Interval-valued importance measures for business continuity management

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Interval-valued importance measures for business continuity considering simulation errors

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ABSTRACT: As a proactive approach to protect the business and reduce the potential losses caused by these disruptive events, Business Continuity Management (BCM) has gained more and more attentions these days. Since various measures are involved in BCM, (e.g., protection measures, mitigation measures, emergency measures and recovery measures), how to rank their relative importance becomes a practical issue when designing BCM plans. Traditional importance measures cannot be directly applied for business continuity since they fail to consider the simulation errors, which are frequently encountered in the evaluation the business continuity. In this paper, we develop two interval-valued importance measures. The developed importance measures allow us to compare the importance considering the influence of simulation errors. The developed methods are demonstrated on a case study of an oil tank storage farm from literature.

1 INTRODUCTION

As modern systems grow in scales and complexities, they are more and more vulnerable to threats from various disruptive events (Zio, 2016), e.g., unexpected system failures (Hameed, et al., 2016), natural disasters (Meng, et al., 2015), terrorist attacks (Reniers and Audenaert, 2014), etc. How to keep the system in operational states under these threats is a key challenge to system designers and operators. Hence, business continuity, defined by the International Organization of Standards (ISO) as the capability of an organization to continue delivery of products or services at acceptable levels following disruptive events (ISO, 2012), has received more and more attentions in recent years (Rabbani, et al., 2016).

A lot of researches have been conducted with respect to business continuity. For example, Cerullo and Cerullo (2004) proposed a comprehensive approach to business continuity management, with particular focuses on internal and external information security threats. Castillo (2005) surveyed the application of business continuity management to achieve organizational disaster preparedness to various disruptive events at Boeing. Sahebjamnia (2013) proposed a framework to integrate BCM and disaster recovery planning, to ensure that the system would resume and recover its operation in an efficient and effective way. However, these works are mainly based on a qualitative analysis of the major contributors to business continuity. Very few works consider the quantitative modeling and analysis of business continuity, which limits their application in practice.

In a recent work of the authors (Zeng and Zio, 2016), an integrated model is developed for quantitative business continuity analysis. It allows us to calculate the business continuity metrics given information of the business continuity measures, i.e., the protection, mitigation, emergency and recovery measures (Zeng and Zio, 2016).

In this paper, we consider another practical issue: how to rank the relative importance of different business continuity measures. This is a critical problem if one wants to design a more effective business continuity management plan. Due to the complexity of the business continuity models, the business continuity metrics often need to be evaluated using Monte Carlo simulations. Traditional importance measures, e.g., Birnbaum measures, differential importance measures, risk improvement worth, risk reduction worth, etc., therefore, cannot be directly applied since they are based on a single point-valued and fail to account for the possible simulation errors in business continuity analyses. In this paper, we address this issue by developing two interval-valued importance measures.

The rest of this paper is organized as follows. In Sect. 2, the quantitative business continuity metrics and models are briefly reviewed. The two interval-valued importance measures are defined in Sect. 3. A case study is presented in Sect. 4 to demonstrate the developed methods. Finally, the paper is concluded in Sect. 5.

2 BUSSINESS CONTINUITY METRICS AND MODELS

In this section, we review the quantitative metrics and models for business continuity developed in Zeng and Zio (2016), which serves as a basis for the importance measures to be developed in Section 3.

Normally, business continuity is manifested in terms of performance indicators of a business process, denoted by PPI_B. The value of PPI_B represents to which degree the objective of the business process is satisfied. For example, the PPI_B of an electric power distribution system can be the fraction of satisfied demands. When the electric power distribution system is under normal operation, its PPI_B remains its nominal value; when the electricity distribution system is interrupted by the disruptive events, the PPI_B drops to some degraded values.

In Zeng and Zio (2016), three quantitative metrics for business continuity are defined based on the losses caused by the disruptive events, i.e., EBCV, P_{BI} and P_{BF}.

