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► **To cite this version:**

Jinduo Xing, Zhiguo Zeng, Enrico Zio. Dynamic business continuity assessment using condition monitoring data. *International Journal of Disaster Risk Reduction*, 2019, 41, pp.101334. 10.1016/j.ijdr.2019.101334 . hal-02428516

**HAL Id: hal-02428516**

**<https://hal.science/hal-02428516>**

Submitted on 13 Jan 2020

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# Dynamic business continuity assessment using condition monitoring data

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## Abstract

Concerns on the impacts of disruptive events of various nature on business operations have increased significantly during the past decades. In this respect, business continuity management (BCM) has been proposed as a comprehensive and proactive framework to prevent the disruptive events from impacting the business operations and reduce their potential damages. Most existing business continuity assessment (BCA) models that numerically quantify the business continuity are time-static, in the sense that the analysis done before operation is not updated to consider the aging and degradation of components and systems which influence their vulnerability and resistance to disruptive events. On the other hand, condition monitoring is more and more adopted in industry to maintain under control the state of components and systems. On this basis, in this work, a dynamic and quantitative method is proposed to integrate in BCA the information on the conditions of components and systems. Specifically, a particle filtering-based method is developed to integrate condition monitoring data on the safety barriers installed for system protection, to predict their reliability as their condition changes due to aging. An installment model and a stochastic price model are also employed to quantify the time-dependent revenues and tolerable losses from operating the system. A simulation model is developed to evaluate dynamic business continuity metrics originally introduced. A case study regarding a nuclear power plant (NPP) risk scenario is worked out to demonstrate the applicability of the proposed approach.

## Keywords

Business continuity management (BCM), Dynamic business continuity assessment (DBCA), Condition monitoring, Prognostic and health management (PHM), Particle filtering (PF), Event tree (ET)

29 **Acronyms**

30	BCA	business continuity assessment
31	BCM	business continuity management
32	BCV	business continuity value
33	DBC	dynamic business continuity
34	DBCA	dynamic business continuity assessment
35	DRA	dynamic risk assessment
36	ET	event tree
37	MBCO	minimum business continuity objective
38	MTPD	maximum tolerable period of disruption
39	NPP	nuclear power plant
40	PDF	probability density function
41	PF	particle filtering
42	PRA	probabilistic risk assessment
43	RCS	reactor coolant system
44	RTO	recovery time objective
45	RUL	remaining useful life
46	SGTR	steam generator tube rupture

47 **Notation**

48	$a$	Crack size
49	$BCV([t, t+T])$	Business continuity value at $t$ with reference to a time horizon $T$
50	$C_o$	Operation cost
51	$C_p$	Repayment cost
52	$C_{s1}$	First consequence
53	$C_{s2}$	Second consequence
54	$D_p$	Down payment
55	$EDBCV$	Expected value of dynamic business continuity at time $t$
56	$f(\cdot)$	State function

57	$f_{ET}(\cdot)$	Event tree model
58	$h(\cdot)$	Observation function
59	$IN_{tol}$	Total investment
60	$L_d$	Direct loss
61	$L_{in}$	Indirect loss
62	$L_{tol}$	Tolerable loss
63	$N_s$	Sample size of PF
64	$N_p$	Repayment period
65	$P_{BF}([t, t+T])$	Probability of business failure in $[t, t+T]$
66	$P_{BI}([t, t+T])$	Probability of business interruption in $[t, t+T]$
67	$P_{ID}$	Indirect loss per unit of time
68	$q$	Time length of condition monitoring
69	$Q_0$	Initial funding
70	$t_{recv}$	Recovery time
71	$T$	Time length of BC estimation
72	$\omega_k^{(i)}$	Weight of particle $i$
73	$\psi$	Indicator function
74	$\rho$	Interest rate
75	$\delta_k$	Observation noise at $t = t_k$
76	$\lambda_{st}$	Intensity of rupture event (for static business continuity)
77	$\Delta K$	Stress intensity factor
78	$\Delta\sigma$	Stress range
79		

## 80 **1. Introduction**

81 Business organizations are faced with threats from various disruptive events, such as natural disasters[1, 2],  
82 intentional attacks [3] and hardware failures [4], etc. As reported in [5, 6], 43% of the companies that have suffered  
83 from severe disruptive events have been permanently closed. Among these companies, around 30% failed within two  
84 years. Being prepared for disruptive events, including prevention in pre-event phase and response in post-event phase,  
85 is, then, important for modern businesses [7]. This is the reason why business continuity management (BCM) has  
86 received increasing attention in recent years as a holistic risk management method to cope with disruptive events [8-  
87 12]. BCM is formally defined in [13] as “holistic management process that identifies the potential threats to an  
88 organization and the potential impacts they may cause to business operations those threats, if realized, might cause,  
89 and which provides a framework for building organizational resilience with the capability of an effective response  
90 that safeguards the interest of its key stakeholders reputation, brand and value-creating activities”. Compared to  
91 conventional risk analysis method, BCM not only focuses on the potential hazards and their impacts, but also  
92 considers how to mitigate the consequence and quickly recover from the disruption. Therefore, it provides a  
93 framework for building organizational resilience that safeguards the interests of the business stakeholders.

94 Most existing works mainly discuss BCM from a management perspective [14]. For instance, the necessity and  
95 benefit of implementing BCM in a supply chain has been discussed in qualitative terms in [11]. In [15], a framework  
96 for the design, implementation and monitoring of BCM programs has been proposed. In [16], the evolution of BCM  
97 related to crisis management has been reviewed, in terms of practices and drivers of BCM. In [17], BCM has been  
98 compared with conventional risk management methods, showing that BCM considers not only the protection of the  
99 system against the disruptive event, but also the recovery process during and after the accident. The importance of  
100 reliability and simulation in BCM has been discussed in [18]. In [19], a framework for information system continuity  
101 management has been introduced. Standards concerning BCM of the Brazilian gas supply chain have been discussed  
102 in [20]. A practice on BCM in Thailand has been reviewed and a few suggestions on BCM approaches have been  
103 presented in [21]. In [22], the conceptual foundation of BCM has been presented in the context of societal safety.

104 From an engineering point of view, it is needed to define numerical indexes that support quantitative business  
105 continuity assessment (BCA). A few numerical indexes have been defined in [13], e.g., maximum tolerable period of  
106 disruption (MTPD), minimum business continuity objective (MBCO) and recovery time objective (RTO). However,  
107 these numerical indexes are usually directly estimated based on expert judgements. Only a few attempts exist  
108 concerning developing quantitative models to evaluate these numerical indexes. For example, a statistical model

109 integrating Cox’s model and Bayesian networks has been proposed to model the business continuity process [23]. In  
110 [24], a simulation model has been developed to analyze the business continuity of a company considering an outbreak  
111 of pandemic disease, where the business continuity is characterized by the operation rate and the plant-utilization  
112 rate. In [5], an integrated business continuity and disaster recovery planning framework has been presented and a  
113 multi-objective mixed integer linear programming has been used to find efficient resource allocation patterns. In [9],  
114 BCM outsourcing and insuring strategies have been compared based on the organization characteristics and the  
115 relevant data through a two-step, fuzzy cost-benefit analysis. Moreover, in [10], an enhanced risk assessment  
116 framework equipped with analytical techniques for BCM systems has been proposed. Two probabilistic programming  
117 models have been developed to determine appropriate business continuity plans, given epistemic uncertainty of input  
118 data in [25]. In [26], a new model for integrated business continuity and disaster recovery planning has been presented,  
119 considering multiple disruptive incidents that might occur simultaneously. An integrated framework has been  
120 developed in [12] for quantitative business continuity analysis, where four numerical metrics have been proposed to  
121 quantify the business continuity level based on the potential losses caused by the disruptive events.

122 Most quantitative BCA models mentioned above are time-static in the sense that the analysis is performed before  
123 the system of interest comes into operation, with no further consideration of the changes that occur due to aging and  
124 degradation. In particular, in practice, business continuity is influenced by the degradation of safety barriers. On the  
125 other hand, the advancing of sensor technologies and computing resources has made it possible to retrieve information  
126 on the state of components and systems, by collecting and elaborating condition monitoring data [27, 28]. For  
127 example, a condition-based fault tree has been used for dynamic risk assessment (DRA) [29], where the condition  
128 monitoring data are used to update the failure rates of specific components and predict their reliability. In [30], a  
129 Bayesian reliability updating method has been developed for dependent components by using condition monitoring  
130 data. In [4], a holistic framework that integrates the condition monitoring data and statistical data has been proposed  
131 for DRA. A sequential Bayesian approach has been developed in [31], for dynamic reliability assessment and  
132 remaining useful life prediction for dependent competing failure processes. Usually, information fusion can add  
133 values for decision support [32]. A quantitative model for information risks in supply chain has been developed where  
134 the proposed model can be updated when new data are available [33].

