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To cite this version:

Yang Wang, Shanshan Fu, Enrico Zio, Di Zhang, Xinping Yan. Modeling epistemic uncertainty in resilience assessment for water transportation systems . 2016. hal-01347361

HAL Id: hal-01347361

https://hal.science/hal-01347361v1

Preprint submitted on 25 Jul 2016

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Modeling epistemic uncertainty in resilience assessment for water transportation systems

Y.Wang & S.Fu
National Engineering Research Center for Water Transport Safety, Wuhan University of Technology, Wuhan, 430063, China

E. Zio
Chair on Systems Science and the Energy Challenge, Ecole Centrale Paris and Supélec, 92295, France
Energy Department, Politecnico di Milano, 20133, Milan, Italy

D. Zhang & X.P. Yan
National Engineering Research Center for Water Transport Safety, Wuhan University of Technology, Wuhan, 430063, China

ABSTRACT: The study of resilience has aroused significant interest in the literature recently. The domain-specific applications of the concept have led to diverse definitions and characteristics described therein. In general, resilience is measured with respect to a system performance or figure-of-merit. Three foundational aspects have to be taken into consideration for this. Firstly, the description of the pre-, during and post- disruptive event should be built upon a model that can account for the evolution and intervention of the dynamic trajectory of the potential adverse event. Secondly, the subjective and epistemic nature of resilience analysis is to be reflected in the family of curves, which convey the knowledge of the analysts. Thirdly, resilience is dependent upon the foreseen adverse scenarios, especially the stress of the disruptive event: thus, a spectrum of scenarios with varying profiles should be scrutinized.

1 INTRODUCTIONS

1.1 *Resilience in water transportation systems*

Safety has been a major concern in water transportation due to the potentially hazardous and dangerous environment. The state-of-the-art technology has provided advanced equipment for waterborne navigation and shore-side surveillance, yet the inherent complexity and the uncertainty in water transportation still make it a safety-critical system for the researchers and practitioners.

Risk is strongly featured in water transportation, and the study on the maritime risk analysis or assessment has attracted sustained work for years. For this reason, risk analysis has attracted sustained work for years in the field of water transportation. Recently, resilience is receiving growing attention (Zio 2016). The resilience study analyzes the adverse situation with multiple facets rather than only from the angle of pre-event prediction. Strategic planning, pre-event preparedness and post-event recovery are all encompassed in the resilience study (Zobel et al. 2014). Emphasis is placed on the capability of the system to withstand disruptions and the actions taken to hedge against the damages or losses by absorption, adaption and restoration.

This shift of paradigm in safety research is expected to bring forth profound influence upon the domain-specific research. Nevertheless, the study of resilience encounters similar difficulties as follows.

The first challenge comes from the setup of the problem, i.e., how to formulate resilience for water transportation, which are human-intensive, loosely coupled system, with autonomous bodies (the ships) distributedly moving a large area. Some recent research work has been carried out on resilience of water transportation. John et al (2016) studied the resilience of a seaport system by using Bayesian networks, with the CPT (conditional probability table) being estimated by a fuzzy analytical hierarchy process; Praetorius et al (2015) investigated the resilience aspect of the VTS (Vessel Traffic Service) operation in maritime administration by using FRAM (Functional Resonance Analysis Method).

The second challenge is the quantification of resilience. Results from theory exist (Ferrario & Zio 2014) in the literature, yet the engineering application to the transportation domain calls for a practical, explainable and suitable quantitative model such that the process and behavior of the system is clearly reflected(Gao et al. 2016). Currently, the resilience quantification is conceptually prescribed in terms of the system performance curve, but to compute such curve in compliance with multiple and interrelated factors, with uncertainties and evolution over time, is quite challenging.

The third challenge relates to the pre-event assessment. Resilience analysis can be applied as both pre-event and post-event assessment in which ex ante knowledge is indispensable because there usually do not exist absolute laws with which the inducing factors can conform(Kaplan & Haimes 2001). Prior knowledge from past experience, and subjective judgement from analysts should be highly accommodated in the evaluation model(Creaco et al. 2014).

To meet the above challenges, this paper proposes a network of factor model according to the function, component and structure analysis of water transportation systems. The contribution aims to build a way to formulate knowledge for obtaining resilience curve and its quantitative assessment.