Expected Business Continuity Value (EBCV) is defined by

$$\mathrm{EBCV} = E\left[\frac{L_{tol} - L}{L_{tol}}\right], \tag{1}$$

where L_{tol} is the maximum tolerable losses for an organization and L is a random variable that describes the losses that the organization suffers due to disruptive events in $[0,T]$. Suppose the number of disruptive events in $[0,T]$ is $n(T)$, L can be further expressed as

$$L = \sum_{i=1}^{n(T)} \left(L_{D,i} + L_{I,i}\right), \tag{2}$$

where $L_{D,i}$ is the losses caused directly by the disruptive event; $L_{I,i}$ is the revenue losses caused by the system downtime in the recovery process. Usually, it is assumed that $L_{I,i}$ is determined by the length of the recovery time and the severity of the degradation of the PPI_B.:

$$L_{I,k} = k \cdot t_{recv,i} \cdot \left(\mathrm{PPI}_{B,N} - \mathrm{PPI}_{B,i}\right), \tag{3}$$

where k is the loss caused by the disruptive event per unit time per unit PPI_B, $t_{recv,i}$ is the recovery time, $\mathrm{PPI}_{B,N}$ and $\mathrm{PPI}_{B,i}$ are the nominal and degraded performance indicators, respectively.

The physical meaning of EBCV is the relative difference between the average losses caused by the disruptive events and the maximum losses that an organization could stand. It is easy to verify that $\mathrm{EBCV} \in (-\infty, 1]$ and a higher value of EBCV indicates better business continuity. Also, $\mathrm{EBCV} = 0$ is a borderline state: a EBCV less than zero indicates that the organization might have trouble in recovering from the disruptive events.

The second business continuity metric defined in Zeng and Zio (2016) is P_{BI}:

$$P_{BI} = \Pr\left(L > 0\right). \tag{4}$$

The physical meaning of P_{BI} is the probability that at least one Business Interruptions (BI) has been caused by the disruptive event in $[0,T]$. Therefore, P_{BI} measures the business continuity in terms of the system's resistance to the influence of the disruptive event: a lower value of P_{BI} indicates better business continuity.

The third business continuity metric defined in Zeng and Zio (2016) is P_{BF}:

$$P_{BF} = \Pr\left(L > L_{tol}\right). \tag{5}$$

The physical meaning of P_{BF} is the probability of Business Failure (BF) occurs in $[0,T]$, i.e., the losses caused by the disruptive events are beyond tolerable. As shown in (5), P_{BF} considers both resistance and recoverability of the system and a lower value of P_{BF} indicates better business continuity.

To reduce the losses caused by the disruptive events and ensure the business continuity, various business continuity measures are often implemented. Generally speaking, these measures can be divided into four categories, i.e.,

– protection measures, for defending the system from the disruptive events and preventing them from damaging the system. If protection measures succeed, the business process is not interrupted;
– mitigation measures, which are automatically activated when the protection measures fail and initial damage has been caused by the disruptive events. The aim of the mitigation measures is to contain the evolution of the disruptive events at the early stages of development, so that damages can be mitigated;
– emergency measures, which happen when the mitigation measures fail to contain the damage, and often require significant human intervention;
– recovery measures, which aim at re-establishing normal operation.

Business continuity of a system is, then, determined by these measures. In Zeng and Zio (2016), an integrated modeling framework is developed for business continuity, as shown in Figure 1, where the protection and mitigation measures are modeled by a fault tree and an event tree, the emergency measure is modeled by an event sequence diagram and the recovery measures are modeled by a semi-Markovian model.

