of experiments and ANOVA are utilized. We have tested well-known resilience metrics to compare performance using a power network system. Because those metrics exhibited a large variation in performance, a new resilience metric was developed. Using the proposed assessment methodology, the new resilience metric was evaluated and compared with the existing metrics. The results showed that the proposed metric is a valid resilience metric, which is not biased towards any of the abilities of a resilient system. As an extension to this work, one can include pre-disaster information for the resilience metric, i.e., "anticipation" ability. Such a metric may be able to capture the resilience of a system more accurately.

APPENDIX A : SECURITY CONSTRAINED UNIT COMMITMENT

The objective of the SCUC problem is to find a unit commitment schedule that minimizes the commitment and dispatch costs while meeting the forecasted system load. It takes into account various physical or intertemporal constraints of generating resources, transmission, and system reliability requirements (Bertsimas et al., 2013). The following notations will be used in the mathematical model:

- **Sets/indices**: GG stands for the number of gas generation units, NG the number of units, NT the number of periods, and NB the number of buses. Index b is for the buses, index i for units, l for lines, and t for the time.
- **Parameters**: The parameters in the mathematical formulation consist of, H for gas heating value (39 MJ/MBTU), $P_{D,t}$ for system demand at time t, $P_{L,t}$ for system losses at time t,

$P_{\min}$/ $P_{\max}$ for the Lower / upper limit of the real power generation of the unit, $PL^t_{l,max}/PL^t_{l,min}$ for the maximum/minimum capacity of the line l, $R_{O,t}$ / $R_{S,t}$ for the system operating / spinning reserve requirement at time t, T_i^{off} / T_i^{on} for minimum down and up time of the unit i, UR_i/ DR_i for the maximum Ramp up/down, and finally η_i for the efficiency of the generator. Parameter Z_{it} and G_{it} are the control variables in our simulations that are designed specifically for each scenario.

- **Decision variables**. I_{it} is the commitment state of the unit i at time t , P_{it} is the generation of unit i at time t, PL^t_l is the real power flow on line l, $R_{O,it}$ and $R_{S,it}$ are the operating and spinning reserve of the unit i at time t respectively. X_{it}^{off} and X_{it}^{on} are the OFF and ON time of the unit i at time t, θ_{bi} is the phase angle, and Q_{it} the quantity of gas consumed by the (gas fired) generator i at time t.

Equation (7) is the objective function, which is the cost of generation and load shedding cost with a value of lost load (VOLL) $1000/MWh. The objective function is comprised of the fuel cost for producing electric power, the startup cost, and the shutdown cost. Originally the fuel cost is a quadratic and convex function, and we used a piecewise linear function to estimate it. Equation (8) is the generation limit. Constraint (9) indicates the capacity boundaries of each unit. The C problem must meet the required system spinning and operating reserves (10) which are defined by the independent system operator (ISO). The ramp up (11) and ramp down (12) constraints, minimum uptime and minimum down time (13) constraints have to satisfy in operation of the power system. Constraint (14) shows the static network security constraints, including power flow and transmission line flow. The constraint (15) reflects the dependency of power generation dispatch and natural gas supply as an input of a power plant. We extract load shedding from the last equation (16).

$$min\sum_{i=1}^{NG}\sum_{t=1}^{NT}[F_{ci}(P_{it})+SU_{it}+SD_{it}]+\sum_{i=1}^{NB}\sum_{t=1}^{NT}Voll\times LS_{it} \tag{7}$$

$$P_{\min}I_{it}\le P_{it}\le P_{\max}I_{it} \qquad \forall \boldsymbol{i},\forall \boldsymbol{t} \tag{8}$$

$$\sum_{i=1}^{NG}p_{it}=P_{D,t} \qquad \forall \boldsymbol{t} \tag{9}$$

$$\sum_{i=1}^{NG}R_{S,it}\times I_{it}\ge R_{S,t}\quad ,\sum_{i=1}^{NG}R_{O,it}\times I_{it}\ge R_{O,t} \qquad \forall \boldsymbol{t} \tag{10}$$