2 THE BACKGROUND

2.1 *The resilience and modeling of system evolution*

The ex ante resilience assessment should be conducted in terms of more specific disruption. Figure 1 illustrates the conceptual resilience curve proposed by Henry et al (2012).

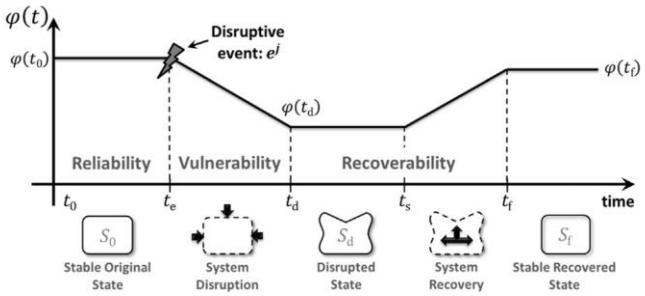

Figure 1. The conceptual resilience curve (Henry et al. 2012).

A resilient system should show a curve with shallow drop and a steep rise after the point of minimum system resilience is reached. However, this quantitative description only conveys a conceptual basis for the analysis, and in order to obtain a more rigorous quantitative form, various aspects should be addressed, which including the system dynamics and modeling the uncertainty of system behavior under disruption.

Possibly relevant methodologies for quantification are DET (Dynamic Event Tree) (Hofer 2004), and the DBN (Dynamic Bayesian Networks) (Murphy 2002). DET is utilized to analyze the stochastic events that occur during accidental evolution from an initial adverse event (Karanki et al. 2015). DBN is a time-sliced Bayesian network, in which the conditional probability among the nodes is dependent upon the correlation of the factors not only in-slice but also cross-slice. Both DET and DBN models have been extended from their original static versions to model the discrete event (Mercurio & Podofillini, 2009). However, limitations exist for the two models. DET does not fully account for the inter-restrictions among factors, and DBN does not explicitly indicate the time scale. Besides, DBNs assume that the values of some of the nodes can be observed, which is not the case for an ex ante study.

The rest of the paper is organized as follows. Section 3 discusses the methodology and proposes a model in response to the requirements; section 4 introduces some of the properties of the model; section 5 conducts numerical study by Monte Carlo simulation and discusses the inclusion of knowledge; section 6 summarizes the work and suggests the future research.

3 MODELING THE CYCLE OF DISRUPTION IN WATER TRANSPORTATION

3.1 *The generic model of incident disposal*

Human-intensiveness in water transportation system implies that the interactions between the human and the software/hardware are closely interweaved, and that the decisions and actions from some key individuals can largely influence the overall situation. Moreover, the main decision/action entities in a context of water transportation accident are the ship and the shore-side administration. Figure 2 illustrates the simplified process of parallel decision and action dynamics between the two entities, when confronting an incident. The humans in the system mainly include the crews (at the ship-side) and the administrative personnel (at the shore-side). Decision objective refers to the aims of decision, and action plan refers to the implementation options.

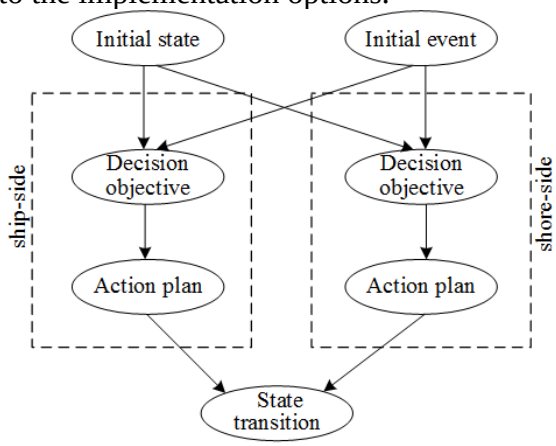

Figure 2. Accident management model of the ship-shore coordination.

Although the diagram above is structured with some resemblance to Bayesian networks by a DAG (Directed Acyclic Graph), the process would hardly be straightforwardly modeled by it, as traditional Bayesian network model does not support the duration of a status. In this regard, the following two lay-

er structure is proposed as a generic model, as is depicted in Figure 3.

