An integrated modeling framework for quantitative business continuity assessment

Zhiguo Zeng, Enrico Zio

An integrated modeling framework for quantitative business continuity assessment

Zhiguo Zeng,[†] Enrico Zio (*),[†‡]

[†]Chair on System Science and the Energy Challenge, Fondation Electricite de France (EDF), CentraleSupélec, Université Paris-Saclay, Grande Voie des Vignes, 92290 Chatenay-Malabry, France

[‡]Energy Department, Politecnico di Milano, Milano, Italy

Abstract

Systems are increasingly exposed to threats of disruptive events, e.g., failures, natural disasters, terrorist attacks, etc. A proactive approach is needed to protect the business and reduce the potential losses caused by these disruptive events. Business Continuity Management (BCM) is a way to integrate the recovery process within the preventive framework of risk assessment. Such integrated risk management strategy offers great potential benefits. However, the complexity of applying it in practice is such that existing BCM strategies are mainly based on qualitative methods only, which limits the potential added values. To support quantitative BCM, in this paper we define a set of quantitative business continuity metrics. The defined metrics are based on the estimated losses incurred by the disruptive event in the whole business process. For this, the business process is divided into four sequential phases, i.e., protection phase, mitigation phase, emergency phase and recovery phase. For each phase, a specific modeling method is developed and an integrated modeling framework is constructed for the business continuity. Simulation can, then, be used to quantify the business continuity metrics. The developed methods are applied to assess the business continuity of an oil storage tank farm.

Index Terms

Business continuity management, risk analysis, event tree, event consequence diagram, semi-Markovian model

* Email of the corresponding author: enrico.zio@ecp.fr, enrico.zio@polimi.it

An integrated modeling framework for quantitative business continuity assessment

I. Introduction

Nowadays, systems, especially critical infrastructures in process industries, are increasingly exposed to threats from disruptive events [1], e.g., unexpected system failures [2], natural disasters [3], terrorist attacks [4], etc. Usually, organizations rely on risk analysis and management methods to protect them from the potential losses caused by the disruptive events [5–8]. Khan et al. [9] presented a thorough review of the commonly applied safety and risk management methods in process industries. Most of the existing risk analysis and management methods focus on damage processes by analyzing the possible consequences of a disruptive event and their likelihoods [10]. The recovery process, however, is not considered by these methods. In practice, the potential losses that an organization might suffer also depend on the recovery process. According to a survey by IBM Global Services [11], in 2008, enterprises in IT sectors have been estimated to suffer from an average revenue cost of 2.8 million US dollars per hour for an unplanned application outage. Another report from Ponemon Institute reveals that for a company that operates data centers, the average downtime cost per minute has exceeded $\$5,000$ [12]. For these systems, conventional risk analysis and management methods should be extended, so that the recovery process can be integrated in risk management.

Business Continuity Management (BCM) is a way to integrate the recovery process within the preventive view of risk assessment [13]. It is defined by the International Organization of Standards (ISO) as "holistic management process that identifies the potential threats to an organization and the impacts to business operations that those threats, if realized, might cause, which provides a framework for building organizational resilience with the capability of an effective response that safeguards the interests of its key stakeholders, reputation, brand and value-creating activities " [14]. As an integrated management strategy aiming at reducing the technological and operational risks that threaten an organization's recovery from hazards and interruptions, BCM has attracted a lot of attention in the last decade [15].

Cerullo et al. [13] proposed a comprehensive approach to BCM planning, with particular focuses on internal and external information security threats. Zsidisin et al. [16] discussed the necessity and benefit of implementing BCM in an organization. Castillo [17] surveyed the application of BCM planning to achieve organizational disaster preparedness at Boeing. Gibb and Buchanan [18] presented an integrated framework to support BCM planning. Herbane et al. [15] reviewed the historical evolution of BCM and summarized critical events that motivate its development. Snedaker [19] compared BCM to the conventional risk management methods and pointed out that BCM not only focuses on the protection of the system before the crisis, but also the recovery process during and after the crisis. Randeree et al. [20] developed a model to assess the maturity of the BCM programs and applied it on a case study from UAE banking sector. Faertes [21] used system reliability models to plan BCM. Sahebjamnia et al. [22] 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. Parise et

al. [23] discussed methods that are used to ensure the business continuity of a safety-related power supply system. Torabi et al. [24] developed an enhanced risk assessment framework to support business continuity management. Rabbani et al. [25] presented a fuzzy cost-benefit analysis method for planning BCM strategies.

As a holistic, integrated risk management strategy, BCM offers great potential benefits but the complexity of the problem is such that most currently existing BCM strategies are based on qualitative methods only, and this limits practical application. Very few works concern the quantitative modeling and analysis of business continuity. Boehmer et al. [26] presented an approach, which is based on process algebra and modal logic, to model the system behavior in the business continuity process. Similar models have been applied in Brandt et al. [27] to describe the business continuity process of a credit card company. A multi-layer model is developed in Asnar [28] to model the business continuity of a loan originating process. Bonafede et al. [29] combined Cox's model and Bayesian networks to model the business continuity process. Tan and Takakuwa [30] developed a simulation model to investigate the business continuity of a company considering the outbreak of a pandemic disease, where the business continuity is characterized by the operation rate and the plant-utilization rate. These models describe the post-crisis behavior of the system. However, no clearly-defined business metrics have been defined from these models, which prohibits the quantitative analysis of business continuity based on these models and therefore, limits their application in practice.

This paper focuses on the modeling and quantitative analysis of business continuity. The contributions of this paper are summarized as follows.

- Four quantitative metrics for business continuity are defined, based on the potential losses caused by the disruptive events.
- An integrated modeling framework is developed to model the whole business process.
- A simulation-based method is presented to calculate the defined business continuity metrics based on the integrated model.

The rest of the paper is organized as follows. In Section II, we present a four-phase conceptual model for business processes. Based on the conceptual model, the definition of the quantitative business continuity metrics are presented in Section III. An integrated modeling framework is developed in Section IV for the modeling and assessment of business continuity. The developed methods are applied in Section V to assess the business continuity of an oil storage tank farm. Finally, the paper is concluded in Section VI with a discussion on potential future works.

II. A CONCEPTUAL MODEL FOR BUSINESS CONTINUITY PROCESS

In this section, we present a conceptual model that describes the business continuity process and identifies its major contributing factors. Business continuity is defined as the capability of an organization to continue delivery of products or services at acceptable levels following disruptive events [14]. It measures the capability of an organization to remain at or quickly recover to operational states after being affected by disruptive events. Usually, the business process of an organization can be characterized by a performance indicator, denoted by PPI_B, whose value reflects the degree to which the objective of the organization is satisfied. For example, for an oil refinery, the PPI_B is its daily production yield; for a manufacturing factory, the PPI_B is the products produced per day. The values of PPI_B are determined by the operation state of the organization: the PPI_B

remains at its nominal value when the system is under normal operation and drops to a degraded value when the normal operation of the system is disrupted. In practice, an organization is susceptible to various disruptive events, which might jeopardize its business continuity. Commonly encountered disruptive events include

- technological disruptions, caused by component or system failures;
- natural disruptions, caused by natural disasters, e.g., floods, earthquakes, lightening, etc.;
- social disruptions, caused by social movements, e.g., terrorist attacks, strikes, supply chain disruptions, etc.

