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Hybrid Hidden Markov Models for Resilience Metric in a Dynamic Infrastructure System

S. Zhao*. X. Liu**. Y. Zhuo**

* Department of Industrial & Systems Engineering, National University of Singapore, Singapore.
** Department of Industrial Engineering and Management, Shanghai Jiao Tong University, P. R. China (e-mail: x_liu@sjtu.edu.cn)}

Abstract: In this study, we propose a resilience analysis framework and a metric for measuring resilience. Then, nonhomogeneous Hidden Markov Models (HMM) are designed to evaluate resilience capacities including adaptive capacity, absorptive capacity, and recovery capacity under different disruption scenarios. Finally, a case study of water supply system taken from Shanghai City demonstrates that the proposed approaches are effective on system resilience assessment.

Keywords: Resilience, infrastructure system, time-varying capacity, hidden Markov model, uncertainty

1. INTRODUCTION

When facing sever disruptions that may lead to systems cascading failures and significant consequences, how to endow systems with capabilities to withstand the adverse events and facilitate recovery of the disrupted systems is a challenging issue (Klein et al., 2003; Manyena, 2006).

Resilience is one of the most important indicators of system safety. The challenge lies in developing comprehensive resilience measurement are its multidimensional and sophisticated nature of inputs/outputs, such as time-varying and interdependent system performances, uncertain system consequences, dynamics of disruption scenarios, and limited and incomplete information for learning from historical events (Chang et al., 2014). Many scholars have done a great deal of work in resilience measurement both in quantitative and qualitative ways (Bruneau et al. 2003; Cutter et al. 2010; Rochas et al., 2014). However, few attentions have been paid in resilience metric considering time-varying and coupled system capacities. When a dynamic infrastructure system suffers multiple related disruptions, assessment for time-varying resilience capacities is necessary as the system manifests different performances in sub-disruptions due to drifting of capacity states. The objective of this study is to establish resilience metric in dynamic infrastructure systems with consideration of dependent/interdependent and time-varying resilience capacities, and present a framework and solution procedure for the metric.

2. SYSTEM RESILIENCE MEASUREMENT FRAMWORK

To address the issues previously described, we propose a resilience metric based on the characteristics of infrastructure, and present the analyses of each components in the resilience metric in this section.

2.1 Definition of System Resilience

A resilient infrastructure system is capable to provide continuous and sufficient service during disruptions period and return to desired operation within a tolerable time, thus service satisfaction level is adopted as the indicator of system performance function to measure infrastructure system resilience.

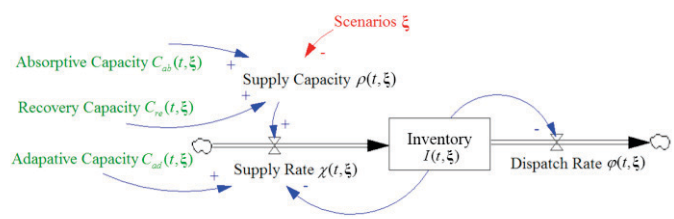

Fig. 1. Stock and flow chain of infrastructure system resilience

We can see from Fig. 1 clearly that infrastructure system can be regarded as a stock and flow chain consist of, an inflow denoting the supply rate to generate service, an controllable outflow denoting the service dispatching rate to meet customers' needs, and dynamic inventory level depending on the rates of supply and dispatch.

Definition 1. Total resilience (*TR*) of an infrastructure system is defined as the ability recovering to a desired level from disruption scenarios within acceptable time, which is measured by the total satisfaction level under the interactions of resilience capacities, dispatch strategies, and disruption scenario.

Let $\tau(\xi)$ be the duration of scenario, after which the supply rate $\rho(t,\xi)$ is recovered to a desired level that can suffice the demand of customers $d(t)$. Let $\bar{\tau}$ denote the maximum tolerable recovery time, which is characterized by the features or management criterion of target system. Prior to the resilience assessment, we should firstly compare $\tau(\xi)$ with $\bar{\tau}$. If $\tau(\xi) > \bar{\tau}$, then system redesign is needed to enhance recovery capacity via resources allocation, as current recovery time is unacceptable. Let $p(\xi)$ be the probability of scenario ξ $(\xi \in \Omega)$, t_1^{ξ} be the start time of scenario ξ. The metric of

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total resilience based on the above definition can be presented as below:

$$TR = \sum_{\boldsymbol{\xi}\in\Omega} p(\boldsymbol{\xi}) \sum_{t_1^{\xi}}^{t_1^{\xi}+\tau(\boldsymbol{\xi})} \frac{\varphi(t,\boldsymbol{\xi})}{d(t)} \quad (1)$$

2.2 Scenario Modes and Recovery Modes

Scenario characterizes the severity, risk, and occurrence time of disruptions. Measurement of system resilience is scenario-specific, as different types of scenario require different technical or organizational supports for a system to cope with it. We address two basic scenario modes, single-disruption scenario and multiple-disruptions scenario. Let $\boldsymbol{\xi} = [\xi_1, \xi_2, ..., \xi_k]$ denote the scenario with k number of disruptions, where ξ_i $(\xi_i \in \boldsymbol{\xi})$ is the ith disruption, and let $\tau(\xi_i)$ denote the duration of each ξ_i $(i \in k)$. If $k = 1$, scenario $\boldsymbol{\xi}$ is defined as single-disruption scenario; if $k > 1$, before the recovery process of ξ_{i-1} is completed, ξ_i $(1 < i \le k)$ ensues, then we define $\boldsymbol{\xi}$ as multiple-disruptions scenario (shown as Fig. 2).