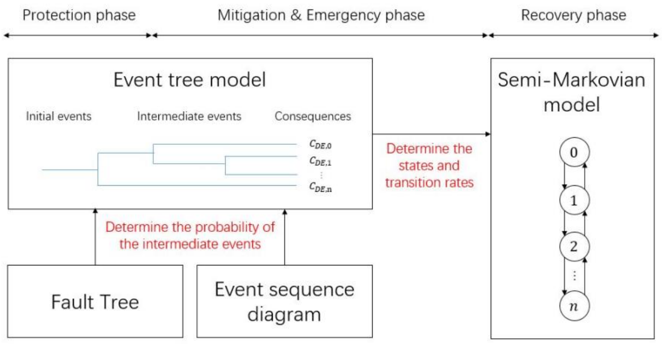


Figure 1 Integrated business continuity model Zeng and Zio (2016)

3 IMPORTANCE MEASURES FOR BUSINESS CONTINUITY

Conceptually, a business continuity model can be represented as

$$\left[\mathrm{EBCV}, P_{BI}, P_{BF}\right] = g\left(I_{BCM,1}, I_{BCM,2}, \cdots, I_{BCM,n}\right), \quad (6)$$

where $I_{BCM,1}, I_{BCM,2}, \cdots, I_{BCM,n}$ are the performance indicators for each business continuity measure. Due to the complexity of the business continuity in (6), the business continuity metrics often need to be calculated using Monte Carlo simulations.

Traditional importance measures only consider point values, i.e., the importance is measured by comparing the changes in the business continuity metrics before and after some changes in the $I_{BCM,i}$. When applied these measures directly to business continuity models, the errors of Monte Carlo simulation become an essential problem: the changes in the business continuity metrics might purely come from simulation errors. The problem becomes even more severe for business continuity metrics, since the nominal values of these metrics are always very small, which makes them more vulnerable to simulation errors.

For this, we extend the definitions of point-valued importance measures to define some interval-valued importance measure for business continuity. The key idea is straightforward: use the $(1-\alpha)$ confidence interval, rather than the point estimator, to measure the importance. To demonstrate this idea, we derive two interval-valued importance measures: interval-valued Business Continuity Achievement Worth (BCAW) and interval-valued Business Continuity Reduction Risk (BCRR).

Similar to Risk Achievement Worth (Zio et al., 2006), BCAW measures the amount that the business continuity metrics would improve if a business continuity measure could reach its ideal conditions. In this paper, we use the difference between the ideal and nominal scenarios for the evaluation of BCAW:

$$\mathrm{BCAW}_i = M_{BC} \mid I_{BCM,i}^{(Ideal)} - M_{BC}^{(N)}, \quad (7)$$

where BCAW_i is the BCAW of the ith business continuity measure; M_{BC} represents the business continuity metric of interest, e.g., the EBCV, P_{BI} or P_{BF}; $M_{BC} \mid I_{BCM,i}^{(Ideal)}$ is the value of M_{BC} when $I_{BCM,i}$ takes its ideal value; $M_{BC}^{(N)}$ is the value of M_{BC} when all the parameters take their nominal values. The physical meaning of BCAW_i is the maximum improvement one can achieve by improving the ith business continuity measure.

In (7), both $M_{BC} \mid I_{BCM,i}^{(Ideal)}$ and $M_{BC}^{(N)}$ are calculated by Monte Carlo simulations, which is, in essence, an average of a series of Monte Carlo samples:

$$M_{BC} \mid I_{BCM,i}^{(Ideal)} = \frac{1}{N_S}\sum_{i=1}^{N_S} M_{BC,ideal}^{(i)}, \quad (8)$$

$$M_{BC}^{(N)} = \frac{1}{N_S}\sum_{i=1}^{N_S} M_{BC}^{(i)}, \quad (9)$$

Where $M_{BC} \mid I_{BCM,i}^{(Ideal)}$ and $M_{BC}^{(N)}$ are the point estimator of the corresponding business continuity metrics, respectively, N_S is the sample size, $M_{BC,ideal}^{(i)}$ and $M_{BC}^{(i)}$, $i = 1, 2, \cdots, N_S$ are the generated Monte Carlo samples.