When one or some of these disruptive events occur, the normal operation is disrupted and PPI_B drops to a degraded value, as a consequence of the disruptive events. The organization and its stakeholders, then, suffer from losses caused by the business interruption. To reduce such losses, various business continuity measures can be taken to guarantee the continuity of the business process. Generally speaking, those 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.

For example, lightning is a severe threat to oil & gas systems [31]. Often, a lightening protection mast is installed at oil and gas tank farms as a protection measure against the threat of lightning [32]. If the protection mast fails to protect the system, the oil storage tank might catch fire [33]. Mitigation measures, such as the automatic fire extinguishing system, are automatically activated to fight the fire in order to prevent it from spreading to other tanks, causing a domino effect [33]. Emergency measures, e.g., the intervention of a fire brigade, are needed when the mitigation measures fail to stop the propagation of the accident [34]. Then, recovery measures, e.g., the repair and restoration of the affected tanks, are carried out to recover operation and minimize the losses caused by the business interruption.

Figure 1 presents a conceptual model that schematically illustrates the evolution of a business process under a disruptive event. The business process is divided into four phases: protection, mitigation, emergency and recovery. Each phase is associated with the corresponding business continuity measure. As shown in Figure 1, the PPI_B of an actual business process might deviate from its nominal value due to the presence of various disruptive events. The severity and duration of the business interruption caused by the disruptive event can be controlled by implementing business continuity measures in the different phases. Among them, protection measures affect the resistance of the system to disruptive events. Mitigation and emergency measures determine how much system performance is degraded from the damage caused by the disruptive event. Recovery measures influence how quickly the system can recover to normal operation.

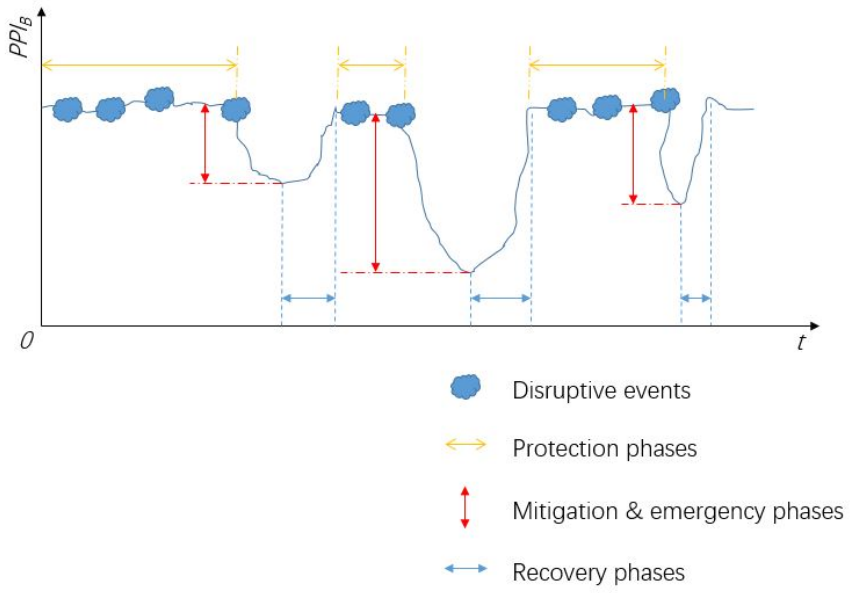

Fig. 1. A conceptual model for the business continuity process

III. Loss-based Business Continuity Metrics

In this section, we define a set of quantitative business continuity metrics to cover the whole business continuity process. Evidently, business (performance) continuity is inversely related to the losses caused by the disruptive event, i.e., a higher value of business continuity indicates less losses caused by the business interruption. Therefore, we define the business continuity metrics as a function of the losses due to the disruptive event.

Two kinds of losses are considered in this paper, i.e., direct losses and indirect losses. Direct losses, denoted by L_D, are those caused directly by the disruptive event. For example, when a lightning strike hits an oil storage tank, L_D might include the structural damage of the tank, the loss of the oil contained in the tank due to leakages in the damaged structure, and other possible losses that occur right after the lightning strikes. Indirect losses, denoted by L_I, are those incurred during the recovery process. In the previous example of the storage tank, the tank needs to be shutdown or at least operated at degraded performances during the recovery process, which causes revenue losses to the organization. Besides, L_I also includes the costs of replacing or restoring the affected tank, e.g., the costs of spare parts, maintenance personnel, etc.

Let L_i denote the losses caused by the ith disruptive event. The loss L_i includes direct loss and indirect loss. Therefore, we have

$$L_i = L_{D,i} + L_{I,i}, \tag{1}$$

where $L_{D,i}$ and $L_{I,i}$ are the direct loss and indirect loss caused by the ith disruptive event, respectively. The indirect loss, $L_{I,i}$, measures the lost profits due to the degraded performance and the potential system downtime in the recovery process. To further quantify $L_{I,i}$, it is assumed that

$$L_{I,i} = k \cdot t_{recv,i} \cdot (\text{PPI}_{B,N} - \text{PPI}_{B,i}), \tag{2}$$

where k is the indirect loss caused by the disruptive event per unit time per unit PPI_B; $t_{recv,i}$ is the time that is taken to recover the business process to its nominal performance; $\text{PPI}_{B,N}$ is the nominal PPI_B for the business process and $\text{PPI}_{B,i}$ is the performance indicator of the business process after the damage of the ith disruptive event.

We are interested in the business continuity over a time interval $[0, T]$ (e.g., the life of the system). Suppose that the number of disruptive events that occur in $[0, T]$ is $n(T)$. From (1), the loss due to the disruptive events that occur in $[0, T]$, denoted by L_T, is

$$L_T = \sum_{i=1}^{n(T)} \left(L_{D,i} + L_{I,i} \right), \tag{3}$$

where $L_{D,i}$ and $L_{I,i}$ are the direct loss and indirect loss of the ith disruptive event, respectively, and $L_{I,i}$ is calculated using (2). It should be noted that due to various uncertainties, the $n(T), L_{D,i}$ and $L_{I,i}$ are random variables; therefore, L_T is also a random variable. Based on (3), we can define quantitative metrics for business continuity.

Definition 1. We define the Business Continuity Value (BCV) as

$$\text{BCV} = 1 - \frac{L_T}{L_{tol}} \tag{4}$$

where L_{tol} is the maximum loss that an organization can withstand.

It is easy to verify that that BCV $\in (-\infty, 1]$ and a high value of BCV indicates high business continuity. The physical meaning of (4) is the relative difference between the losses caused by the disruptive events and the maximum losses that an organization could stand. Since L_{tol} represents the maximum tolerable losses for an organization, BCV $= 0$ is a borderline case: a BCV whose value less than zero indicates that the organization might have trouble in recovering after the occurrence of the disruptive events.