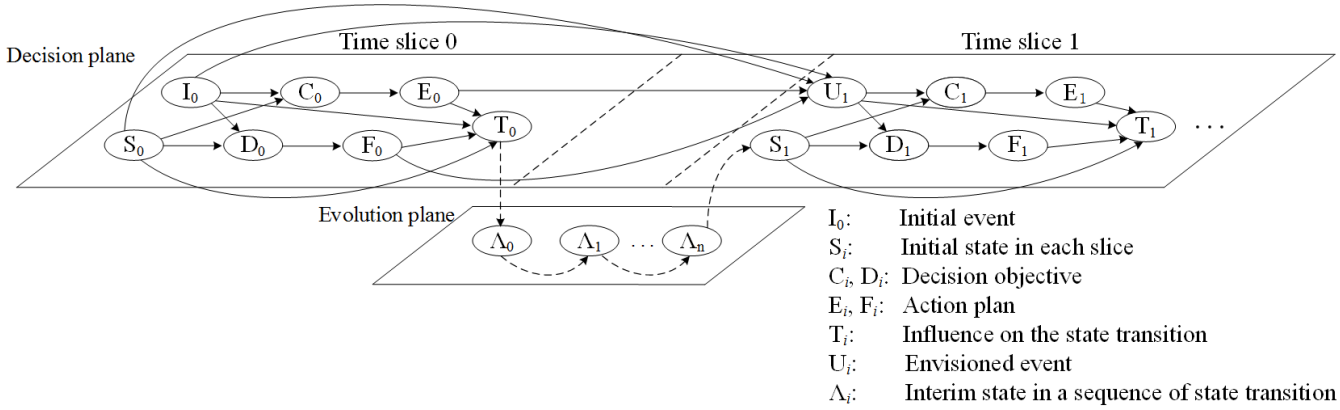

Figure 3. An intuitive two layer structure of accident management.

With the two layer structure, the process of the accident development is divided into two planes: the decision plane (DP) and the evolution plane (EP). The decision plane is described by a series of Bayesian networks, which illustrate the logical dependence. The evolution plane is used to depict the evolving process by sequential state transitions.

The idea behind is to create a plane that can accommodate the system state transition over time, while the nodes in the original plane are regarded as transient nodes that do not reflect time factors. In Figure 3, the node S_1 has logically direct interlace with T_0. Obviously, there should be a time elapse between the time slice 0 and time slice 1, hence the two time slices are bridged by a continuum of state transitions. It is worth noting that, each time slice is a snapshot of the system, and that the time elapse is represented by the number of transitions in EP.

3.2 *Quantification*

The conventional BN is formulated as a DAG, in which each node stands for a variable. These variables represent the factors that make the building blocks of the whole reasoning map. We use a triplet $\boldsymbol{G}=(\boldsymbol{N},\boldsymbol{E},\boldsymbol{P})$ to denote the BN, where $\boldsymbol{N}=\{X_1,X_2,\vdots...,X_{\mathbf{N}}\}$ denotes the set of nodes, $\boldsymbol{E}=\{\langle X_i,X_j\rangle | X_i,X_j\in\boldsymbol{N},X_i\neq X_j\}$ is the set of directed edges, and the directed pair $\langle X_i,X_j\rangle$ indicates that is the parent of X_j, or X_j is the child of X_i. A node may have none or multi X_i ple parents/children.

Denoted by $\pi(X_j)=\{X_i|\langle X_i,X_j\rangle\in\boldsymbol{E}\}$ the parent set of X_j, then is the CPT set of all the nodes. For a node X_j, each of its parent nodes $\pi(X_j)$ can have impact on X_j, and this dependence is depicted by the CPT. For a BN, the foundational property is given by the factoring of the joint probability distribution as follows:

$$p(X_1,X_2,...,X_{\mathbf{N}})=\prod_{i=1}^{\mathbf{N}}p(X_i|\pi(X_i))$$

By placing a set of BNs in a sliced tandem, a general DBN is formed. In DBN, the directed edges can connect two nodes within a slice, or across two slices. Moreover, DBN allows a node at t_{th} time slice to be conditionally dependent not only on its parents at the same time slice (intra-slice) but also on its parents and its own states at previous time slices (inter-slice) (Khakzad 2015).

The proposed two layer model is based on the DBN with some modifications. For the decision plane, the inter-slice dependence is allowed only in two consecutive slices. This assumption does not lose practical value because the epistemic cognitive capability of an analyst will decay sharply when applied to longer term reasoning. For the evolution plane, the sequential nodes can be regarded as an inter-slice edge connecting two BNs.