$$P_{it}-P_{i(t-1)}\le[1-I_{it}\big(1-I_{i(t-1)}\big)UR_i+I_{it}\big(1-I_{i(t-1)}\big)P_{i,min} \qquad \forall \boldsymbol{i},\forall \boldsymbol{t} \tag{11}$$

$$P_{i(t-1)}-P_{it}\le[1-I_{it}\big(1-I_{i(t-1)}\big)DR_i+I_{it}\big(1-I_{i(t-1)}\big)P_{i,min} \qquad \forall \mathrm{i},\forall \mathrm{t} \tag{12}$$

$$\left[X_{i(t-1)}^{on}-T_i^{on}\right]\left[I_{i(t-1)}-I_{it}\right]\ge 0,\ \left[X_{i(t-1)}^{off}-T_i^{off}\right]\left[I_{it}-I_{i(t-1)}\right]\ge 0 \qquad \forall \boldsymbol{i},\forall \boldsymbol{t} \tag{13}$$

$$-PL_{lt,\max}\ \le PL_{lt}\le PL_{lt,\max}\ \ ,PL_{lt}=\frac{\theta_{bi}-\theta_{bj}}{x_{bi,bj}} \qquad \forall \mathrm{i},\forall \mathrm{t} \tag{14}$$

$$p_{it}=\ \eta_i\,Q_{it}H\ ,\ \ Q_{it}\le QG_{it} \qquad \forall \mathrm{i}\in \mathrm{GG},\mathrm{t} \tag{15}$$

$$\sum_{l=1}^{NL}PL_{lt}=P_{bt}-PD_{bt}+LS_{bt} \qquad \forall \mathrm{b},\forall \mathrm{t} \tag{16}$$

Appendix B: 57-bus system data

Table B1 unit data

bus	pmin	pmax	cnl	sdc	suc	mu	md	ru	rd	msr	qsc	laststat	mn	lastp	mf	psegmax	psegmax	cseg	cseg
1	30	80	74	0	0	4	4	40	40	3	0	1	4	30	96	40	40	17	52
2	5	20	18	0	0	1	1	10	10	1	0	1	1	5	96	10	10	38	114
3	20	50	59	0	0	1	1	50	50	1	0	1	1	20	96	25	25	23	70
6	30	80	74	0	0	4	4	40	40	3	0	1	4	30	96	40	40	17	52
8	5	30	32	0	0	1	1	30	30	1	0	1	1	5	96	15	15	27	82
9	5	20	18	0	0	1	1	10	10	1	0	1	1	5	96	10	10	38	114
12	5	20	18	0	0	1	1	10	10	1	0	1	1	5	96	10	10	38	114

Table B2 line data

start	end	maxFlow	x
23	24	100	0.0492
25	27	500	0.163
31	32	100	0.0985
23	24	100	0.0492
1	3	100	0.0424
25	27	500	0.163
25	27	500	0.163
8	9	100	0.0605
9	10	100	0.0487
9	11	100	0.289
9	12	100	0.291
9	13	100	0.0707
13	14	100	0.00955
13	15	100	0.0151
1	15	100	0.0966
1	16	100	0.134
1	17	100	0.0966
3	15	100	0.0719
4	18	100	0.2293
4	18	100	0.251
5	6	100	0.239
7	8	100	0.2158
10	12	100	0.145
11	13	100	0.15
12	13	500	0.0135
12	16	100	0.0561
12	17	100	0.0376
14	15	500	0.0386
18	19	500	0.02
19	20	500	0.0268
21	20	500	0.0986
21	22	500	0.0302
22	23	500	0.0919
23	24	500	0.0919
24	25	100	0.218
24	25	100	0.117
24	26	500	0.037
26	27	100	0.1015
27	28	500	0.016
28	29	100	0.2778
7	29	100	0.324
25	30	500	0.037