135 In this paper, we propose a framework for DBCA that integrates condition monitoring data and allows updating  
136 the business continuity analysis using information collected during system operation. It should be noted that in this  
137 paper, we focus on “business continuity assessment” rather than “business continuity management”. That is, we are

138 concerning developing quantitative models to evaluate the numerical business continuity metrics, which are further  
139 used in BCM process as quantitative requirements. The developed model contributes to the existing research on BCA  
140 in three aspects:

- 141 1) An integrated DBCA model is proposed, which can provide for BCA updating in time.
- 142 2) New dynamic business continuity metrics are introduced.
- 143 3) A simulation-based algorithm is developed to calculate the dynamic business continuity metrics.

144 The remainder of this paper is organized as follows. In Section 2, numerical metrics for DBCA are proposed.  
145 An integrated framework of DBCA is developed in Section 3. Section 4 describes the application of the proposed  
146 framework on a nuclear power plant (NPP) accident. Section 5 discusses applicability of the proposed DBCA method.  
147 Eventually, Section 6 concludes this work.

## 148 **2. Numerical metrics for dynamic business continuity assessment**

149 Business process is the process of producing products or supporting services by an organization. The business  
150 process of an organization can be characterized by a performance indicator, whose value reflects the degree to which  
151 the objective of the business is satisfied. For instance, for a NPP, this indicator can be monthly electricity production.  
152 As reviewed in Section 1, there are a few numerical indexes for quantifying the continuity of a business process  
153 (MTPD, MBCO, RTO, etc.) [13]. These numerical indexes, however, focus only on one specific phase of the whole  
154 process. For example, RTO focuses only on the post-disruption recovery phase., MBCO focuses only on the post-  
155 disruption contingency activities. In this paper, we use the numerical business continuity indexes developed in [12],  
156 which are defined in a more integrated sense that they are able to cover the whole process, from pre-disruption  
157 preventions to post-disruption contingency and recovery.

158 In the quantitative framework developed in [12], the business continuity is quantified based on the potential  
159 losses caused by the disruptive events. The business process is divided into four sequential stages: preventive stage,  
160 mitigation stage, emergency stage and recovery stage. Various safety measures are designed in different stages to  
161 guarantee the continuity of the business process. Business continuity value (BCV) was formally defined as [12]:

$$162 \quad BCV([0, T]) = 1 - \frac{L([0, T])}{L_{tol}} \quad (1)$$

163 where  $L$  denotes the loss in  $[0, T]$  from the disruptive event;  $T$  is the evaluation horizon for the assessment  
164 (e.g., the lifetime of the system);  $L_{tol}$  is the maximum loss that can be tolerated by an organization, which manifests

165 system tolerance ability against disruptive event [34]. Negative value of  $BCV$  means that  $L$  is higher than  $L_{tol}$ ,  
 166 which is unacceptable for the targeted system. When  $BCV = 0$ , it implies that the loss is exactly what the system  
 167 can maximally tolerate. Regarding  $BCV = 1$ , it means no loss has been generated. Equation (1) measures the  
 168 relative distance to a financially dangerous state by taking into account the possible losses generated by the business  
 169 disruption. It should be noted that only one business process is considered in this paper, while in practice, an  
 170 organization might be involved in multiple business processes at the same time. For multiple-business system, the  
 171 developed framework can be naturally extended based on the potential losses and profit generated by the different  
 172 business processes together.

173 The business continuity metrics discussed above are time-static in nature. In practice, however, various factors  
 174 influencing the business continuity are time-dependent. These dynamic influencing factors can be grouped into  
 175 internal factors and external factors. Internal factors are related to the safety barriers within the system of interest,  
 176 such as the dynamic failure behavior of the safety barriers (e.g., corrosion [35], fatigue crack [36], and wear [37]).  
 177 External factors refer to the influence from external environment. For example, variations in the price of products  
 178 will affect the accumulated revenue of the organization, and, then, the tolerable loss in Equation (1). To consider  
 179 these factors, the business continuity metrics are extended to the dynamic cases:

$$180 \quad DBCV([t, t+T]) = 1 - \frac{L([t, T+t])}{L_{tol}(t)}, \quad (2)$$

181 where  $t$  is the time instant when the dynamic business continuity assessment is carried out;  $DBCV([t, t+T])$   
 182 represents the business continuity value evaluated at time  $t$ , for a given evaluation horizon of  $T$ ;  $L([t, t+T])$   
 183 represents the potential losses in  $[t, t+T]$ ;  $L_{tol}(t)$  denotes the maximal amount of losses that the company can  
 184 tolerate at  $t$ : beyond that level of losses, it will have difficulties in recovering. It is assumed that once an  
 185 organization suffer a loss beyond  $L_{tol}$ , it is unable to recover from the disruption due to the financial critical  
 186 situations. The physical meaning of  $DBCV$  is the relative distance to a financial dangerous state at time  $t$ , by  
 187 considering the possible losses in  $[t, t+T]$  due to business disruption; it measures the dynamic behavior of  
 188 business continuity in a time interval of interest  $[t, t+T]$ . By calculating the  $DBCV$  at different  $t$ , the dynamic  
 189 behavior of business continuity can be investigated.

190 In [12], two kinds of losses need to be considered when calculating  $L([t, t+T])$ : direct loss and indirect loss  
 191 Direct loss, denoted by  $L_d([t, t+T])$ , represents the losses that are caused directly by the disruptive event, including



192 structural damage of the system. For example, in a NPP leakage event,  $L_d[t, t + T]$  includes all equipment damage  
 193 directly caused by the event. Indirect loss, denoted by  $L_{in}([t, t + T])$ , is the revenue loss suffered during the  
 194 shutdown of the plant [38]. Hence, the total loss is calculated by:

$$195 \quad L([t, T + T]) = L_d([t, t + T]) + L_{in}([t, t + T]). \quad (3)$$

196 In terms of other types of accident, for instance, workplace accidents, damages to the surroundings, etc. they  
 197 may also affect the business continuity. Due to page limits, we did not include them in the developed model in this  
 198 paper. However, the developed method can be naturally generalized by including more initiating events in the analysis.

199 The DBCV defined in (2) is a random variable. Three numerical metrics are, then, proposed for its  
 200 quantification:

$$201 \quad EDBCV = E[DBCV] \quad (4)$$

$$202 \quad P_{BI}([t, t + T]) = \Pr(BCV < 1, t) \quad (5)$$

$$203 \quad P_{BF}([t, t + T]) = \Pr(BCV < 0, t) \quad (6)$$

204  $EDBCV$  is the expected value of the dynamic business continuity value. A higher  $EDBCV$  indicates higher  
 205 business continuity.  $P_{BI}([t, t + T])$  represents the probability that at least one disruptive event causes business  
 206 interruption in time interval  $[t, t + T]$ ;  $P_{BF}([t, t + T])$  is the probability that business failure occurs in  $[t, t + T]$ ,  
 207 i.e., of the event that the losses caused by the disruptive event are beyond  $L_{tol}$ . It is assumed that once an  
 208 organization suffers a loss beyond  $L_{tol}$ , it is unable to recover from the disruption due to the financial critical  
 209 situations. In this work, both of current time  $t$  and the estimation horizon  $T$  have influences on BCV. We manage  
 210 to propose a real-time BCA by considering the time-dependent variables.

### 211 3. An integrated framework for dynamic business continuity assessment

212 In this section, we first present an integrated modeling framework for the dynamic business continuity metrics  
 213 defined in Section 2. Then, particle filtering (PF) is used to estimate the potential loss  $L_{tol}$  in real time using  
 214 condition monitoring data (Section 3.2). The quantification of tolerable losses  $L_{tol}$  is, then, discussed in Section 3.3.