Referring to Figure 3, we use the italic font to indicate the variables that are hosted in the corresponding nodes. In the conventional BN, each node stands for exactly one variable. However, in real problems, if a combination of variables can be treated as one, it will help to make the model more concise. Theoretically, there *does* exist an equivalent variable in the product space for the combination of the sub-variables, hence, we also use one italic capitalized letter to denote the variable when necessary and with little ambiguity.

4 IMPLEMENTATION OF THE MODEL

4.1 *System status and scoring*

The essential information that a resilience curve aims to convey is the quantified system status and its changes over time. In this sense, the status of a system is associated with a scored value. Denote by $\Omega=\{s_1,s_2,\cdots,s_m\}$ the state set of the system in question, $\boldsymbol{P}=\{p(X_i|\pi(X_i))|X_i\in\boldsymbol{N}\}$ and by $R(s_i)\in[0,1]$ $1\le i\le m$ the

scoring of each state. It can be assumed without loss of generality that

$1 = R(s_1) > R(s_2) \geq R(s_3) \geq \cdots \geq R(s_m) = 0$,

meaning the sequential states of s_i are of descending order in terms of the system score, with being normal and s_m being complete failure. In this manner, the S_i ($i \in \mathbb{N} \cup \{0\}$) of node S_i in DP are probability vector variables over $[0,1]^m$, where the sum of the vector components is 1. If one is concerned with the resilience curve from the very beginning, i.e., the normal state, he can set the initial distribution for the root node as $S_0 = \{1,0,...,0\}$ (almost sure), implicating that $p(\text{System State} = s_1) = 1$.

4.2 *State transition matrix*

The system dynamics is modeled by the state transition matrix. Let $M = [P_{ij}]_{m \times m}$ be the one-step Markov state transition matrix over Ω. We assume that the state transitions take place at uniform step, so that the time gap between two consecutive transitions is a constant K. In other words, the number of transitions determines the evolution time. According to the Markov property, if the distribution of the system states is $\pi(r)$ at the rth transition, then $\pi(r+1) = \pi(r)M$.

As is illustrated in Figure 3, after the action plans, when E_i and F_i take effect, the system enters the evolving process until another external event occurs. The action plans are modeled by the state transition matrix. Furthermore, the initial state and the initial event within the time slice on the DP are also the causal factors that lead to the beginning state of the evolution on the EP. The third key parameter is how long the evolution will last before a renewed evolution starts.

All necessary parameters are obtained from the data in the knowledge, and are grouped in the node T_i in the model of Figure 3.

The nodes T_i and S_{i+1} are bridged by a series of interim states in EP. This network setup reflects the dependence relationship that the node T_i involves. In fact, the node T_i is a comprehensive variable that in fact consists of three components: T_i^{def}, T_i^{inst} and $T_i^{forword}$, where T_i^{def} is the time for the evolution till the next event U_{i+1}, T_i^{inst} is the instant state distribution when the evolution begins, and $T_i^{forword}$ is the one-step Markov state transition matrix M introduced in in the previous section. As also discussed in the previous section, T_i^{def} can be represented as the number of state transitions for the inter-slice evolution.

For the input dependence, the T_i is jointly determined by the prior state (S_i), the nature of the event (I_0 for the initial and U_i for the follow-up), and the actions taken to dispose the event from the ship-side (F_i) and from the shore-side (E_i).

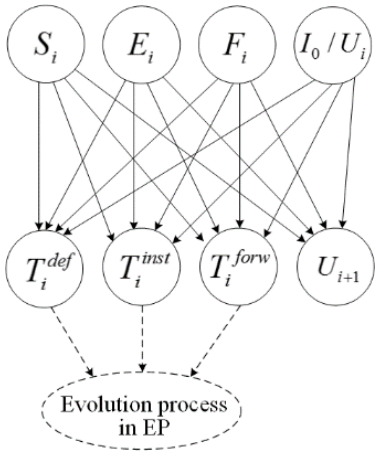

Figure 4. A partial enlargement of the node T_i's dependence.

5 THE TEST CASE

5.1 *Application background and the states set*

In this section, the proposed two-layer model is applied to the case of *not under command* (NUC) ships. NUC is a kind of accident with non-negligible occurring-rate in the middle and lower reaches of Yangtze River, and it will give raise to secondary accident if it is not tactically handled. The main causes of NUC include the failures of main engine/rudder, or black out. For the purpose of simplicity, we define six elements for the state set of the system, as is described in Table 1 below.