The relationship between BCV and PPI_B is that, the BCV is defined based on the expected losses L_T, which includes both direct losses and indirect losses, as shown in (3). The indirect losses $L_{I,i}$ are, then, determined by the value of PPI_B, according to (2). The physical meaning of (2) is to measure the revenue losses due to the potential partial operation period of the system (i.e., operating at a reduced capacity) after the strike of the disruptive events.

The BCV defined in (4) is conceptually similar to a widely applied resilience metric, the resilience triangle: if we let $k = 1$ and $t_{recv,i} = 1$ in (2), the L_T in (4) is, then, equivalent to the resilience triangle metric defined in [35]. Although seems similar, the BCV differs from resilience since the concept of resilience mainly focuses on the performance degradation and recovery process, but does not relate the process to the losses suffered by the organization. The BCV, on the other hand, explicitly considers the losses and therefore, allows to evaluate the possibility of recovery from financial perspectives.

Since BCV is a random variable, for practical applicability, four numerical metrics, i.e., Expected Business Continuity Value (EBCV), Standard Deviation of Business Continuity Value (SDBCV), P_{BI} and P_{BF}, are derived based on the probability distribution of BCV. EBCV is calculated as the expected value of BCV. SDBCV is calculated as the standard deviation of BCV, to measure the variability in the BCV values.

The probability that disruptive events causes business interruption in the considered time interval, denoted by P_{BI}, is the third numerical metrics defined in this paper:

$$P_{BI} = Pr\left(\text{BCV} < 1\right). \tag{5}$$

It measures the likelihood of business interruption caused by the disruptive events.

When the losses caused by the disruptive events are beyond tolerable, the organization might have trouble recovering: this situation is called Business Failure (BF), in this paper. The probability of business failure, denoted by P_{BF}, is calculated by

$$P_{BF} = Pr\left(\text{BCV} < 0\right). \tag{6}$$

The value of P_{BF} measures the capability that an organization cannot recover from potential disruptive events.

It should be noted that the four numerical metrics can be explained in financial terms using monetary values (e.g., in U.S. dollars). For example, suppose that the organization objective of the analysis can withstand financial losses up to $\$100,000$ (i.e., $L_T = \$100,000$) and EBCV $= 0.8$, SDBCV $= 0.01$, $P_{BI} = 0.8$, $P_{BF} = 0.1$:

- EBCV $= 0.8$ indicates that the organization can accept to suffer on average a financial loss of $100,000 \times (1 - 0.8) = \$20,000$;
- SDBCV measures the variations in the acceptable expected losses: a larger SDBCV indicates that the expected losses are subject to large variations and vice versa;
- $P_{BI} = 0.8$ indicates that with probability 0.8, the organization could suffer financial losses;
- $P_{BF} = 0.1$ indicates that with probability 0.1, the organization could suffer financial losses larger than $\$100,000$.

IV. An integrated modeling framework for business continuity assessment

In this section, we first present an integrated modeling framework for business continuity (Section IV-A). Then, a simulation-based method is developed to calculate the defined business continuity metrics (Section IV-B).

A. The integrated modeling framework

To model the business process, we make the following assumptions to capture its characteristics:

1) The occurrence of disruptive events follows a homogeneous Poisson process with a rate parameter λ_{DE}.
2) The consequences of the disruptive event are classified into n discrete states with increasing degree of severity, denoted by $C_{DE,0}, C_{DE,1}, \cdots, C_{DE,n}$, where $C_{DE,0}$ represents the consequence state that no damage is caused by the disruptive event.
3) The times it takes to recover the business process from state $C_{DE,i}$ to $C_{DE,i-1}$, denoted by $t_{recv,i}, i = 1, 2, \cdots, n$ are independent and identically distributed random variables, with probability density functions $f_{recv,i}(t)$.
4) The reliability of the business continuity measures does not change with time.

As shown in Figure 1, the business process comprises of the protection, mitigation, emergency and recovery phases. Since each phase has its own characteristics, different modelling approaches are needed for different

phase to capture the phase-specific characteristics. An example of integrated modeling framework is presented in Figure 2. The protection, mitigation and emergency phases determine the consequences of the disruptive event. Event trees can be used to model these phases [36]. In an event tree model, the probabilities of the intermediate events represent the reliabilities/uncertainties of the allocated business continuity measures. The outcomes of protection phase and mitigation phase depend on the reliabilities of the protection and mitigation measures, respectively, which, according to Assumptions 4, do not depend on time. Then, fault tree models can be used to calculate these intermediate probabilities [36]. The result of the emergency phase, on the other hand, involves the modeling of a sequence of activities by the emergency response team. Models capable of considering the sequential dynamics of such activities should be used for the emergency phase, e.g., the event sequence diagram [37]. The recovery process also involves the dynamics of maintenance actions, which can be effectively described in terms of the process of transitions between system states, e.g., by semi-Markovian models [38].

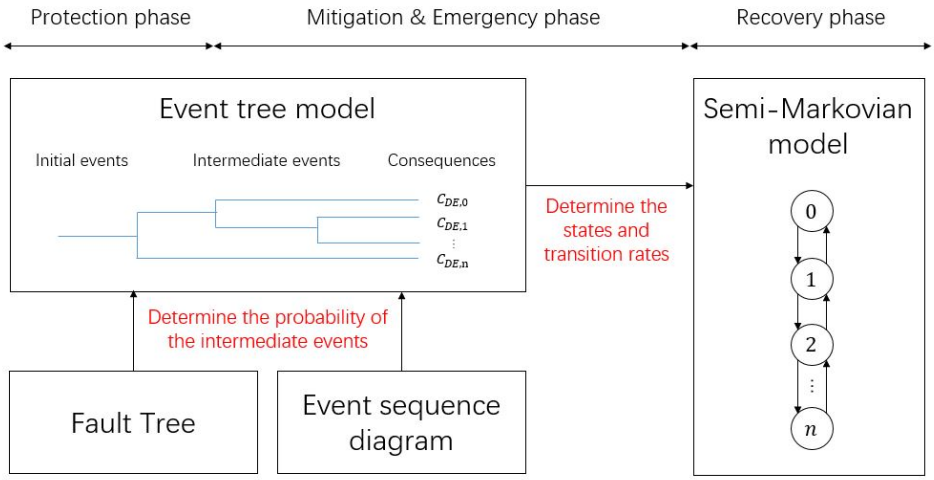

Fig. 2. An integrated model for business continuity assessment

1) Event tree model for the disruptive events and consequences: Event tree (see [36]) is used to model the disruptive events and consequences. In the event tree, the initial event is the disruptive event, which is assumed to follow a Poisson process with a rate parameter λ_{DE}. Each intermediate event represents the success or failure of a business continuity measure. The end events in the event tree represents the consequences of the disruptive events and are expressed as combinations of the states (success or failure) of the business continuity measures. The occurrence probabilities of the intermediate events associated with the protection and mitigation phases are determined by the reliability of these measures. Reliability models, e.g., Fault Tree Analysis (FTA) [36], can be used to calculate these probabilities. The occurrence probabilities of the intermediate events associated with the emergency phase, on the other hand, are calculated by the Event Sequence Diagram (ESD) [37], since the modeling of the emergency phase involves a sequence of activities taken by the emergency response team. As a result of the event tree modeling, the consequences of the disruptive event, $C_{DE,0}, C_{DE,1}, \cdots, C_{DE,n}$, and the probabilities of these consequences, denoted by $P_{C_0}, P_{C_1}, \cdots, P_{C_n}$, can be obtained. Based on the rule of the decomposition of Poisson processes [39], each possible consequence, $C_{DE,i}, i = 0, 1, \cdots, n$, can

be characterized by a Poisson process with the rate $\lambda_{DE} \cdot P_{C_i}$.