#### 215 3.1 The integrated modeling framework

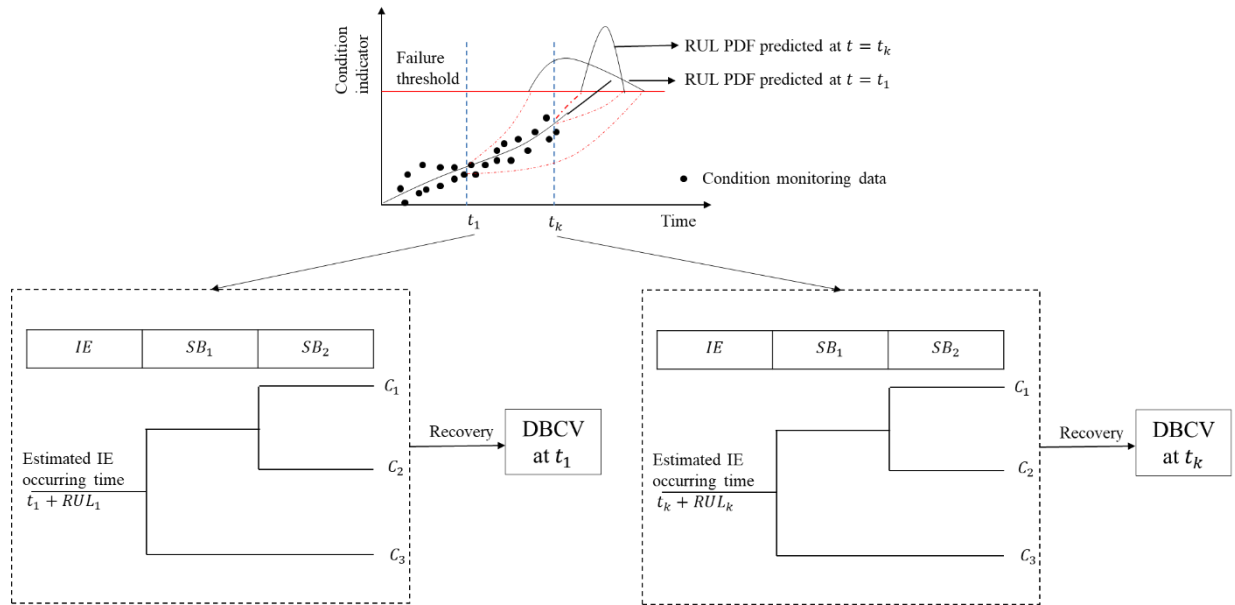
216 To model the dynamic business continuity, we make the following assumptions:

- 217 1) The evolution of the disruptive event is modeled by an event tree (ET). Depending on the states of safety  
 218 barriers, different consequences can be generated from an initialing event. These consequences can be

219 grouped into different categories based on their severities. Each consequence generates a certain amount  
 220 of loss. However, it should be noted that different consequences might have the same degree of losses.  
 221 According to their severities, possible consequences of a disruptive event are classified as  $C_i, i = 1, 2, \dots, n$ ,  
 222 where  $n$  is the number of severity level. The severity and duration of the business interruption  
 223 corresponds to different losses.

- 224 2) Some safety barriers in the ET are subject to degradation failure processes. Condition monitoring data are  
 225 available for these safety barriers at predefined time instants  $t_k, k = 1, 2, \dots, q$ .
- 226 3) The other safety barriers have constant failure probabilities.
- 227 4) Recovery means repairing the failed component and restarting the business. The time for the recovery from  
 228 consequence  $C_i$  is a random variable  $t_{recv,i}$ , with a probability density function (PDF)  $f_{recv,i}$ .

229 An integrated framework for DBCA is presented in Figure 1. The DBCA starts from collecting condition  
 230 monitoring data, denoted as  $c_k$ , which is collected from sensors and can be used to characterize the degradation  
 231 states of the component. The degradation of the safety barriers is estimated based on the condition monitoring data  
 232 and used to update the estimated losses. Then, the potential profits are predicted and used to calculate the tolerable  
 233 losses. Finally, the dynamic business continuity metrics can be calculated.



234 Figure 1. Integrated modeling framework for DBCA.

### 235 3.2 Loss modeling

236 To capture the dynamic failure behavior of a safety barrier as it ages in time, PF is employed in this work to  
 237 estimate its degradation and predict its remaining useful life (RUL) based on condition monitoring data [39-41]. PF

238 is applied because of its capability of dealing with the complex non-linear dynamics and non-Gaussian noises that  
 239 are often encountered in practice [42, 43].

240 Suppose the degradation process of a safety barrier can be described by Equation (7), in which the current state  
 241  $x_k$  at the  $k$ -th discrete time step depends on the previous state  $x_{k-1}$ . Here,  $f$  is a non-linear function and  $v_k$   
 242 represents process noise that follows a known distribution. In practice, Equation (7) is often determined based on  
 243 physics-of-failure models [39]:

$$244 \quad \mathbf{x}_k = f(\mathbf{x}_{k-1}, v_k) \quad (7)$$

245 A sequence of condition monitoring data  $\mathbf{z}_k$  is assumed to be collected at predefined time points  $t_k$ . The  
 246 sequence of measurement values is assumed to be described by an observation function:

$$247 \quad \mathbf{z}_k = h(\mathbf{x}_k, \boldsymbol{\sigma}_k) \quad (8)$$

248 where  $h$  is the observation function (possibly nonlinear),  $\boldsymbol{\sigma}_k$  is the observation noise vector sequence of known  
 249 distribution. The measurement data  $\mathbf{z}_k$  are assumed to be conditionally independent given the state process  $\mathbf{x}_k$ .  
 250 Equation (8) quantifies the observation noise from the sensors.

251 The PF follows two steps [44]:

- 252 1) Filtering step, where the available condition monitoring data  $\mathbf{z}_k$  are used to estimate the current  
 253 degradation state of the system.
- 254 2) Prediction step, in which the RUL is predicted based on the estimated degradation state and the condition  
 255 monitoring data.

256 In the filtering step, the posterior PDF of variable  $\mathbf{x}_k$  is approximated by the sum of weighted particles

257  $\{\mathbf{x}_k^{(i)}, \omega_k^{(i)}\}$ :

$$258 \quad p(\mathbf{x}_k | z_1, z_2, \dots, z_k) \approx \sum_{i=1}^{N_s} \omega_k^{(i)} \delta(\mathbf{x}_k - \mathbf{x}_k^{(i)}) \quad (9)$$

259 where  $p(\mathbf{x}_k | z_1, z_2, \dots, z_k)$  is the estimated posterior PDF of  $\mathbf{x}_k$ ,  $\delta$  is the Dirac Delta function,  $\omega_k^{(i)}$  is the  
 260 weight assigned to particle  $\mathbf{x}_k^{(i)}$  and is generated by sequential importance sampling [32]. When the new  
 261 measurement  $z_k$  is available, the required posterior distribution of the current state  $x_k$  can be obtained by updating  
 262 the prior distribution:

$$p(\mathbf{x}_k | \mathbf{z}_k) = \frac{p(z_k | \mathbf{x}_k) p(\mathbf{x}_k | \mathbf{z}_{k-1})}{\int p(z_k | \mathbf{x}_k) p(\mathbf{x}_k | \mathbf{z}_{k-1}) d\mathbf{x}_k} \quad (10)$$

where  $p(z_k | \mathbf{x}_k)$  is the likelihood function that can be derived from the observation function (8). Generally, if the samples  $\mathbf{x}_k^{(i)}$  are drawn from the sampling distribution  $p(\mathbf{x}_k | \mathbf{z}_k)$ , then, the particle weight can be updated with a new observation  $z_k$ , as follows [32]:

$$\omega_k^{(i)} = \omega_{k-1}^{(i)} \frac{p(z_k | \mathbf{x}_k^{(i)}) p(\mathbf{x}_k^{(i)} | \mathbf{x}_{k-1}^{(i)})}{p(\mathbf{x}_k^i | \mathbf{x}_{0:k-1}^i, \mathbf{z}_k)}. \quad (11)$$

Note that the weights are normalized as  $\sum_{i=1}^{N_s} \omega_k^{(i)} = 1$ .

Algorithm 1 summarizes the major steps of PF [45].

---

Algorithm 1: Procedures of PF.