From Central Limit Theorem (CLT) (Zio, 2013), when N_S is large enough, both $M_{BC} \mid I_{BCM,i}^{(Ideal)}$ and $M_{BC}^{(N)}$ approximately follow normal distributions, whose mean values are their true values, respectively. The standard deviations, denoted by σ_1 and σ_0, can be calculated from

$$\sigma_1 = \frac{\sigma_{BC,ideal}}{\sqrt{N_S}}, \qquad \sigma_0 = \frac{\sigma_{BC,N}}{\sqrt{N_S}}, \quad (10)$$

where $\sigma_{BC,ideal}$ and $\sigma_{BC,N}$ are the standard deviations of $M_{BC,ideal}^{(i)}$ and $M_{BC}^{(i)}$, respectively.

When N_S is large, (10) is approximated well using the sample standard deviations S_1 and S_0:

$$\sigma_1 = \frac{S_1}{\sqrt{N_S}}, \qquad \sigma_0 = \frac{S_0}{\sqrt{N_S}}, \quad (11)$$

where S_1 and S_0 are calculated by

$$S_1 = \sqrt{\frac{1}{N_S - 1}\sum_{i=1}^{N_S}\left(M_{BC,ideal}^{(i)} - M_{BC} \mid I_{BCM,i}^{(Ideal)}\right)^2}, \qquad S_0 = \sqrt{\frac{1}{N_S - 1}\sum_{i=1}^{N_S}\left(M_{BC}^{(i)} - M_{BC}^{i}\right)^2}. \quad (12)$$

From (7), when N_S is large, the estimator of BCAW from Monte Carlo simulation, denoted by BCAW_i, also follows a normal distribution with an expected value equals to its true value. The standard deviation of BCAW_i is

$$
\begin{aligned}
\sigma_{PE} &= \sqrt{\sigma_1^2 + \sigma_0^2} \\
&= \sqrt{\frac{S_1^2 + S_0^2}{N_S}},
\end{aligned}
\tag{13}
$$

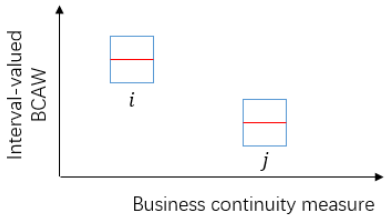
where σ_1 and σ_0 are calculated from (11).

Interval-valued BCAW (IBCAW) is, then, defined as the $(1-\alpha)$ confidence interval of the Monte Carlo simulation. From (13), IBCAW can be calculated by:

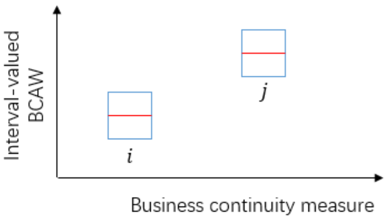
$$
\mathrm{IBCAW}_i = \begin{bmatrix} \mathrm{BCAW}_i - Z_{\alpha/2}\sqrt{\dfrac{S_1^2 + S_0^2}{N_S}}, \\ \mathrm{BCAW}_i + Z_{\alpha/2}\sqrt{\dfrac{S_1^2 + S_0^2}{N_S}} \end{bmatrix}, \tag{14}
$$

where $Z_{\alpha/2}$ is the $\alpha/2$ percentile of the standard normal distribution; S_1 and S_0 are determined from (12).

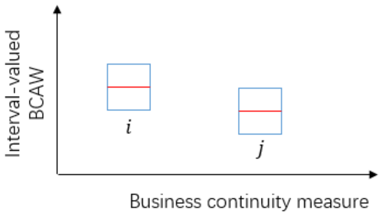
The EBCAW defined in (14) allows comparing the relative importance of business measures while considering the possible errors in the simulation. Suppose we have two business continuity measures i and j, whose IBCAW do not overlap, as shown in Figure 2 (a) or (b). This means that the improvements in the business continuity metrics are significant enough when compared to the simulation errors. Therefore, we can justifiably conclude that i is more important than j (Figure 2 (a)) or vice versa (Figure 2 (b)). If, on the other hand, IBCAW_i overlap with IBCAW_j, as shown in Figure 2 (c). This indicates that we do not have sufficient evidence to differentiate the importance of the two business continuity measures: a larger sample size might be needed for more convincible conclusions. It should be noted that in Figure 2, the box represents the IBCAW, while the solid line inside the box indicates the point estimator of the BCAW.