5.2 *The envisioned event set* Ψ

Let Ψ be the event set that makes the basic sample space for I_0 and U_i. Table 2 lists the elements of the event set for the problem of interest. These events are considered within the scope of epistemic knowledge, and the sequence and inter-dependence are described by a series of Conditional Probability Tables related to actions and system states.

Table 1. The state set of the NUC incident.

State	Description		Resilience Scoring
	Pre-accident	**Post-accident**	
s_1	Normal state.	All the post-accident operation is completed, and the loss and damage have been ascertained.	1
s_2	If no action is taken, accident is unavoidable.	A major part of search and rescue (SaR) operation is completed.	0.8

s_3	Potential accident looms up.	The accident is largely under control, and the SaR operation is proceeding linearly.	0.6
s_4	Close-quarters situation; special effort and maneuver is needed to get out of trouble.	Minor accident occurs, which may be intentionally made to prevent a serious accident; SaR operation is being conducted, but the total loss is still unknown.	0.4
s_5	The serious accident is approaching steadily and the stakeholders make efforts to reduce the intensity of the accident as far as possible.	SaR resources is available and SaR operation begins.	0.2
s_6	Serious accident, i.e. collision, capsizing etc., actually occurs, with life loss or damage to the environment.	SaR forces are yet to come.	0

Table 2. The event set of the NUC accident.

Event	Description	Remark
i_0	Ship not under command (NUC) is detected.	The initial event
u_1	A bridge appears at the downstream between the NUC ship and the nearest anchorage.	The pre-accident event.
u_2	There is dense vessel traffic between the NUC ship and the nearest anchorage.	
u_3	The anchorage is at the downstream shortly ahead.	
u_4	There are relatively open waters around the NUC ship.	
u_5	Collision with other ships.	The accident occurs factually.
u_6	Contact with bridge or other hydraulic structures.	
u_7	Strand on the shore.	
u_8	The NUC ship anchors.	The accident is partially under control.
u_9	First/More Tug(s) or maritime cruiser is approaching.	
u_{10}	The whole accident is completely settled. (There may be different extent of damage and loss.)	The final event.

Table 3. The decision objectives of the NUC incident.

D_i (ship-side decision objectives)		C_i (shore-side decision objectives)	
Variable outcomes	Description	Variable outcomes	Description
d_1	Immediately dispose the incident at the cost of potential hindrance to the circumambient traffic or other ships.	c_1	Protecting the hydraulic structures (e.g. the bridge) is of higher priority.
d_2	Tolerate a certain amount of sacrifice to stabilize the situation quickly.	c_2	Protecting the NUC ship and the ships passing by is of higher priority.
d_3	Take adventures to seek the most elegant settlement.		
d_4	Scrambled choice is taken.		

Table 4. The option plans of the NUC incident.

F_i (ship-side action plans)		E_i (shore-side action plans)	
Variable outcomes	Description	Variable outcomes	Description
f_1	Ask for tug assistance operation while drifting.	e_1	Send one/more tug(s) to the incident site to facilitate further operation.
f_2	Try to beach or anchor in outer limit of the channel.	e_2	Send one/more maritime cruiser(s) to the incident site.
f_3	Try to traverse crowded waters or a bridge to find the anchorage.	e_3	Regulate the sailing restriction of all ships.
f_4	Try to immediate anchoring in the channel.	e_4	Regulate the one-way traffic organization.

5.3 *The decision objectives of the ship-side and the shore-side*

The decision objectives reflect the preferences of the decision makers. In the resilience assessment context, the analysts do not know exactly which actual preference the decision makers will adopt, and the judgements made by the analysts come from the experience data they know about. In the same way, the quantitative formulation of the epistemic knowledge is presented by CPTs. Table 3 lists the possible outcomes of the variables D_i and the C_i.

5.4 *The action plans of the ship-side and the shore-side*

The action plans belong to the set of control options to be taken by the decision-makers, and they are the implementation tactics in accordance with the given decision objectives. Although confronting the same scenario, the action plan chosen by the two sides(the ship-side and the shore-side) may not necessarily be the most compatible. This compatibility is usually due to the asymmetry of the scenario perception or the ambiguity in the ship-shore communication. Table 4 lists the action plan variables and the possible variable outcomes.