start	end	maxFlow	x
30	31	500	0.127
31	32	100	0.4115
32	33	100	0.0355
34	32	100	0.196
34	35	100	0.18
35	36	100	0.0454
36	37	100	0.1323
37	38	100	0.141
37	39	500	0.122
36	40	100	0.0406
22	38	100	0.148
11	41	100	0.101
41	42	100	0.1999
41	43	100	0.0124
38	44	100	0.0244
15	45	500	0.0485
14	46	500	0.105
46	47	100	0.0704
47	48	500	0.0202
48	49	500	0.037
49	50	100	0.0853
50	51	100	0.03665
10	51	100	0.132
13	49	100	0.148
29	52	100	0.0641
52	53	500	0.123
53	54	500	0.2074
54	55	100	0.102
11	43	100	0.173
44	45	500	0.0712
40	56	500	0.188
56	41	500	0.0997
56	42	100	0.0836
39	57	500	0.0505
57	56	500	0.1581
38	49	100	0.1272
38	48	100	0.0848
9	55	100	0.158

Table B3 demand data for the first 24 hours

Hour	demand	ssr	sor
1.	131.97	0	0
2.	136.12	0	0
3.	128.65	0	0
4.	123.67	0	0
5.	120.35	0	0
6.	120.35	0	0
7.	125.33	0	0
8.	135.29	0	0
9.	138.61	0	0
10.	145.25	0	0
11.	161.02	0	0
12.	177.62	0	0

Hour	demand	ssr	sor
13.	183.43	0	0
14.	188.41	0	0
15.	189.24	0	0
16.	193.39	0	0
17.	199.2	0	0
18.	199.2	0	0
19.	191.73	0	0
20.	191.73	0	0
21.	185.09	0	0
22.	185.09	0	0
23.	180.94	0	0
24.	152.72	0	0

Table B4 percent of total load at each bus

bus	percent load	bus	percent load	bus	percent load
1	0	21	18.05	41	17
2	24.42	22	25.48	42	18
3	37	23	45.65	43	23
4	0	24	62.63	44	113
5	21.23	25	24.42	45	63
6	24.42	26	62.63	46	84
7	24.42	27	35.03	47	12
8	49.89	28	32.91	48	12
9	36.09	29	27	49	277
10	14.86	30	20	50	78
11	95.54	31	37	51	77
12	26.54	32	37	52	39
13	11.68	33	18	53	28
14	63.69	34	16	54	66
15	47.77	35	53	55	68
16	19.11	36	28	56	47
17	14.86	37	34	57	68
18	10.62	38	20		
19	7.43	39	87		
20	65.82	40	17		