2) Event sequence diagram for emergency measures: ESD is a graphical visualization tool to describe the sequence of related events [37]. It has been applied widely to model emergency actions and assess the risk of domino effects after the initial damage event [40–42]. In ESD, events are classified into four categories [42]: initial events, which are the starting point of the evolution of the emergency process, e.g., a tank catches fire; delay events, which are used to model the time required to finish a certain job in the emergency response, e.g., the arrival of the fire brigade at the fire spot. Delay events can be further distinguished as deterministic delay events, which are used to describe a job with fixed working time, and random delay events, which are used to describe a job with random working time; comment events, which describe the development of an event sequence; and terminate events, which indicate the termination of an ESD, e.g., the occurrence /non-occurrence of domino effects.

Usually, ESD is used to model the escalation of accidents, i.e., domino effects, considering the presence of emergency response activities [37]. In ESD, domino effects are expressed by an event chain, starting from initial events to terminate events. The events are connected by logic gates to describe the emergency response activities. Four types of logic gates are considered in ESD, i.e., Output AND Gate, Input AND Gate, Output OR gate, Input OR gate [37]. The times associated with the output of the gates can be determined by the input times of the gate, as shown in Figure 3 [37].

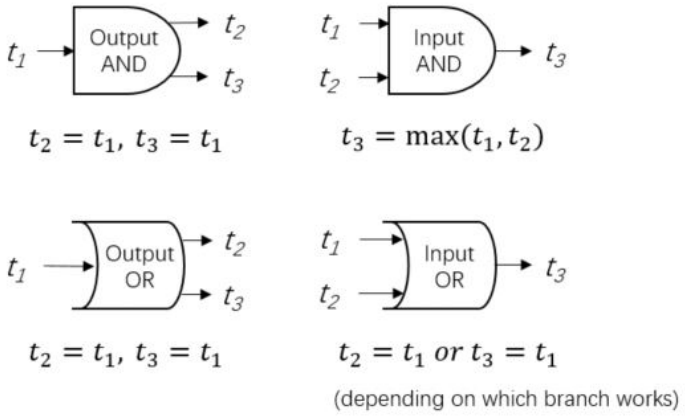

Fig. 3. Output times of the logic gates [37]

The probability of the domino effect, can, then, be calculated based on analytical or simulation procedures, as summarized in [37], which also determines the occurrence probability of the intermediate events associated with emergency measures in the event tree model.

3) Semi-Markovian model for the recovery process: The PPI_B of the business process is degraded by the disruptive events and recovers as a result of the recovery measures. From Assumption 3, the transition rates associated with the recovery process are not constant, since the recovery times do not follow exponential distribution. Hence, the evolution of the PPI_B is modeled by a semi-Markovian model [39], as shown in Figure 2. In the semi-Markovian model, the states $C_{DE,i}, i = 0, 1, \cdots, n$ correspond to the consequences of the disruptive events, obtained from the event tree analysis. The failure rates, $\lambda_{ij}, 0 \leq i \leq n-1, i < j$, are

determined based on the conditional probabilities of the consequences given the occurrence of the initial event of the event tree, which can also be yielded by the event tree analysis. According to Assumption 3, the recovery process is characterized by the probability density distribution of the recovery times, which should be estimated based on historical data or expert judgements.

Based on the developed models, the evolution of the PPI_B in the entire business process, which covers the protection, mitigation, emergency and recovery phases, can be simulated using Monte Carlo simulations [43]. The business continuity metrics can, then, be estimated by further considering the losses incurred in the business process, as described in (1) - (3).

B. A simulation-based method for business continuity assessment

Figure 4 demonstrates how to calculate the loss L associated with the ith disruptive event by simulating the developed integrated model. In Figure 4, $PPI_{B,cur}$ and $PPI_{B,nom}$ represent the PPI_B at current time and its nominal value, respectively. From Assumption 1, the arrival of the disruptive events follows a homogeneous Poisson process with rate parameter λ_{DE}. Therefore, t_{disp} is generated by simulating the next arrival time of a Poisson process with the parameter λ_{DE}. When a simulated disruptive event arrives, its consequence is determined based on the consequence probabilities calculated from event tree analysis. Based on the direct damage corresponding to each consequence, the values of $PPI_{B,cur}$ and L_D are updated. From Assumption 3, the recovery time t_{recv} can be generated from the probability density function $f_{recv,i}(t)$. When a recovery event occurs, the $PPI_{B,cur}$ is updated first, based on the effectiveness of the recovery process. Then, the indirect loss, L_I, is updated by considering the time spent in the previous degraded state.

The algorithm in Figure 4 is repeated N times and the empirical distribution of the BCV can be estimated based on these samples using (4). The numerical business continuity metrics defined in Section III can, then, be calculated from the empirical distribution of the BCV.

V. Application

A. System descriptions

In this section, we consider the crude oil storage tank farm originally reported in [34] as a case study, and apply the developed modeling framework to assess its business continuity. The tank farm is located in Tianjin, China, and its layout is illustrated in Figure 5 [34]. Ten External Floating Roof (EFR) storage tanks make up the tank farm, which is used to store crude oil. Each tank is 21.8 (m) in height and has a diameter of 80 (m). The main material of the floating roof and tank wall is #16 steel, whose thicknesses are 5 (mm) and 35 mm, respectively. The capacity of a single tank is 1×10^5 (m^3) and therefore, the tank farm has a total capacity of 1×10^6 (m^3) [34]. To remain operational at full capacity, all of the ten tanks must be in working state. Therefore, the number of working tanks is used as the PPI_B of the tank farm.

The business continuity assessment starts from the identification of potential disruptive events. According to [31, 44], lightning is the most frequently encountered disruptive event that could damage storage tanks. Hence, for illustrative purposes, we only consider lightning as the potential disruptive event in this paper. For an EFR tank that stores crude oil, two typical accident scenarios might be caused by lightning [34]:

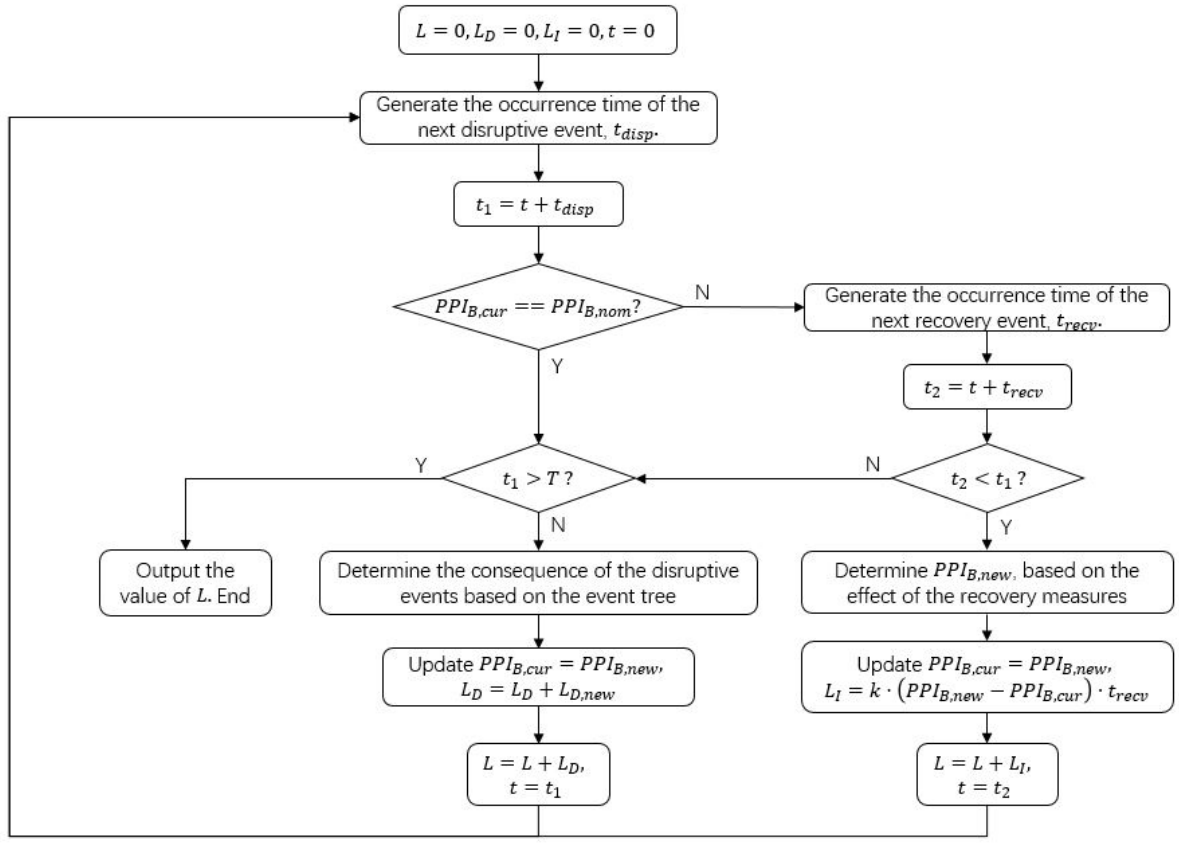

Fig. 4. A simulation-based method to calculate the loss caused by a single disruptive event

- direct puncturing of the tank wall, which leads to leakage and possible ignition of the leaked crude oil (pool fire);
- rim-seal fire, which is caused by the ignition of the flammable vapors by the lightning (full surface fire).

Both scenarios can escalate to cause more severe consequences and losses if not contained properly and promptly, as shown in Figure 6. For a detailed discussion on the escalation of the accident scenarios depicted in Figure 6, readers can refer to [34] and [32]. Protection, mitigation, emergency and recovery measures are designed to ensure the business continuity of the tank farm, as shown in Table I [32, 34].

B. Event tree model for the disruptive events and consequences

An event tree model is constructed in Figure 7 for a single tank throughout the protection, mitigation and emergency phases. In Figure 7, the initial event, a lightning stricking the tank farm, is assumed to follow a Poisson process with rate λ_L; P_{pro} is the probability that the protection mast successfully prevents the lightning from damaging the tank; P_{DD} is the probability that the arrived lightning strike results in a direct damage to the tank; P_{FV} is the probability that flammable vapors exist in the rim area. According to [34], flammable vapors are always present in the rim area of EFR tanks; therefore, we assume $P_{FV} = 1$; P_{AFES} is the probability that the automatic rim seal fire extinguishing system operates normally so that a rim-seal fire could be extinguished promptly; P_{FFS} is the probability that the fixed foam system operates normally so that a full surface fire could

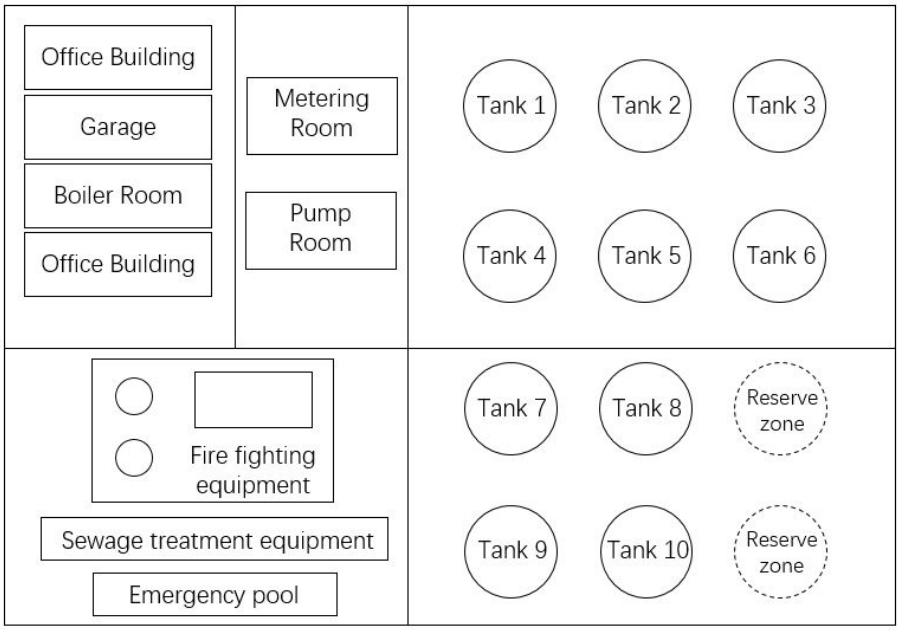

Fig. 5. Layout of the crude oil storage tank farm [34]

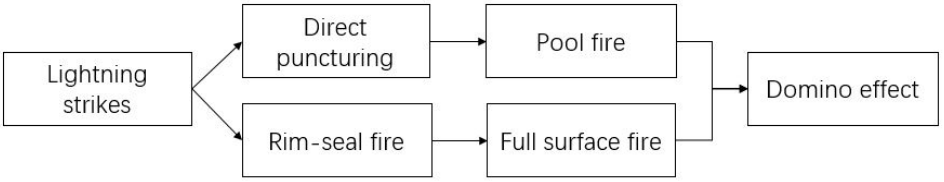

Fig. 6. Escalation of accident scenarios

be extinguished promptly; P_{FB} is the probability that the fire brigade arrives in time and works correctly so that the fires can be controlled before domino effects develop.

1) Determination of λ_L: According to [45], the arrival rate of the lightning strikes on a single tank can be calculated by

$$\lambda_S = N_G \cdot A_D \cdot C_D \times 10^{-6}. \tag{7}$$

In (7), N_G is the arrival rate of the lightning strikes per year per kilometer ($km^{-2} \cdot y^{-1}$); A_D is the equivalent receiving area (m^2) for the storage tank. Suppose R and H denote the radius and height of the tank, respectively. Then A_D is calculated by

$$A_D = \pi(R + 3H)^2 \tag{8}$$

The value of C_D, which represents the location factor of the building, can be determined from Table II [45].