(a) i is significant important than j



(b) j is significant important than i



(c) We cannot determine the relative importance of i and j

Figure 2 Compare the relative importance using IBCAW

Similarly, we can define Interval-valued Business Continuity Reduction Worth (IBCRW) as

$$
\mathrm{IBCRW}_i = \begin{bmatrix} \mathrm{BCRW}_i - Z_{\alpha/2}\sqrt{\dfrac{S_1^2 + S_0^2}{N_S}}, \\ \mathrm{BCRW}_i + Z_{\alpha/2}\sqrt{\dfrac{S_1^2 + S_0^2}{N_S}} \end{bmatrix}, \tag{15}
$$

where BCRW_i is the Monte Carlo point estimator of BCRW, which is defined by

$$
\mathrm{BCRW}_i = M_{BC}^{(N)} - M_{BC} \mid I_{BCM,i}^{(Worst)}, \tag{16}
$$

and S_1, S_0 in (15) can be determined in a similar way as (12). In (16), $M_{BC} \mid I_{BCM,i}^{(Worst)}$ is the value of M_{BC} when $I_{BCM,i}$ takes its value in worst-case scenario; $M_{BC}^{(N)}$ is the value of M_{BC} when all the parameters take their nominal values.

The physical meaning of BCAW_i is the maximum reduction in business continuity one might experience due to the reduction in the ith business continuity measure. The IBCRW defined in (15) allows us to compare the BCRW of business measures while considering the possible simulation errors in their calculations.

4 APPLICATION

4.1 *System description*

In this section, we apply the developed interval-valued importance measure on a case study from literature (Zeng and Zio, 2016). For illustrative purposes, we only present the results for IBCAW since IBCRW can be calculated in a similar way.

Zeng and Zio (2016) considers business continuity assessment of a crude oil storage tank farm. The disruptive event considered in the analysis is lightening. The performance indicator of the tank farm is the number of available tanks. Several business continuity measures are implemented to protect the system from business disruptions:

- lightning protection mast is used to protect the oil storage tank from damages caused by lightning;
- automatic rim seal fire extinguishing system can detect and automatically fight against the rim-seal fire;

– fixed foam fire extinguishing system is automatically activated if the pool fire develops to full surface fire and aims at extinguishing full surface fires;
– fire brigade is the last defensive barrier to control the fire and prevent it from escalating to other tanks;
– restoring and/or replacing the damaged tanks can help to recover the storage capability of the tank farm.

Among them, lightning protection mast belongs to protection measures, automatic and fixed foam fire extinguishing system are mitigation measures, fire brigade is an emergency measure and restoring and / or replacing the damaged tanks belong to recovery measures.

An integrated model is developed in Zeng and Zio (2016) to calculate the three quantitative business continuity metrics, as shown in Figure 3, in which the protection and mitigation measures are modeled by a fault tree and an event tree, the emergency measure is modeled by an event sequence diagram and the recovery measures are modeled by a semi-Markovian model. The business continuity metrics, can, then, be calculated using a simulation-based method (Zeng and Zio, 2016).