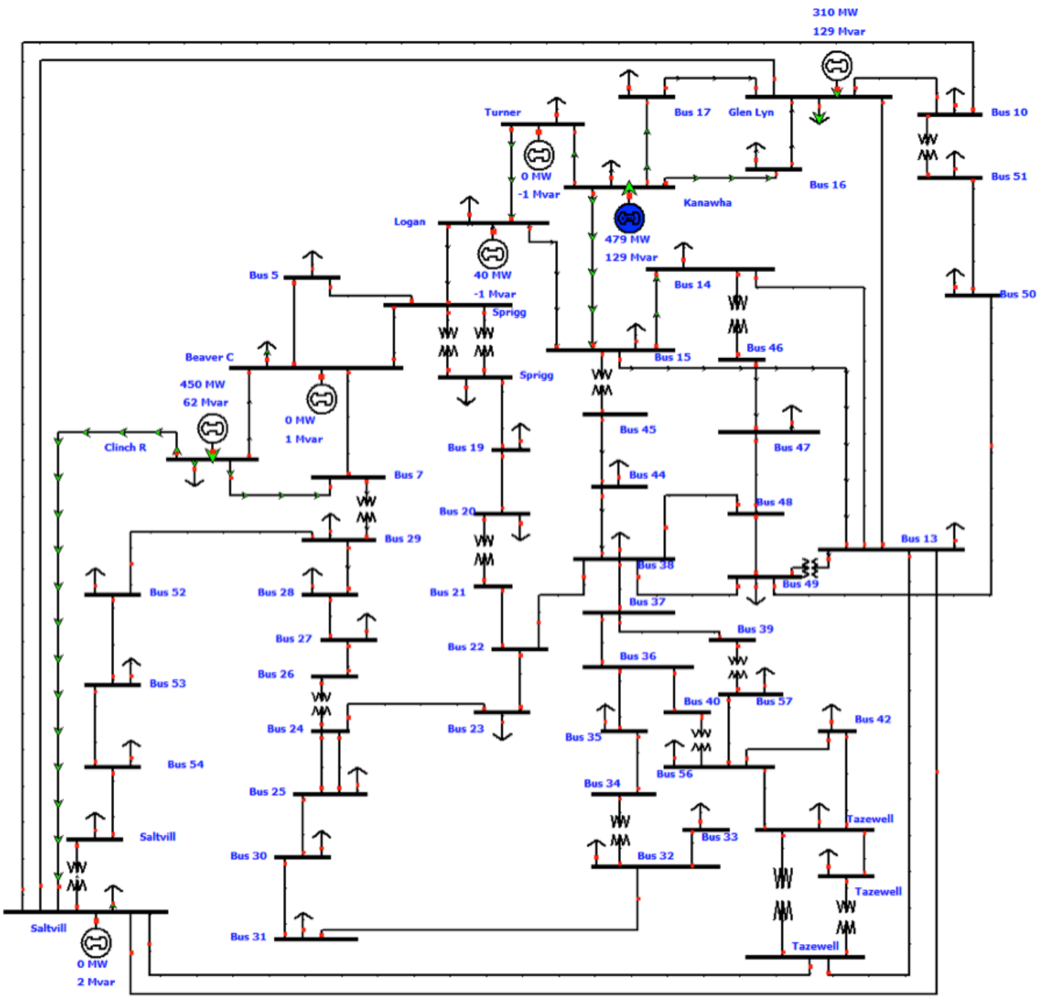

Figure B1 graph of 57-bus, source: http://icseg.iti.illinois.edu/ieee-57-bus-system/