5.5 *Building the conditional probability tables with knowledge*

5.4.1 *The CPT of C_i and D_i*

Considering that the case is focused on the evaluation of NUC ship accident starting from normal state, we set the prior probability of the variable S_0 and I_0 to be the value for the root node S_0 and I_0, such that $S_0 = \{1,0,...,0\}$, I_0=i_0. With this regard, a sample CPT of C_i and D_i is given below in Table 5 and Table 6.

Table 5. The CPT of C_0 and D_0.

S_0	I_0	D_i	Prob	C_i	Prob
$\{1,0,...,0\}$	i_0	d_1	0.4	c_1	0.5
		d_2	0.3	c_2	0.5
		d_3	0.2		
		d_4	0.1		

Table 6. A section of the CPT of C_i and D_i (i⩾1).

S_i	U_i	D_i	Prob	C_i	Prob
-	u_1	d_1	0.2	c_1	0.7
		d_2	0.3	c_2	0.3
		d_3	0.4		
		d_4	0.1		
-	u_2	d_1	0.25	c_1	0.3
		d_2	0.25	c_2	0.7
		d_3	0.4		
		d_4	0.1		
… …					

5.4.2 *The CPT of E_i and F_i*

The variables E_i and F_i depend upon C_i and D_i, respectively. Table 7 depicts the dependence in terms of probabilities.

5.4.3 *The component of T_i and the CPT*

As has been introduced previously, the node T_i hosts three variables, namely T_i^{def}, T_i^{inst} and $T_i^{forward}$. In the context of the current problem, the number of state transition is $1 \le T_i^{def} \le 10$. In practice, if we assume that the time scale of transition is a constant, for instance, one minute, T_i^{def} defines the evolution length for the implementation of the decision. T_i^{inst} is a $1 \times m$ vector to indicate the instant distribution of system state after the event occurs, and $T_i^{forward}$ is a $m \times m$ stochastic matrix to denote the state transition. Due to space limit, the details of these matrices are omitted. Table 8 shows a section of the CPT.

Table 7. The CPT of E_i and F_i.

C_i \ E_i	e_1	e_2	e_3	e_4
c_1	0.4	0.3	0.1	0.2
c_2	0.2	0.2	0.4	0.2
D_i \ F_i	f_1	f_2	f_3	f_4
d_1	0.1	0.4	0.1	0.4
d_2	0.2	0.3	0.2	0.3
d_3	0.2	0.3	0.4	0.1
d_4	0.1	0.3	0.3	0.3

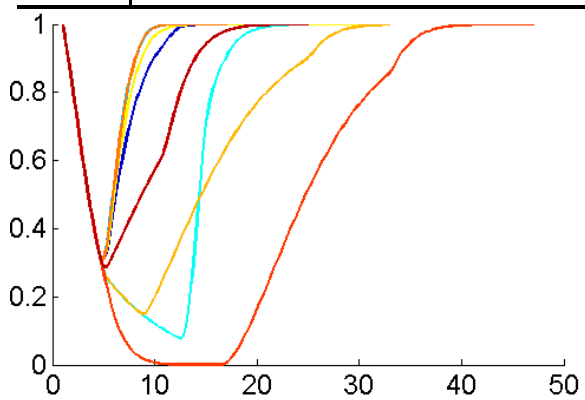

Figure 5. The resilience curves generated by one round of simulations.

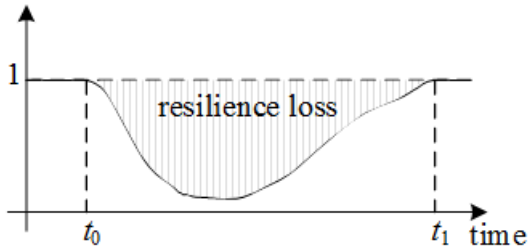

Figure 6. The resilience measure values based on the calculation of the resilience curve.

Table 8. A section of the CPT for the component of T_i.