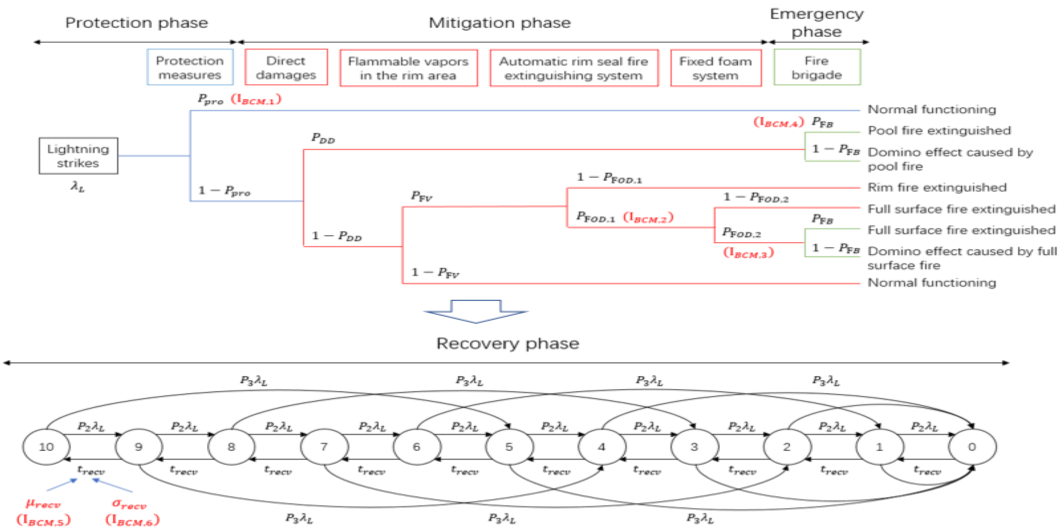


Figure 3 Business continuity model for the tank farm

4.2 *Results and discussions*

We consider six performance indicators, $I_{BCM,1}, I_{BCM,2}, \cdots, I_{BCM,6}$, corresponding to different business continuity measures, as shown in Table 1.

Table 1 Performance indicators for the business continuity measures

Notations	Meanings
$I_{BCM,1}$	Probability that the lightning protection mast successfully defends the lightening.
$I_{BCM,2}$	Failure probability of the automatic rim seal fire extinguishing system.
$I_{BCM,3}$	Failure probability of the fixed foam fire extinguishing system.
$I_{BCM,4}$	Probability that the fire brigade successfully controls the fire.
$I_{BCM,5}$	Expected value of the recovery time for each tank.
$I_{BCM,6}$	Standard deviation of the recovery time for each tank.

Equation (14) is used to calculate the IBCAW for the six business continuity measures. The nominal and ideal values for $I_{BCM,1}, I_{BCM,2}, \cdots, I_{BCM,6}$ are given in

Table 2. The sample size of the Monte Carlo simulation is $N_S = 10^6$. The confidence level is $\alpha = 0.1$.

Table 2 Nominal and ideal values for the performance indicators

Indicators	Nominal value	Ideal value
$I_{BCM,1}$	0.996	1
$I_{BCM,2}$	2.38×10^{-2}	0
$I_{BCM,3}$	7.03×10^{-3}	0
$I_{BCM,4}$	0.693	1
$I_{BCM,5}$	30 (d)	5 (d)
$I_{BCM,6}$	5 (d)	1 (d)

The results are presented in Figure 4-Figure 6. In these Figures, the box represents the upper and lower bounds of the IBCAW, while the solid line inside the box is the point estimator of the BCAW. It can be seen from Figure 4 that if we want to enhance EBCV, the primary focus should be placed on $I_{BCM,1}$, and then on $I_{BCM,5}$. Since the importance of these two business continuity measures are significantly larger than the others. The IBCAW of $I_{BCM,2}$, $I_{BCM,3}$, $I_{BCM,4}$ and $I_{BCM,6}$ overlap with each other, indicating that we cannot differentiate their relative importance due to the presence of simulation errors. Such conclusions can also be justified from the model in Figure 3. Since $I_{BCM,1}$ relates to the first event in the event tree model, it has dominant influence on the failure of the system, which, according to (2), determines the value of the direct losses. On the other hand, the value of $I_{BCM,5}$ determines the length of the recovery process, which is the major contributor to the indirect losses in (2). Therefore, $I_{BCM,1}$ and $I_{BCM,5}$ exhibit significant importance to EBCV.