Inputs:  $\{\mathbf{x}_{k-1}^{(i)}, \omega_{k-1}^{(i)}, \mathbf{z}_k\}$

Outputs:  $\{\mathbf{x}_k^{(i)}, \omega_k^{(i)}\}_{i=1}^{N_s}$

For  $i = 1$  to  $N_s$  do

$\mathbf{x}_k^{(i)} \sim p(\mathbf{x}_k | \xi_{k-1}^{(i)})$  using (7),

$\omega_k^{(i)} \propto p(z_k | \mathbf{x}_k^{(i)}, \theta_k^{(i)})$  using (11),

End for

For  $i = 1$  to  $N_s$  do

$\omega_k^{(i)} \leftarrow \omega_k^{(i)} / \sum_{i=1}^{N_s} \omega_k^{(i)}$

End for

$N_{eff} \leftarrow \left( \sum_{i=1}^{N_s} (\omega_k^{(i)})^2 \right)^{-1}$

If  $N_{eff} < N_s$  then

$\{\mathbf{x}_k^{(i)}, \omega_k^{(i)}\}_{i=1}^{N_s} \leftarrow \text{resample} \left( \{\mathbf{x}_k^{(i)}, \omega_k^{(i)}\}_{i=1}^{N_s} \right)$

End if

Return  $\{\mathbf{x}_k^{(i)}, \omega_k^{(i)}\}_{i=1}^{N_s}$

---

Then, in the prediction step, the RUL associated to the  $i$ -th particle at  $t = t_k$  can be estimated through state function (7) by simulating the evolution trajectory of the particles until they reach the failure threshold  $z_{th}$ :

$$RUL_k^{(i)} = \left\{ (T_{th}^{(i)} - 1 - k) \mid x_{T_{th}^{(i)}-1} < z_{th}, x_{T_{th}^{(i)}} \geq z_{th} \right\}, \quad (12)$$

273 where  $T_{th}^{(i)}$  is the first time the particle reaches the threshold  $z_{th}$ . Thus, the PDF of the RUL can be generated by:

$$274 \quad p(RUL|\mathbf{z}_k, z_{th}) \approx \sum_{i=1}^{N_s} \omega_k^{(i)} \delta(RUL - RUL_k^{(i)}). \quad (13)$$

275 The predicted  $RUL_k^{(i)}, i=1, 2, \dots, N_s$  can, then, be used in a simulation process to generate samples of the total  
 276 loss  $L$ , according to Equation (3). The procedures are summarized in Algorithm 2, where  $P_{ID}$  is the indirect loss  
 277 per unit of time.

---

Algorithm 2: Generating samples for the losses

Input:  $\{RUL_k^{(i)}, \omega_k^{(i)}\}_{i=1}^{N_s}, T$

Output:  $L_k^{(i)}$

Initial value  $L_k^{(i)} = 0, t = 0, t_1 = 0, T = t_k + T, t_2 = 0$ ;

$RUL_{pseudo,k} \leftarrow$  randomly select one element from  $\{RUL_k^{(i)}\}_{k=1}^{N_p}$ , where  $RUL_k^{(i)}$  is selected with probability  $\omega_k^{(i)}$ ;

Calculate  $T_k^{(i)} = t_k + RUL_{pseudo,k}$

```

  ▶ While  $t < T$ 
     $t_1 = t; t_1 = t_1 + TTF_k^{(i)}$ ;
    ▶ if  $t_1 > T$ 
       $L_k^{(i)} = L_k^{(i)}$ 
    else
      Using the event tree determine the consequence;
      Using the  $f_{recv,i}$  generate the  $t_{recv}$ ;
       $t_2 = t_1 + t_{recv}$ ;
      ▶ If  $t_2 > T$ 
         $L_k^{(i)} = L_k^{(i)} + L_d + (T - t_2) \cdot P_{ID}$ 
      else  $t = t_2$ 
         $L_k^{(i)} = L_k^{(i)} + L_d + t_{recv} \cdot P_{ID}$ 
      ▶ end if
    ▶ end if
  ▶ end while
  
```

---

278

### 279 3.3 Tolerable losses modeling

280 Budget limitations are the primary driver of resilience-enhancing investments [46], which influence protection,  
 281 prevention, and recovery capabilities of system. Tolerable losses  $L_{tol}$  depend on the cash flow of the company and  
 282 also the risk appetite of the decision maker [13]. In this paper, we assume that at  $t_k$ , the organization can tolerate  
 283 up to  $\alpha$  (in percentage) of its cash flow  $Q(t_k)$  at  $t_k$ :

$$284 \quad L_{tol}(t_k) = Q(t_k) \cdot \alpha \quad (14)$$

285 For example,  $\alpha = 0.1$  means 10% of the current cash flow can be used to withstand potential losses caused by a  
 286 disruptive event. In practice, the value of  $\alpha$  should be determined by the decision maker and reflects his/her risk  
 287 appetite.

288 We make the following assumptions to model the dynamic behavior of cash flows:

289 (1) At  $t = 0$ , there is an initial capital of  $Q_0$ .

290 (2) Installment is used for the company to purchase the asset, where an equal repayment of  $C_p$  is paid each  
 291 month for  $N_p$  months.

292 It is noteworthy that the cash flow  $Q(t)$  depends on the profit earned by the normal operation of the asset:

$$293 \quad Q(t_k) = Q_0 + I(t_k) - C_o(t_k) - \sum_{i=1}^k (\Psi \cdot C_p(t_i)), \quad (15)$$

294 where  $Q_0$  is the initial capital,  $I(t_k)$  is the accumulated revenues of the organizations up to  $t_k$  by selling the  
 295 product of the asset. For example, in a NPP,  $I(t_k)$  is determined by the electricity price ; in oil exploitation,  $I(t_k)$   
 296 depends on the petroleum price [47].  $C_o(t_k)$  is the operational cost in  $[0, t_k]$ , which is assumed to be not changing  
 297 over time.  $C_p(t_i)$  is the amount of repayment of the installment in  $[t_{i-1}, t_i]$ , which can be modeled by (see [48] for  
 298 details):

$$299 \quad C_p = \frac{(IN_{\text{tol}} - D_p)}{N_p} (1 + \rho)^{N_p}, \quad (16)$$

300 where  $IN_{\text{tol}}$  denotes the total investment and equals the whole value of the system,  $D_p$  represents the down  
 301 payment,  $\rho$  is the interest rate,  $\Psi$  is an indicator function:

$$302 \quad \Psi = \begin{cases} 1, & \text{if } t \leq N_p \\ 0, & \text{otherwise} \end{cases}, \quad (17)$$

303 where  $N_p$  is the repayment period.

#### 304 4. Application

305 In this section, we consider the development of DBCA in a case study regarding a disruptive initialing event for  
 306 a NPP [49]. The business continuity of the NPP is evaluated at different ages  $t = 1, 2, \dots, 40$  (year) and different  
 307 evaluation horizons  $T = 1, 2, \dots, 60$  (year). The evaluation is made with reference to a specific risk scenario, with  
 308 the initialing event being the steam generator tube rupture (SGTR).

309 The targeted system is briefly introduced in Section 4.1. Subsequently, in Section 4.2, the RUL prediction for a  
 310 SGTR and the modeling of the potential losses are conducted. The time-dependent  $L_{tot}$  is calculated in Section 4.3.  
 311 The results of the DBCA are presented and discussed in Section 4.4.

#### 312 4.1 System description

313 For illustrative purposes, it is assumed that the NPP has one reactor with a capacity of 550 MW. It is also  
 314 assumed that the NPP is subject to the threat of only one disruptive event, the SGTR. The whole value of the NPP is  
 315  $10^9$ € and the operator purchases the NPP using an installment, where the down payment is  $5 \cdot 10^8$ € and the  
 316 repayment period is 10 years with an interest rate of 2%.

317 SGTR is a potential accident that is induced by the degradation of the tubes in the steam generator, which can  
 318 lead to tube cracking and rupture [50]. Steam generator tubes transfer the heat from the reactor core to the cooling  
 319 water that is transformed into steam to drive turbines and produce electricity [49]. The steam generator tube is often  
 320 manufactured with alloy material to attain high structural integrity and prevent leakage of radioactive materials. An  
 321 ET has been developed for the probabilistic risk assessment (PRA) of the SGTR for a NPP in South Korea, as shown  
 322 in Figure 2. In Figure 2, eight safety barriers ( $SB_1 \square SB_8$ ) are designed to control the accident and mitigate its impact  
 323 (Table 1). Depending on the states of the safety barriers, 28 sequences are generated ( $S_1 \square S_{28}$ ). Based on the degree  
 324 of their severities, the consequence of the sequences can be categorized into two groups. The first group,

$$325 C_{S1} = \{SE_1, SE_2, SE_4, SE_6, SE_7, SE_9, SE_{11}, SE_{12}, SE_{14}, SE_{16}, SE_{20}, SE_{24}\} \quad (18)$$

326 represents the event sequences in which a SGTR occurs but the consequence is contained by the safety barriers  
 327 without causing severe damages. The remaining event sequences form the second group  $C_{S2}$  and represent severe  
 328 consequences of core damage. Regarding  $C_{S1}$ , albeit no severe losses are caused, normal production of the NPP is  
 329 disturbed because the ruptured tube has to be repaired. For  $C_{S2}$ , it is assumed that the NPP has to be shut down  
 330 permanently and the losses incurred are denoted by  $C_{CD}$ .