In this case study, the N_G of Tianjin is estimated to be $2.82/km^2 \cdot y$ [34]. For each tank in the farm,

$$R = 40\ (m),\ H = 21.8\ (m).$$

Therefore, we have $A_D = 3.49 \times 10^4$. Since the tanks are obviously higher than the surrounding objects, we

TABLE I

THE BUSINESS CONTINUITY MEASURES OF THE TANK FARM

Category	Measures	Descriptions
Protection measures	Lightning protection mast	Lightning protection mast is used to protect the oil storage tank from damages caused by lightning.
Mitigation measures	Automatic rim seal fire extinguishing system	Automatic rim seal fire extinguishing system can detect and automatically fight against the rim-seal fire.
	Fixed foam system	Fixed foam system is automatically activated if the pool fire develops to full surface fire and aims at extinguishing full surface fires.
Emergency measures	Fire brigade	Fire brigade is the last defensive barrier to control the fire and prevent it from escalating to other tanks.
Recovery measures	Restore and / or replace the damaged tanks	The storage capability of the tank farm can be recovered by restoring or replacing the damaged tanks.

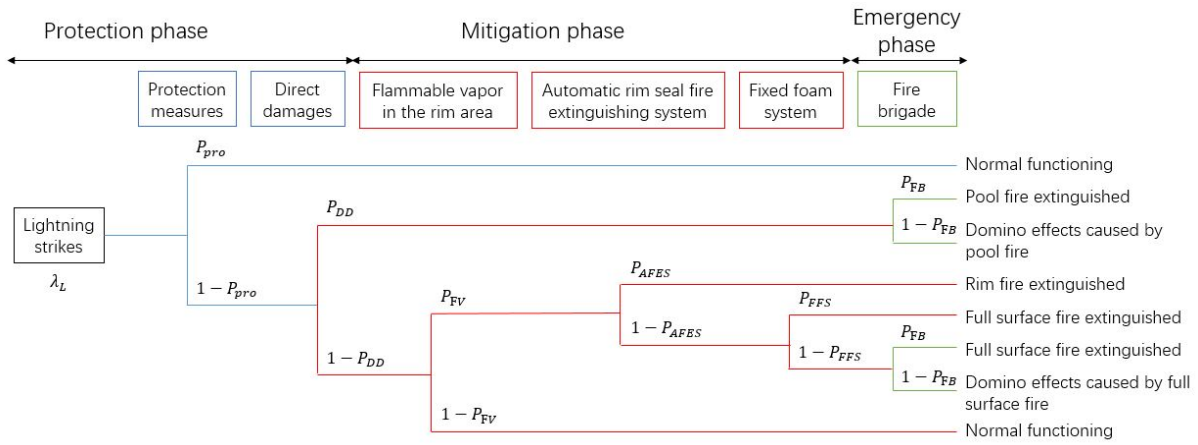

Fig. 7. Event tree model for the protection, mitigation and emergency phases

have $C_D = 1$. From (7), $\lambda_S = 9.842 \times 10^{-4}$ (y^{-1}). Finally, λ_L is determined by

$$\lambda_L = n \cdot \lambda_S,$$

where n is the number of working tanks. Therefore, we have $\lambda_S = 9.842 \times 10^{-3}$ (y^{-1}).

2) Determination of P_{pro}: Reference [33] develops a "capture model" to simulate the number of lightning strikes captured by a storage tank with known geometry. Based on the "capture model" and Monte Carlo

TABLE II

VALUES FOR C_D

Exposure degree of buildings and surrounding objects	C_D
Obviously lower than surrounding objects	0.25
Approach to surrounding objects	0.5
Obviously higher than surrounding objects	1
Isolated buildings on the hill	2

simulations, the reduction rate of the captured lightning strikes after the implementation of the protection masts can be assessed, which is equivalent to the P_{pro} in this paper [46, 47]. Based on their results, given the geometry of the storage tanks and the design information of the protection masts, the value of P_{pro} is $P_{pro} = 0.996$ [47].

3) Determination of P_{DD}: Direct damage of the tank is caused by the heat generated by the lightning strikes, which primarily depends on the peak current of the captured lightning strike. The generated heat would lead to the formation of hemispherical grooves on the walls or roofs of the tank [34]. If the amount of the generated heat is large enough, the radius of the grooves might be greater than the thickness of the walls or roofs, and leads to the perforation of them. Reference [48] points out that to cause direct perforation, the peak current of the captured lightning strike needs to exceed a threshold value, denoted by I_{th}, which is dependent on the thickness of the tank wall or roof, as shown in Table III.

TABLE III

I_{th} FOR DIFFERENT THICKNESSES OF TANK WALLS [48]

Thickness / mm	4	5	6	7	8	9	10
I_{th} / kA	95	158	273	442	666	943	1276

Reference [34] proposes an empirical relationship to calculate the probability that the peak current I_{peak} is greater than I,

$$lgP\left(I_{peak} > I\right) = -\frac{I}{88}. \tag{9}$$

In this case study, the thickness of the tank wall is 35 (mm) and the thickness of the roof is 5 (mm). Since the thickness of the tank wall is much higher than that of the roof, we only consider the possibility of the perforation of the roof in this paper. From Table III, $I_{th} = 158$ (kA); substituting it into (9), we have $P_{DD} = 1.6 \times 10^{-2}$ for the tanks in this case study.

4) Determination of P_{AFES} and P_{FFS}: The failure probabilities of similar AFES and FFS systems have been analyzed by Necci in [32], using fault tree analysis. Here, we use the reference values of P_{AFES} and P_{FFS} from [32], i.e., $P_{AFES} = 0.976, P_{FFS} = 0.993$.

5) Determination of P_{FB}: Fire brigade is the last safety barrier to prevent the fire from spreading to nearby tanks. If fire brigade fails to respond promptly and correctly, domino effects might arise, causing severe damages and losses. According to [37], the value of P_{FB} can be determined by the total response time of the fire brigade, denoted by T_{res}, which accounts for the whole duration from the occurrence of the initial fire to its extinguishment by the fire brigade. Cozzani et al. [49] proposed that to stop the full surface fire from spreading to the nearby tanks, the fire needs to be put off within $T_{th} = 17$ (min).

An ESD similar to that in [37] is constructed to describe the sequential behavior of the fire brigade, as shown in Figure 8. According to the survey in [50], the $T_i, i = 1, 2, \cdots, 5$ follow lognormal distributions with the parameters summarized in Table IV, where e and m are parameters of the lognormal distribution, whose probability density function is

$$f(x) = \begin{cases} \dfrac{1}{\sqrt{2\pi}\sigma x} e^{-\frac{(ln(x)-e)^2}{2m^2}}, & x > 0 \\ 0, & x \leq 0. \end{cases}$$

Then, the value of P_{FB} is calculated by Monte Carlo simulations, i.e., $P_{FB} = 0.693$.