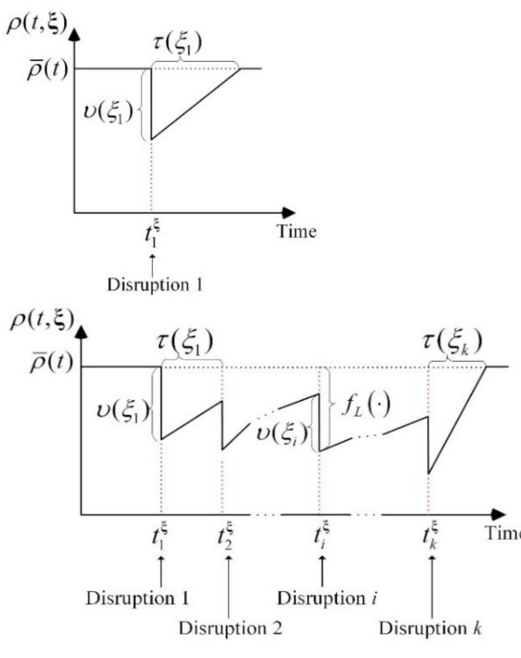

Fig. 2. Scenario modes of single-disruption and multiple-disruptions

Shown as Fig. 2, the duration of scenario $\boldsymbol{\xi}$ can be calculated by summarizing the duration of each disruption:

$$\tau(\boldsymbol{\xi}) = \sum_{i\in k} \tau(\xi_i), \forall \boldsymbol{\xi} \in \Omega \quad (2)$$

Let $\bar{\rho}(t)$ be the maximum supply rate, and capacity of supply rate $\rho(t,\boldsymbol{\xi})$ can be defined by a genetic function:

$$\rho(t,\boldsymbol{\xi}) = \bar{\rho}(t) \cdot \left[1 - f_L\left(t_i^{\xi}, \upsilon(\xi_i)\right) \cdot f_R\left(t, \tau^*(\xi_i)\right)\right], \quad t_i^{\xi} < t \le t_i^{\xi} + \tau(\xi_i),\ \forall i \in k,\ \forall \boldsymbol{\xi} \in \Omega \quad (3)$$

$$0 \le \rho(t,\boldsymbol{\xi}) \le \bar{\rho}(t),\ \ \forall t,\ \forall \boldsymbol{\xi} \in \Omega \quad (4)$$

where $\upsilon(\xi_i)$ is the loss percentage caused by disruption ξ_i, and $f_L\left(t_i^{\xi}, \upsilon(\xi_i)\right)$ is the loss function relative with the previous recovery process of ξ_{i-1} and $\upsilon(\xi_i)$ (shown as Fig. 2). $f_R\left(t, \tau^*(\xi_i)\right)$ is recovery function which represents the percentage of remaining loss caused by $f_L(\cdot)$ that need to be restored, where $\tau^*(\xi_i)$ is the necessary recovery time for ξ_i and determines the recovery rate of $f_R(\cdot)$, and $f_R(\cdot)$ is zero when system is fully restored. The implication assumption in (3) and (4) is that the recovery target is to 100%, and we can modify $\bar{\rho}(t)$ to a desired level if the recovery target is close to, or higher than the original state.

2.3 Resilience Capacities

In this section, the definition and measurement of the three resilience capacities (1) absorptive capacity, (2) adaptive capacity, and (3) recovery capacity are presented (Vugrin et al., 2010).

Absorptive capacity is pre-disruption capacity that can help system structure to absorb the impacts of disruptions, and maintain a high supply rate during scenario. The absorptive capacity of disruption ξ_i ($\xi_i \in \boldsymbol{\xi}$) can be expressed by the following equation:

$$C_{ab}(t,\boldsymbol{\xi}) = 1 - \upsilon(\xi_i), t = t_i^{\xi},\ \forall \xi_i \in \boldsymbol{\xi},\ \forall \boldsymbol{\xi} \in \Omega \quad (5)$$

Adaptive capacity is the ability that system responses to adverse impacts by self-organization during scenario period to mitigate system satisfaction loss. A disrupted system with adaptive capacity is able to supplement services through external sources, substitutes, or scheduling among system sub-components. Define $\omega_j(t,\boldsymbol{\xi})$ as the rate of the jth $(j \in J)$ adaptive source in scenario $\boldsymbol{\xi}$, and we can quantify adaptive capacity as the aggregation rate of adaptive sources during scenario period:

$$C_{ad}(t,\boldsymbol{\xi}) = \sum_{j=1}^{J} \omega_j(t,\boldsymbol{\xi}), \forall t,\ \forall \boldsymbol{\xi} \in \Omega \quad (6)$$

Recovery capacity is the rapidity of a disrupted system to return to a desired service level. Recovery capacity can be denoted as the reciprocal of necessary recovery time for each disruption ξ_i ($\xi_i \in \boldsymbol{\xi}$):

$$C_{re}(t,\boldsymbol{\xi}) = \frac{1}{\tau^*(\xi_i)}, t = t_i^{\xi},\ \forall \xi_i \in \boldsymbol{\xi},\ \forall \boldsymbol{\xi} \in \Omega \quad (7)$$

When $\tau^*(\xi_i)$ is derived, the recovery trajectory of the disturbed system supply rate $\rho(t,\boldsymbol{\xi})$ during period of $\tau(\xi_i)$ can be determined by recovery function $f_R(\cdot)$.

3. MODEL

3.1 The Total Resilience Model