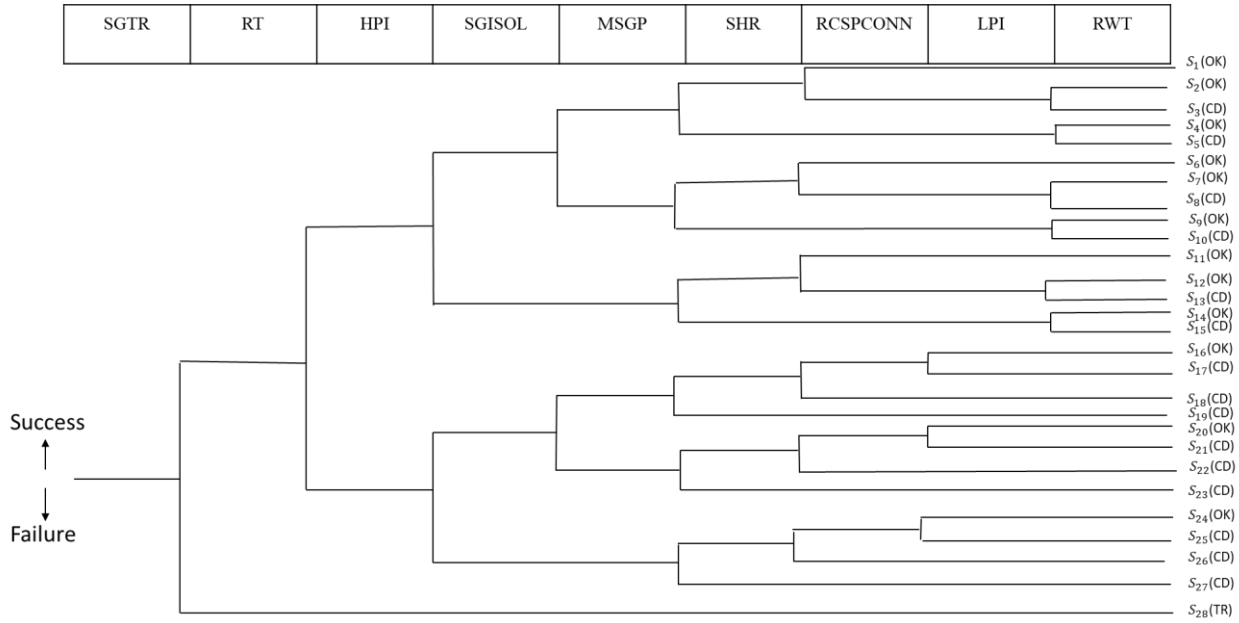


Figure 2. ET for SGTR accident initiating event [49].

Table 1. Safety barriers in the target system [51, 52].

Safety barrier	Failure probability	Description
Reactor trip (RT)	$P_{RT} = 1.8 \times 10^{-4}$	When there is off-normal condition, the protection system automatically inserts control rods into the reactor core to shut down the nuclear reaction.
High pressure safety injection (HPI)	$P_{HPI} = 4.6 \times 10^{-4}$	Inject cool water (at a pressure of about 13.79 MPa) into the reactor coolant system (RCS) to cool the reactor core and provide RCS inventory make-up.
Main steam isolation valve (SGISOL)	$P_{SGI} = 1.0 \times 10^{-4}$	A valve used to isolate the affected steam generator (SG).
Maintain the affected SG pressure (MSGP)	$P_M = 1.5 \times 10^{-4}$	Maintain the affected SG pressure through the pressurizer.
Secondary heat removal (SHR)	$P_{SHR} = 3.4 \times 10^{-5}$	Heat removal by unaffected SG.
Reactor coolant system pressure control (RCSPCON)	$P_{RCSM} = 1.0 \times 10^{-2}$	Open the turbine bypass valve to control the secondary side pressure.
Low pressure safety injection (LPI)	$P_{LPI} = 4.6 \times 10^{-4}$	Inject cool water (at a pressure of about 1.03MPa) to cool down the RCS and provide RCS inventory make-up.
Refill RWT (RWT)	$P_{RWT} = 2.4 \times 10^{-8}$	Refill water storage tank.

The crack growth process that leads to SGTR can be monitored through non-destructive inspection (e.g., ultrasonic testing [53], eddy current testing [54]). In practice, this is done during planned shutdowns of the NPP, often during the refueling stage. The condition monitoring data collected from these inspections are, then, used for the dynamic business continuity assessment.

#### 4.2 Particle filtering and loss modeling

The first step is to update the occurrence probability of the initiating event, based on the condition monitoring data. It is noteworthy that, due to the lack of real data, the condition monitoring data employed in the case study is



340 generated from a known physical model. For illustrative purposes, the evolution of the tube crack growth process is  
 341 assumed to follow the Paris-Erdogan model, which has been applied to model SGTR in [52, 55],

$$342 \quad \frac{da}{dt} = C(\Delta K)^m, \Delta K = \Delta\sigma\sqrt{\pi a}, \quad (19)$$

343 where  $a$  is the crack length,  $C$  and  $m$  are constant parameters related to the component material properties,  
 344  $\Delta K$  is the stress intensity factor,  $\Delta\sigma$  is the stress range. The model can be rewritten in the form of a state transition  
 345 function [56]:

$$346 \quad a_k = C_k (\Delta\sigma\sqrt{\pi a_k})^{m_k} dt + a_{k-1} \quad (20)$$

347 The crack size  $a_k$  at  $t=t_k$  is obtained from non-destructive inspection, such as ultrasonic testing; the  
 348 corresponding observation  $z_k$  is:

$$349 \quad z_k = a_k + \delta_k, \quad (21)$$

350 where  $\delta_k$  is the observation noise with  $\delta_k \sim N(0, \delta_o^2)$ .

351 Due to environment and measurement noise, the measured crack lengths are different from the true values. In  
 352 this paper, we generate the true value of cracks in Figure 3 using a theoretical model with known parameters and  
 353 generate the observation data by adding a random noise. The purpose of using PF is to estimate the true crack length  
 354 from the noised observation data and predict the RUL. The number of particles simulated is  $N_s = 5000$ . It should  
 355 be noted that for the tube degradation process, the state vector  $\mathbf{x}$  includes the crack size  $a$  and the model  
 356 parameter variables  $C$ ,  $m$ . The initial values for these variables are drawn uniformly from the intervals of values  
 357 listed in Table 2:

$$358 \quad \begin{cases} C_k = C_{k-1} + N(0, \sigma_c^2) \\ m_k = m_{k-1} + N(0, \sigma_m^2) \end{cases} \quad (22)$$

359 Table 2. Initial intervals for the parameters.

Parameters	Initial interval
$C$	[0.1,0.2]
$m$	[1.1,1.3]
$\sigma_c$	$[0.9 \times 10^{-3}, 0.2 \times 10^{-2}]$
$\sigma_m$	$[0.9 \times 10^{-3}, 0.2 \times 10^{-2}]$
$\sigma_o$	[0.65,0.85]

360

361 The results of PF are shown in Figure 4, where we find that the RUL prediction results become more accurate  
 362 when more condition monitoring data are available.

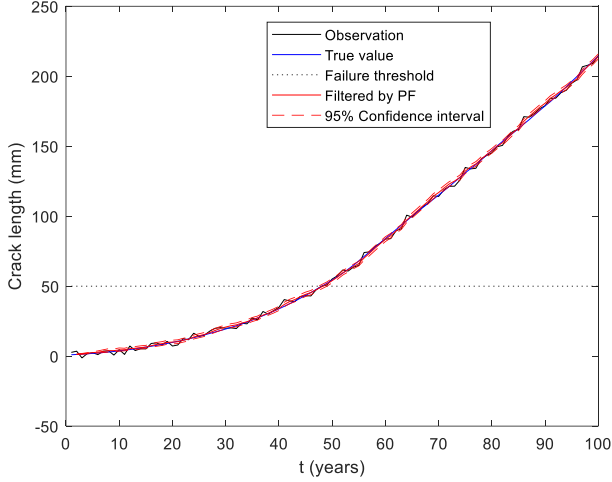


Figure 3. Crack growth process.

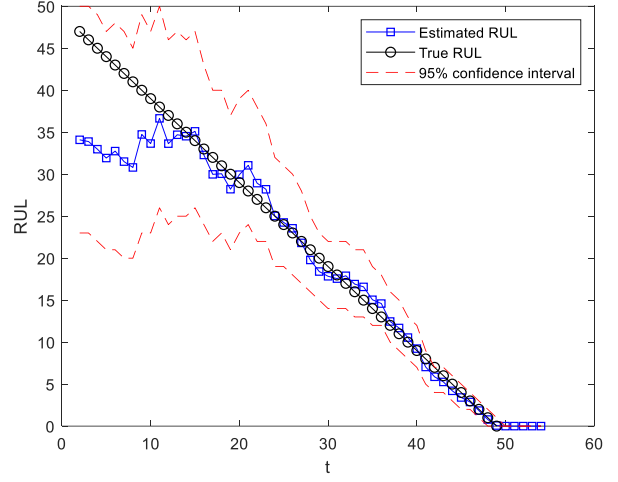


Figure 4. RUL prediction results.