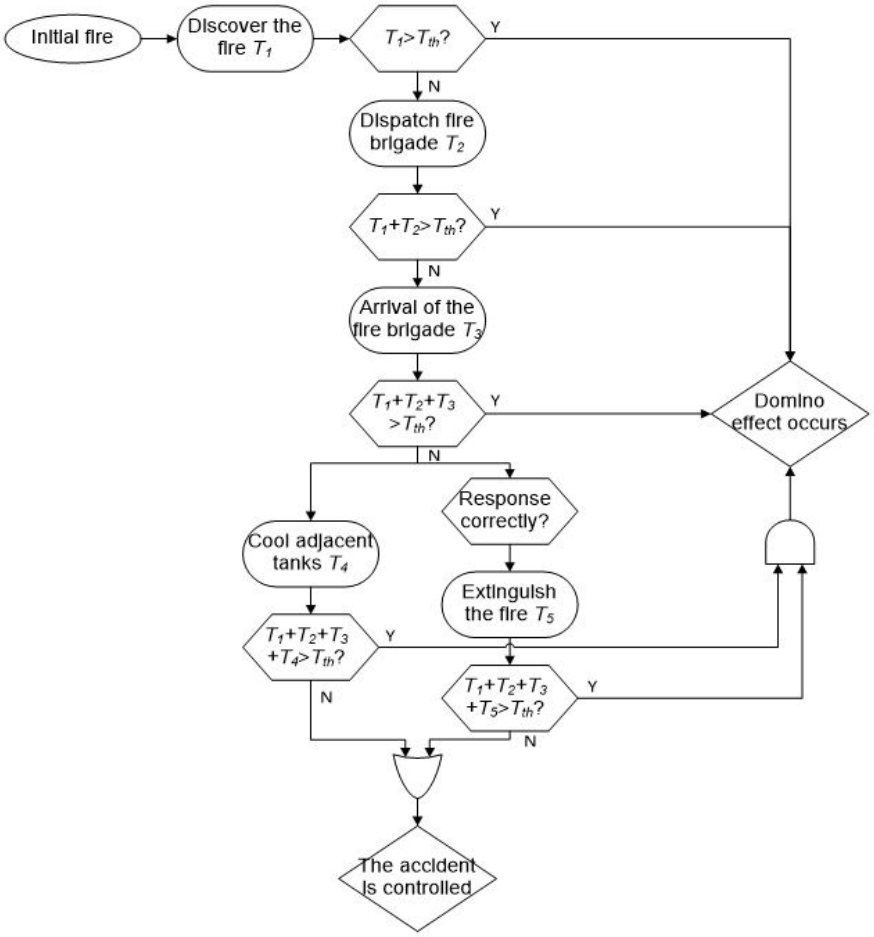

Fig. 8. Event sequence diagram of the emergency responses

TABLE IV

THE DISTRIBUTION OF THE EVENTS IN THE EVENT SEQUENCE DIAGRAM [50]

Event	e	m
T_1	1.30	0.40
T_2	0.88	0.78
T_3	1.56	0.31
T_4 / T_5	1.20	0.34

6) Calculate the probability of the consequences: Following the rules of event tree analysis [36], the conditional probability of each consequence given the occurrence of the initial event can be calculated, as shown in Table V.

C. Semi-Markovian model for the recovery process

The consequences $C_1, C_2, \cdots, C_6$, listed in Table V, can be further grouped into three categories, based on the number of affected storage tanks, as shown in Table VI. When the consequence of the lightning strike is C_6, there is no storage tank affected by the lightning. When the consequence of the lightning strike is C_1, C_3 or C_4, there are local damages to the hit tank, without spreading to domino effects: therefore, only one tank

TABLE V

THE PROBABILITIES OF THE CONSEQUENCES

Symbols	Consequence	Descriptions	$P_i = P(C_i$|a lightning strike has occurred)
C_1	Pool fire extinguished	A pool fire has occurred and extinguished; Local damage is caused to the tank hit by the lightning.	$P_1 = (1 - P_{pro})P_{DD}P_{FB}$
C_2	Domino effect caused by pool fire	Fire spread to the neighboring tanks; Damages are caused to the tank where the fire started and the four neighboring tanks.	$P_2 = (1 - P_{pro})P_{DD}(1 - P_{FB})$
C_3	Rim seal fire extinguished	A rim seal fire has occurred and extinguished; Local damage is caused to the tank where the incident occurs.	$P_3 = (1 - P_{pro})(1 - P_{DD})P_{FV}P_{AFES}$
C_4	Full surface fire extinguished	A full surface fire has occurred and extinguished; Local damage is caused to the tank where the incident occurs.	$P_4 = (1 - P_{pro})(1 - P_{DD})P_{FV}(1 - P_{AFES})(P_{FFS} + (1 - P_{FFS}P_{FB}))$
C_5	Domino effect caused by full surface fire	Fire spread to the neighboring tanks; Damages are caused to the tank where the fire started and the four neighboring tanks.	$P_5 = (1 - P_{pro})(1 - P_{DD})P_{FV}(1 - P_{AFES})(1 - P_{FFS}(1 - P_{FB}))$
C_6	Normal functioning	No damages are caused to any tank.	$P_6 = P_{pro} + (1 - P_{pro})(1 - P_{DD})(1 - P_{FV})$

is affected. When the consequence of the lightning strike is C_2 or C_5, the fire caused by the lightning spreads to the nearby tanks and domino effects are caused. In this paper, we assume that if domino effects occur, the number of affected tanks is 5.

TABLE VI

CLASSIFICATION OF THE CONSEQUENCES

Category	Consequences	Descriptions	Affected tanks
S_1	C_6	Normal functioning	0
S_2	C_1, C_3, C_4	Pool fire extinguished; rim seal fire extinguished; full surface fire extinguished	1
S_3	C_2, C_5	Domino effects caused by pool fire; domino effects caused by full surface fire	5

The number of available tanks is used as the PPI_B of the business process for the tank farm. When a tank is hit by the lightning or affected by domino effects, it becomes unavailable until it is repaired. Recovery measures should be performed to replace or restore the affected tank, so that it could return to normal operations. The behavior of the PPI_B is described in the state diagram in Figure 9, where the states represent the number of available tanks. As shown in Table VI, the PPI_B might degrade in two manners, i.e., either by S_2 or by S_3. Since the arrival of lightning strikes follows a homogeneous Poisson process with a rate λ_L, the transition rates associated with S_2 and S_3 are determined by the decomposition of Poisson processes [39], i.e., $\lambda_2 = P_{S_2}\lambda_L, \lambda_3 = P_{S_3}\lambda_L$. According to Table V and VI, $P_{S_2} = P_1 + P_3 + P_4, P_{S_3} = P_2 + P_5$. In this paper, for brevity, we just assume that only one tank can be repaired at a time and the recovery time t_{recv} follows a LogNormal distribution with a mean value 30 (d) and a standard deviation 5 (d). Since the transition rates

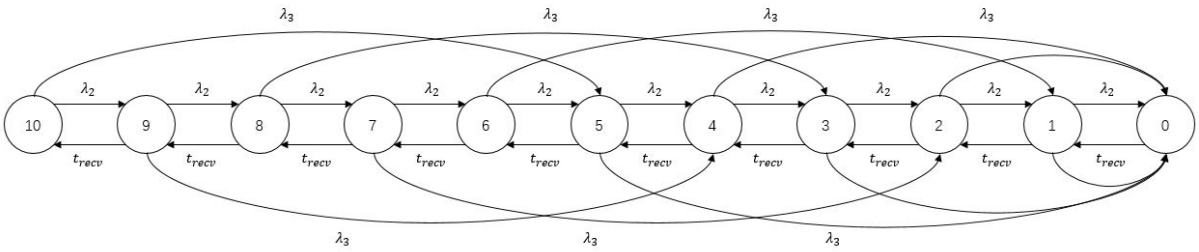

Fig. 9. Behavior of the PPI_B under the threat of lightning

of the recovery process are not constant while the transition rates of the degradation process are, the dynamics of the PPI_B, as described in Figure 9, follow a Semi-Markovian process. Simulation-based methods, such as those in [38], can be exploited to investigate the time-dependent behavior of the PPI_B.