Appendix C: λ scenarios

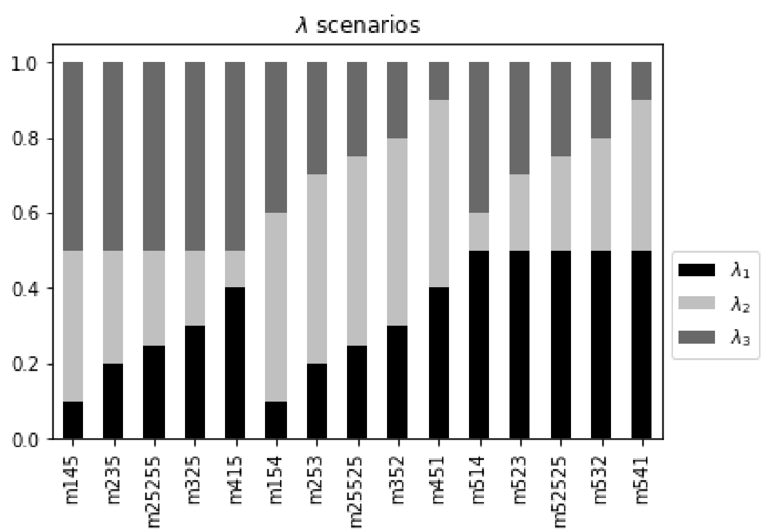

Figure C1: different λ combinations

Appendix D: Interaction plots

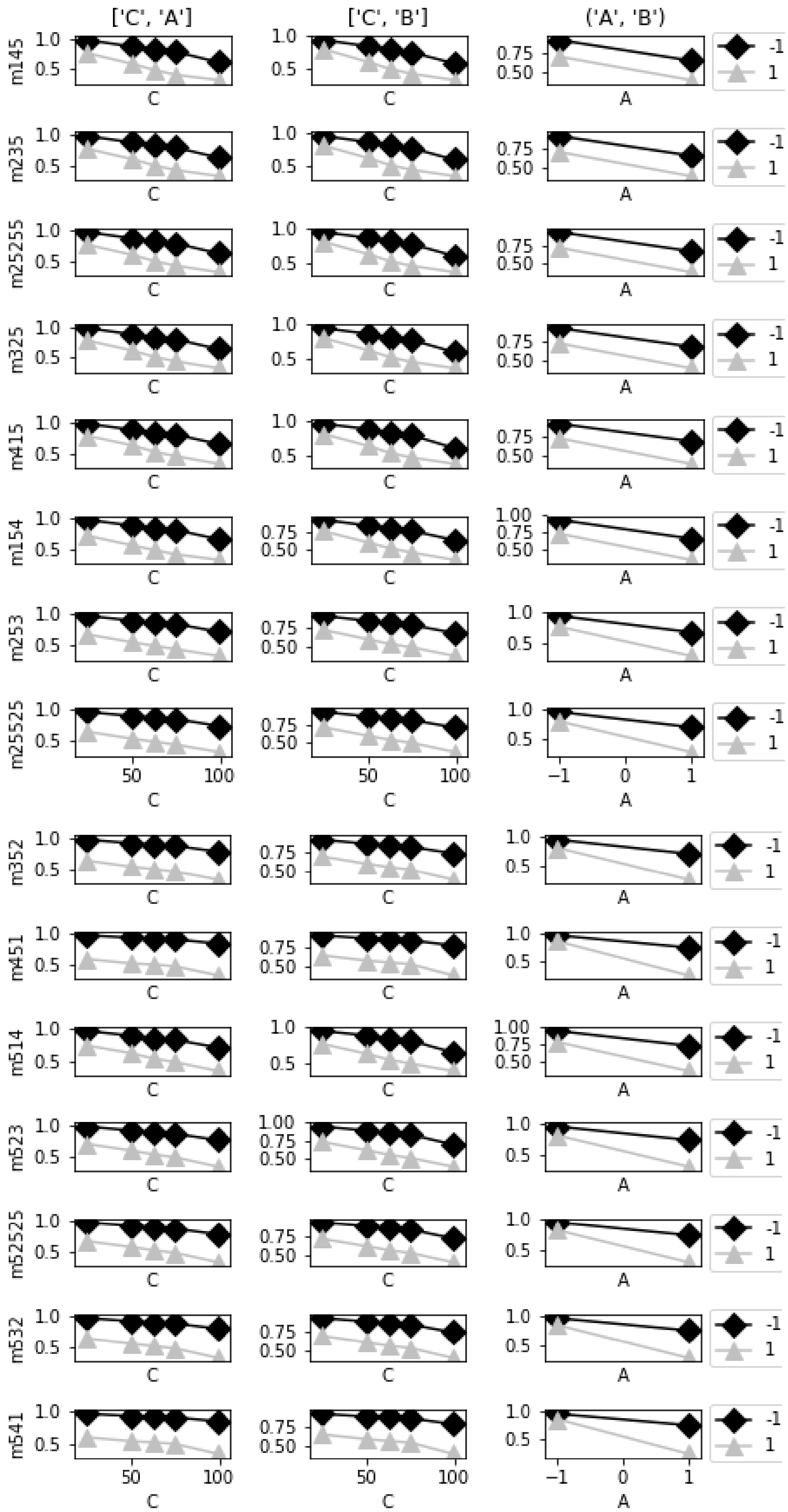

Figure D1 Interaction plots

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