363 Afterwards, the loss  $L([t, t+T])$  in Equation (2) can be calculated. The losses caused by a SGTR event,  
 364 include the direct losses and indirect losses. In this case study, the direct losses, denoted by  $L_d$ , equal to the value  
 365 of the damaged equipment. For the consequence  $C_{S1}$ ,  $L_d$  is identical to the value of the ruptured tube. For the  
 366 consequence  $C_{S2}$ ,  $L$  equals the value of the NPP production since the NPP has to be shutdown. In this paper, we  
 367 assume that if  $C_{S2}$  occurs, we have  $L = 5 \cdot 10^9 \text{ €}$  [57].

368 The indirect losses  $L_{in}$  are calculated considering the revenue losses during the recovery process, which  
 369 depends on the recovery time and electricity price. Due to the common use of lognormal distribution for modeling  
 370 the repair process [58-60], we also assume that the recovery time follows a lognormal distribution with the parameters  
 371 summarized in Table 3, where  $\varepsilon$  and  $\beta$  are parameters of the lognormal distribution, whose PDF is

$$372 \quad f(t_{recv}) = \begin{cases} \frac{1}{\sqrt{2\pi}\beta t_{recv}} e^{-\frac{(\ln(t_{recv})-\varepsilon)^2}{2\beta^2}}, & t_{recv} > 0 \\ 0, & t_{recv} \leq 0. \end{cases} \quad (23)$$

373 Then, the value of  $L_{in}$  is calculated by Monte Carlo simulation.

374 Table 3. Values of the recovery model parameters.

Parameter	Description	Value
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$\varepsilon$	The mean value of the lognormal distribution.	1 year
$\beta$	The variance value of the lognormal distribution.	0.1 year <sup>2</sup>

375

### 376 4.3 Tolerable loss modeling

377 We assume that the decision-maker of the NPP determines that the organization can tolerate losses up to 10%  
378 of the cash flow. Therefore, we have  $\alpha = 0.1$ . For the NPP,  $I(t_k)$  depends on the electricity price, which often  
379 exhibits large variabilities. In this paper, we use the following model, as much as possible incorporating the features  
380 of electricity price (such as seasonal volatility, time-varying mean reversion and seasonally occurring price spikes)  
381 to simulate the stochastic behavior of the electricity price [61]:

$$382 \quad dx_t = \theta\tau(t)(\mu_p - x_t)dt + \sigma\sqrt{\tau(t)}dW_t + dZ_t \quad (24)$$

383 where  $x_t$  is the electricity price at  $t$ ,  $\theta > 0$  and  $\mu_p$  is the mean value of the price,  $W_t$  is a standard Brownian  
384 motion and  $Z_t$  is a compound Poisson process with levy measure  $\nu(dx) = \lambda g(x)dx$ ,  $\lambda$  is the jump intensity  
385 and  $g$  is the density of the jump size distribution,  $\tau(t)$  is a positive stochastic process which satisfies:

$$386 \quad \tau(t) = s(t) + \nu(t) \quad (25)$$

387 where  $s(t)$  is a deterministic, time-dependent and positive seasonal component, which is often modeled by a  
388 trigonometric function:

$$389 \quad S_1(t) = a_1 \sin\left(\frac{a_2 + 2\pi t}{5}\right) + a_3 \left(\frac{a_4 + 2\pi t}{251}\right) + a_5. \quad (26)$$

390 The value of the seasonal component parameters are shown in Table 4.

391 Table 4. Values of the seasonal component parameters of the spot prices.

Parameter	Value
$a_1$	0.41
$a_2$	1.90
$a_3$	0.40
$a_4$	43.11
$a_5$	0.29

392

393  $\nu(t)$  is a stochastic process, representing the stochastic part of the time change. The Cox-Ingersoll-Ross process  
 394 [62] is used to model  $\nu(t)$ ,

$$395 \quad d\nu(t) = \kappa(\eta - \nu(t))dt + \sqrt{\nu(t)\sigma_2}dW_2(t). \quad (27)$$

396 By using Itô's lemma [61], Equation (24) can be solved and we can derive the following form:

$$397 \quad x(t) = x(0) + \int_0^t \theta(\mu - x(t))dt + \int_0^t \sigma\sqrt{\tau(t)}dB(t) + \int_0^t dZ(t). \quad (28)$$

398 The parameters of the stochastic electricity model are tabulated in Table 5, which is estimated from the German  
 399 EEX<sup>1</sup> (a market platform for energy and commodity products), from 12.03.2009 until 31.12.2013. The interested  
 400 readers may refer to details and derivations in [61].

401 Table 5. Parameters in the stochastic electricity model [61].

Parameter	Value
$x_0$	40
$\theta$	0.22
$\mu$	50
$\sigma$	5.98
$dt$	1
$\lambda$	0.12
$\mu_1$	1.02
$\sigma_1$	1.35

402

403 Eventually, the generated stochastic electricity price trajectory is shown in Figure 5.

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<sup>1</sup> <https://www.eex.com>

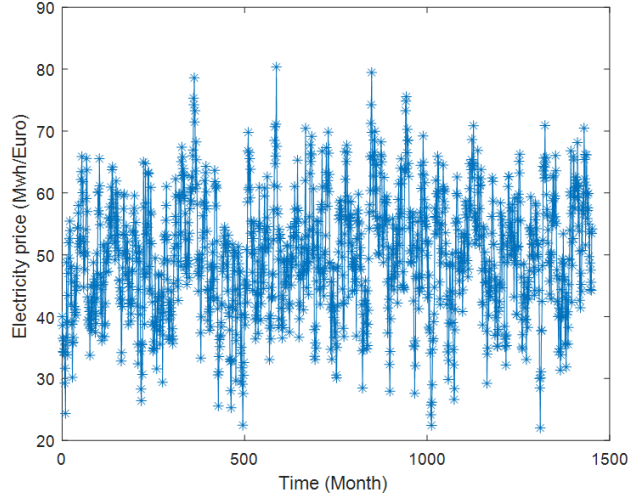


Figure 5. Simulated time-varying electricity price trajectory for 1500 months.

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The operation cost  $C_o(t_k)$  in Equation (15) is set as constant  $20 \text{ €/MWh}$ , which includes the cost of uranium

406

fuel and the cost of disposing used fuel and wastes [63]. Finally, the cash flow at different time points is shown in

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Figure 6. We can see that the accumulated profit is small at the beginning. This is because this period is still under

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the repayment period and a large amount of the revenue is used for repaying the installment. After  $t = 10$  years, the

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repayment is paid off and, thus, the profit increases significantly.

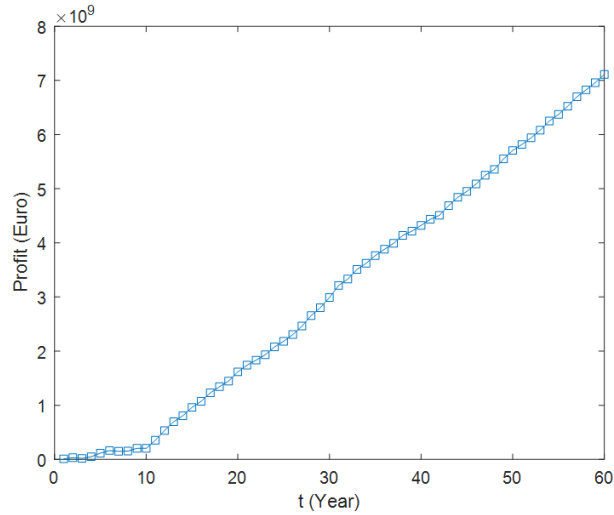


Figure 6. Profit trajectory at different estimation points.