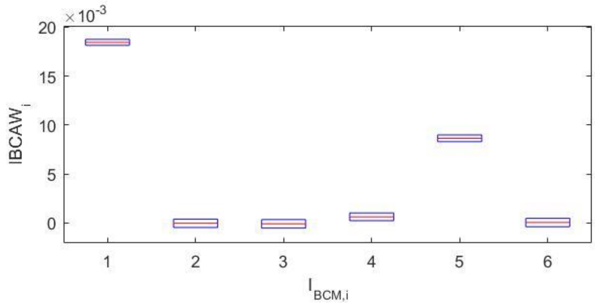


Figure 4 IBCAW of $I_{BCM,1}, I_{BCM,2}, \cdots, I_{BCM,6}$ with respect to EBCV

Figure 5 shows the IBCAW of different business continuity measures with respect to P_{BI}. It can be seen that improving the performance of $I_{BCM,1}$ can significantly improve P_{BI}, while the rest IBCAWs overlap with each other, makes them indifferentiable considering the influence of simulation errors. It should be noted for P_{BI}, a BCAW less than zero indicates its improvement. Also, from the definition of P_{BI} in (4), we can see that P_{BI} measures the system's capability to resist damage caused by the disruptive events and it is closely related to the protection measures. This explains why the $I_{BCM,1}$, the only protection measures among the six business continuity measures, ranks first in terms of importance with respect to P_{BI}, while the other measures do not significantly affect the P_{BI}.

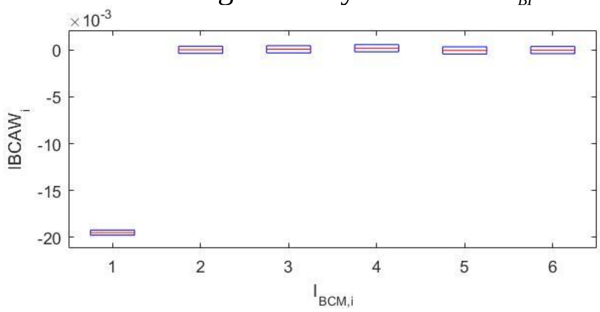


Figure 5 IBCAW of $I_{BCM,1}, I_{BCM,2}, \cdots, I_{BCM,6}$ with respect to P_{BI}

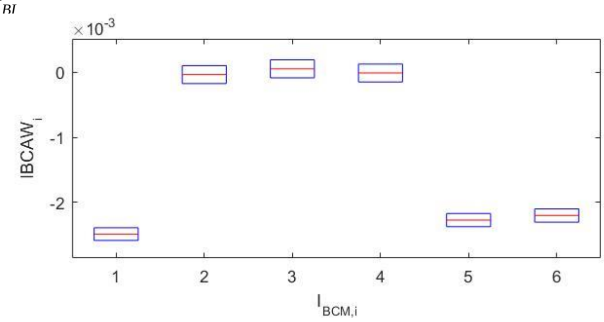


Figure 6 IBCAW of $I_{BCM,1}, I_{BCM,2}, \cdots, I_{BCM,6}$ with respect to P_{BF}

Figure 6 shows the IBCAW of different business continuity measures with respect to P_{BF}. Since P_{BF} is the probability of business failure, a negative BCAW indicates its improvement. From Figure 6, it can be seen that $I_{BCM,1}, I_{BCM,5}$ and $I_{BCM,6}$ are significantly more important than the rest three business continuity measures. This is because, P_{BF} is closely related to the direct and indirect losses. As shown in Figure 3, $I_{BCM,1}$ is the major contributor to the direct losses, while $I_{BCM,5}$ and $I_{BCM,6}$ determine the indirect losses together. However, the relative importance of $I_{BCM,1}, I_{BCM,5}$ and $I_{BCM,6}$ are cannot be differentiated considering the influence of simulation errors, since their IBCAWs overlap.

5 CONCLUSIONS

In this paper, we developed two interval-valued importance measures for business continuity. The importance measures are defined based on confidence intervals of Monte Carlo simulation and allow us to compare the importance of different business continuity measures considering the influence of simulation errors in calculating the business continuity metrics. A case study from literature is conducted to demonstrate the developed importance measures.

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