E_i	F_i	I_0/U_i	S_i	T_i^{def}	T_i^{inst}	$T_i^{forword}$	U_{i+1}	Probability
e_1	f_1	i_0	$\{1,0,\cdots,0\}$	3	M_{1101}^{inst}	$M_{1101}^{forward}$	u_4	0.4
				3	M_{1102}^{inst}	$M_{1102}^{forward}$	u_2	0.4
				4	M_{1102}^{inst}	$M_{1102}^{forward}$	u_3	0.1
				4	M_{1102}^{inst}	$M_{1102}^{forward}$	u_1	0.1
e_1	f_1	u_1	$\{0.2,0.8,\cdots,0\}$	2	M_{1111}^{inst}	$M_{1111}^{forward}$	u_5	0.1
				3	M_{1112}^{inst}	$M_{1112}^{forward}$	u_6	0.1
				5	M_{1113}^{inst}	$M_{1113}^{forward}$	u_4	0.4
				5	M_{1114}^{inst}	$M_{1114}^{forward}$	u_2	0.3
				4	M_{1115}^{inst}	$M_{1115}^{forward}$	u_9	0.1
… …								

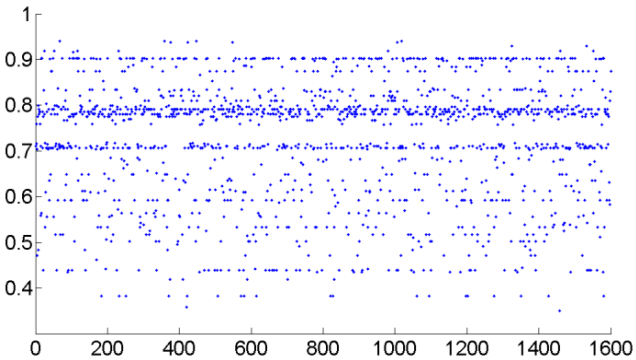

Figure 7. The resilience measure of multiple tests.

5.4.4 *Monte Carlo simulation results and analysis*

Using the above setup, a series of Monte Carlo simulations are conducted to gain a family of resilience curves given the NUC as the initial event. Figure 5 depicts the sampling of one round of simulation. The curves convey the rough resilience behavior under the epistemic estimation provided by the analysts. To characterize the resilience in a more straightforward way, we employ the resilience measurement for each resilience curve, as follows:

$$R = \frac{\int_{t_0}^{t_1} f(t)dt}{t_1 - t_0} \tag{1}$$

This definition of resilience measure is very similar to what is given by Bruneau et al (2003). The main idea of (1) is to find the proportion of non-loss part during the disruption and recovery process. t_0 stands for the starting point of disruptive event, and t_1 stands for the time point of complete recovery. Figure 6 shows the interpretation of the measure based upon the resilience curve. Obviously, greater R implies a stronger capability to withstand the disruption. Figure 7 displays the resilience measures of the multiple simulation tests where the simulation is repeated for 1600 times to account for the complexity of the resilience process. From the result, it can be seen that the samples of full-cycle disruption handling show their resilience measure largely within the interval [0.7, 0.9], while there may be extremely negative cases with resilience as low as 0.4 or even less.

6 CONCLUSION AND FUTURE WORK

In this paper, we present a method for the epistemic assessment of system resilience by using a revised model of a dynamic Bayesian Network and a discrete Markov process. The key features of the work are outlined below.

(i) Resilience focuses on the process and dynamics of system evolution under negative accident, and this is the very point of difference between the resilience study and the traditional risk study. The process-based view calls for a temporal change of system state instead of the cause-effect analysis, and this proves to be a challenge in modeling. In this paper, the revised DBN is used to represent the time-sliced system performance.

(ii) When we deal with subjective assessment, uncertainty is a major concern. There are many mathematical tools to treat the issue; this paper employs the Bayesian network as the reasoning engine due to the human-intensive, loosely coupled and autonomous nature of the application domain. As the knowledge of individuals is usually confined to local causal relationship, the DBN can mechanically extend the reasoning to longer spans of time and broader interlace of factors.

(iii) There are some limitations in the presented work. For the utmost, the knowledge is finally represented by CPTs and state transition matrices. However, when the states (or outcomes) of the variables increase, the size of CPTs will grow exponentially and usually, we have to resort to some rule-based reasoning or merging to reduce the size of CPTs. This will hinder the practical assessment setup, and improvement to this problem will be of interests for future work.

(iv) Despite the aforementioned limitations, the presented work provides a useful method of ex ante assessment for system resilience with respect to a given disruptive scenario. The quantitative results can facilitate choices of system design. For instance, a possible improvement is to enhance the capability maturity of the ship-side and shore-side operators, such that the joint tactics can be reached with less time and more compatibility.

ACKNOWLEDGEMENT

The research is supported by Key Project in the National Science & Technology Pillar Program (Grant No. 2015BAG20B05), and by National Natural Science Foundation of China (Grant No. 51479158).

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