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#### 4.4 Results

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A DBCA is conducted using Algorithm 2. The analyses investigate the dynamic business continuity behavior

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for the plant at different ages  $t = 1, 2, \dots, 40$  (years) and under different evaluation horizons  $T = 1, 2, \dots, 60$  (years),

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as shown in Figures 7~9. To show the difference between DBCA and (time-static) BCA, a comparison is also carried

415

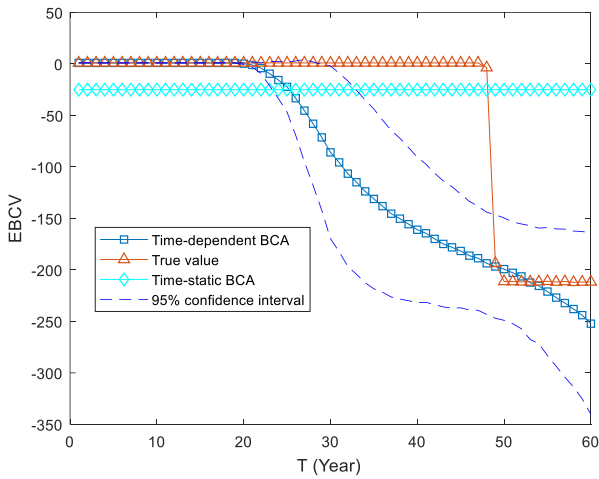
out. For the BCA, the occurrence of SGTR is assumed to follow a Poisson process, where  $\lambda_{st} = 7.0 \times 10^{-3}$  per year

416 [49]. The estimated time horizon is chosen to be the lifetime of the NPP,  $T = 60$  years. The time-static business  
 417 index is defined as:

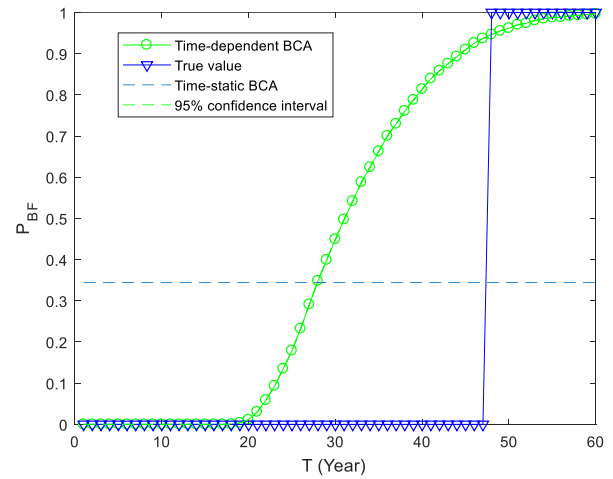
$$418 \quad BCV(0,T) = 1 - \frac{L(0,T)}{L_{tol}} \quad (29)$$

419 where  $BCV$  is the business continuity value;  $L_{tol}$  is the tolerable losses and is assumed to be a constant value,  
 420 which equals  $Q_0$  (i.e., the initial capital). The recovery time model for the BCA is identical to the one employed in  
 421 DBCA.

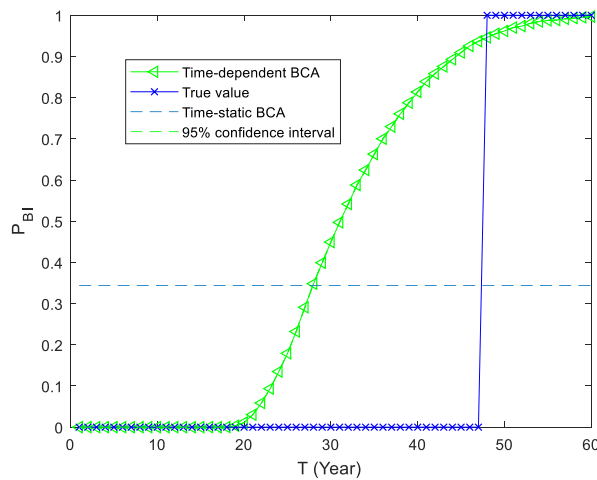
422 The results from the time-static and time-dependent BCA are compared in Figure 7~9, where the true value is  
 423 generated based on a theoretical model with known parameters. Abscissa axis shows the estimation horizon  $T$ , and  
 424 the vertical axis stands for the different BCV indexes. Therefore, these results show the business continuity of NPPs  
 425 at different age ( $t$ ), if it is operated for different lengths of time ( $T$ ).



(a) EDBCV



(b)  $P_{BF}$



(c)  $P_{BI}$

Figure 7. Business continuity metrics at  $t=1$  year.

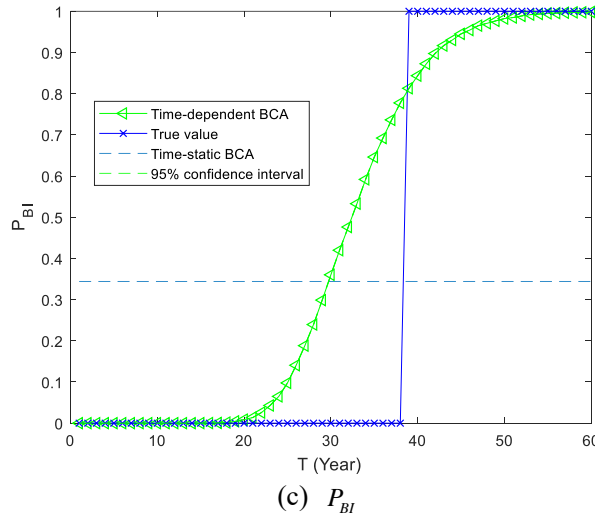
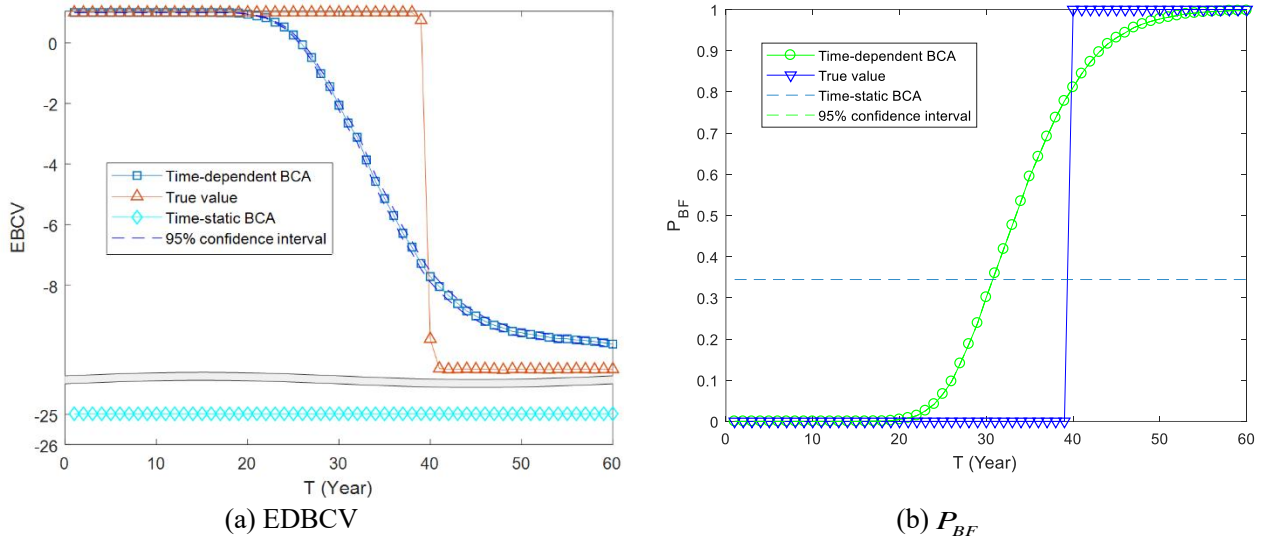
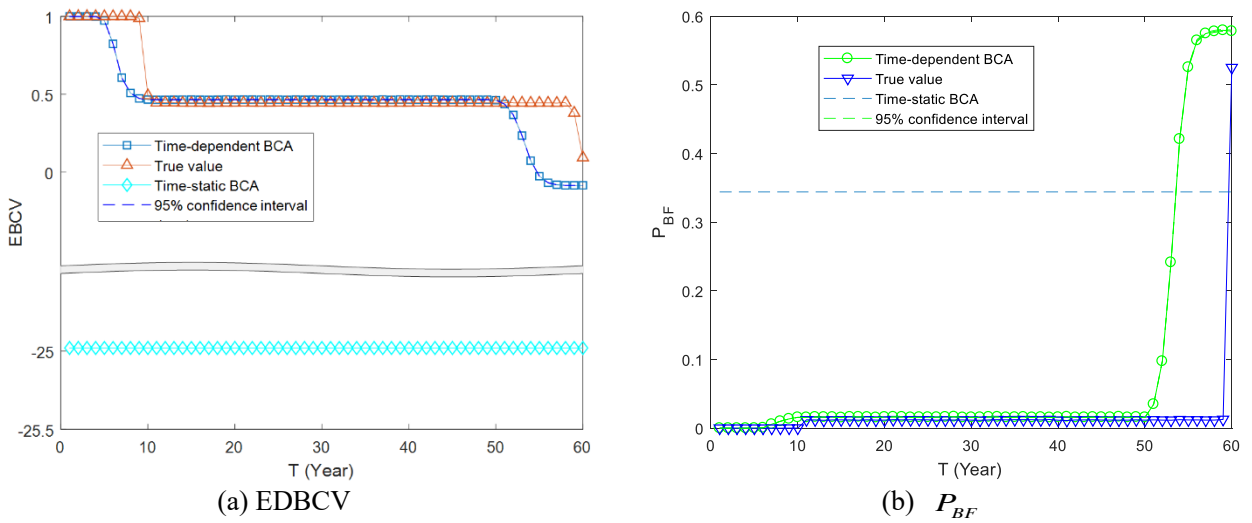
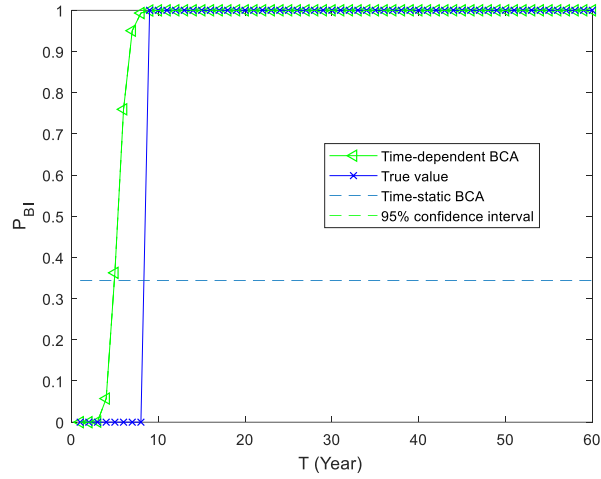


Figure 8. Business continuity metrics at  $t=10$  years.





(c)  $P_{BI}$

Figure 9. Business continuity metrics at  $t=40$  years.

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- 1) At each  $t$ , with the increase of the estimation horizon  $T$ , the DBCV decreases. This means that regardless of the age  $t$  of the NPP, the longer the NPP is operated, the worse its business continuity: this is logical, as it is primarily caused by the tube's degradation process. No rupture is supposed to occur at the beginning of system operation. Subsequently, as the crack grows, rupture will occur eventually and lead to system failure. In addition, the dynamic business continuity (DBC) indexes curves drop (Figure 7 (a), Figure 8 (a), Figure 9 (a)) or rise (Figure 7 (b, c), Figure 8 (b, c), Figure 9 (b, c)) significantly after a certain value of  $T$ . In practice, intervention measures like overhauls need to be taken before this  $T$ , in order to prevent serious losses from occurring failures and ensure the business continuity.
- 2) For the same estimation horizon  $T$ , with the increase of NPP age  $t$ , the EDBCX moves toward left, which means the financial safety margin is narrowing over time  $t$ . This is because the steam generator tube is getting closer to a dangerous state as the NPP ages.
- 3) When  $T$  is beyond a certain value, the business continuity metrics becomes invariant. This is mainly because when  $T$  is sufficiently long, the rupture event will surely happen and after that no loss occurs any more.
- 4) There are plateau sections in the curves of EBCV (Figure 7 (a), Figure 8(a), Figure 9 (a)); the height of these plateaus increases with time  $t$ , which makes sense because the system potential profits increase over time  $t$ .
- 5) The comparison between DBCA and time-static BCA shows that the time-static BCA grossly underestimates the damage of SGTR on system business and, thus, underestimates the NPP's business loss.



448 Moreover, the results from the DBCA using condition-monitoring data are closer to the true BCV than  
449 those of the time-static BCA. This is because the DBCA using condition monitoring data incorporates the  
450 time-dependent behavior of SGTR degradation.

451 6) Confidence interval quantifies the level of confidence that the BCV metrics are captured by the interval.  
452 From Figures 7~9, we can see that with more data available, the width of confidence interval is narrowing.  
453 That is because, the more condition monitoring, the more precise of the component state estimation and  
454 the less uncertainty in the BCA results.

## 455 **5 Discussion**

456 In this work, although the developed method is only applied on a case study of NPP, it can also be applied in a  
457 wide variety of scenarios. To apply the developed method for DBCA, a system needs to satisfy the following premises:  
458 (1) the business continuity is related to financial losses; (2) the system behavior and/or the profit of the system are  
459 potentially time-dependent; (3) condition monitoring data are available to describe the time-dependent system  
460 behaviors. For instance, in the example of oil storage tanks in [4], the profits of the oil storage tank depend on the  
461 price of the oil and are therefore time-dependent. Lithium batteries are used to drive some critical safety barriers. As  
462 the Lithium battery is subject to degradation, the performance of the safety barriers is also time-dependent. Besides,  
463 condition monitoring data are available from the mounted sensors and can be used for online updating the failure  
464 probability of the safety barriers. Therefore, the developed methods can be applied for DBCA of the oil tanks. For IT  
465 service, the profits also exhibit time-dependent behaviors. The failure behaviors of the hardware in the IT  
466 infrastructure are also time-dependent due to the presence of various degradation failure mechanisms. If condition  
467 monitoring data are available to monitor the state of the hardware, the developed model can also be applied for a  
468 DBCA.

469 Compared to the original time-static BCA method, the developed model captures the time-dependent features  
470 of both profits and system failure behaviors. Therefore, the proposed method can more precisely quantify the business  
471 continuity that exhibits time-dependent behaviors. However, the price we need to pay is that our model is more  
472 complex in both model development and analysis. In practice, we often need to choose the most appropriate method  
473 based on a tradeoff between the complexity of the modelling and the accuracy of the results. For example, for systems  
474 whose failure behavior is not time-dependent or not significant to safety, the traditional time-static BCA method  
475 might be sufficient. However, for safety critical systems that have significant time-dependency (e.g., NPP), the  
476 developed method is preferred due to its potential to provide a more accurate assessment.

477 It should be noted that in this work, we assume that the operation costs (including the inspection and maintenance  
478 cost) do not change over time (as seen in Equation (15)). This assumption is reasonable for NPP, because NPPs are  
479 usually designed with a large margin so that even though they reach their designed life, their performance does not  
480 degrade very severely. However, for other products, these costs might also be time-dependent and increasing with  
481 time. This fact should be considered for a more precise modelling.

482 Moreover, to illustrate the proposed DBCA model, we use a stochastic electricity model to predict the electricity  
483 price as it considers a large variety of features contributing to electricity price variations (such as seasonal volatility,  
484 time-varying mean reversion and seasonally occurring price spikes). The predicted electricity price is shown in Figure  
485 5. It should be noted that the predicted values here are used to illustrate the developed method only. There are  
486 numerous factors that have the potential influence on the electricity price (such as new energy source and new  
487 consumption patterns), which make the predicted results inevitably subject to various sources of uncertainty  
488 concerning the long-time span for prediction. Therefore, when the developed method is applied in practice, up-to-  
489 date electricity information should be used, instead of this predicted value, in order to reduce the uncertainty and  
490 assessment errors.

491 It should be noted that in this work, we only look at disruptive events that are caused by safety related hazards.  
492 In practice, however, the problem of business continuity might also be caused by disruptive events other than safety  
493 related hazards, e.g., strike, natural hazards. The developed models can be extended to capture also these disruptive  
494 events.

## 495 **6. Conclusions**

496 In this paper, a DBCA method that integrates condition monitoring data is proposed. Two factors that influence  
497 the dynamic behavior of business continuity are considered explicitly. The first one is the dynamics of the  
498 degradation-to-failure process affecting the safety barriers. Condition monitoring data are used to update and predict  
499 the time-dependent failure behavior by PF. The second factor is the time-dependent profit and tolerable losses. This  
500 is quantified by applying a stochastic price model and an installment model. A simulation-based framework is  
501 developed to calculate the time-dependent business continuity metrics originally introduced. A case study regarding  
502 the analysis of an accident initiated by SGTR in a NPP shows that the proposed framework allows capturing the  
503 dynamic character of business continuity.

504 The outcomes of such dynamic analysis can provide insights to stakeholders and decision-makers, that can help  
505 them to identify when best to take actions for preventing serious losses and ensuring business continuity.

506 **Acknowledgement**

507 The work of Ms. Jinduo Xing is supported by China Scholarship Council (No. 201506450020). The work by  
508 Professor Enrico Zio has been developed within the research project "SMART MAINTENANCE OF INDUSTRIAL  
509 PLANTS AND CIVIL STRUCTURES BY 4.0 MONITORING TECHNOLOGIES AND PROGNOSTIC  
510 APPROACHES - MAC4PRO ", sponsored by the call BRIC-2018 of the National Institute for Insurance against  
511 Accidents at Work – INAIL in Italy.

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