D. Loss modeling and business continuity assessment

The losses an organization might suffer from the disruptive events include the direct losses and the indirect losses. In this case study, the direct losses depend on the number of affected tanks, denoted by n:

$$L_{D,i} = n \cdot k_{L_D}, \tag{10}$$

where k_{L_D} is the average direct damage per tank caused by lightning and domino effect. In this case study, for illustrative purposes, we assume that $k_{L_D} = 6$ (in arbitrary units) per tank.

The indirect losses are calculated using (2), where the number of available tanks is used as the PPI_B of the tank farm and the nominal PPI_B is 10. The indirect constant k is assumed to be 0.25 units per day per tank. That is, if n tanks are unavailable for N days, the organization would suffer $0.25 \times (10 - n) \times N$ units of indirect losses. The value of L_{tol}, which represents the maximum loss that an organization could withstand, should be determined considering the financial conditions of the organization. For the tank farm, we assume $L_{tol} = 15$ units for illustrative purposes. The simulation-based methods that are developed in Section IV-B are used to calculate the quantitative business continuity metrics, with a sample size of 10^6. The results and discussions are given in the next subsection.

E. Results and discussions

The results of the simulation are summarized in Figure 10, which displays the empirical distribution of BCV. BCV values are manly distributed in four regions (Region 1 - Region 4 in Figure 10):

- Most of the samples have a BCV equal to 1 (Region 1 in Figure 10), which indicates that no business interruption has been caused by the lightning (either no lightning strike hits the tank farm or the consequence of the lightning strike has been blocked by the protection measures so that no damage is caused).
- A closer examination at the samples that fall in Region 2 in Figure 10 reveals that for these samples, the lightning strike hits a tank and makes it catch fire. The fire is controlled promptly so that no domino effect results, which corresponds to state S_2 in Table VI. Moreover, the recovery process is smooth: no lightning

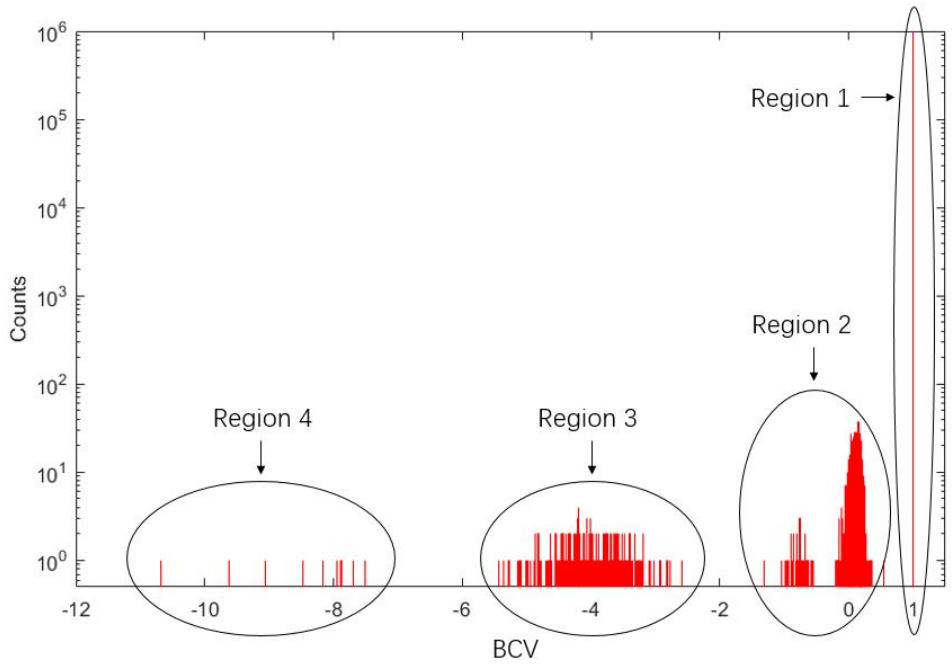

Fig. 10. Histogram of the BCV

strike hits the fire tank during the recovery process. Therefore, the mean value of BCV in this region is

$$1 - \frac{1 \times 6 + 0.25 \times 30}{15} = 0.867.$$

The scatter of this region is due to the variability of the recovery time.

- A similar analysis is done to the samples in Region 3. Most of the samples in this region suffer from domino effects (the state S_3 in Table VI). Therefore, the affected number of the storage tanks is 5. Moreover, the recovery process is smooth: no lightning strike hits the fire tank during the recovery process. Hence, the mean value of BCV in this region is

$$1 - \frac{5 \times 6 + 5 \times 0.25 \times 30}{15} = -3.5.$$

The scatter of this region is again due to the variability of the recovery time.

- The samples that fall in Region 4 suffer from more severe damages. For example, two or more lightning strikes hit the tank farm and cause domino effects. Therefore, there samples have much lower and more spread BCV values than in the previous cases.

The four numerical business continuity metrics can be calculated based on the simulation results:

$$\text{EBCV} = 0.9783, \text{SDBCV} = 0.2203, P_{BI} = 1.78 \times 10^{-2}, P_{BF} = 4.10 \times 10^{-3}.$$

For this case study, given the related assumptions and numerical values used for the parameters, we can conclude with high confidence that the tank farm would demonstrate high business continuity under the threat of lightning.

VI. Conclusion

This paper focuses on the quantitative modeling and assessment of business continuity. A conceptual model that divides the business process into four sequential phases, protection, mitigation, emergency and recovery, is

proposed as a foundation of the metrics and models for business continuity assessment. An integrated framework is developed to model business continuity. In the integrated model, the protection, mitigation and emergency phases are modeled by event tree models, where fault trees and event sequence diagrams are exploited for the characterization of the probabilities associated with the intermediate events. The recovery phase is modeled by a semi-Markovian model. A simulation-based method is developed to calculate the business continuity metrics based on the developed models. A case study on a crude oil storage tank farm demonstrates the applicability of the modeling framework.

In this paper, we only considered the system subject to a single disruptive event. In the future, the framework should be extended to multiple disruptive events. Moreover, we rely on event trees to describe the protection, mitigation and emergency phases. Since the event tree is a static model, it cannot capture the time-dependent dynamics and the dependencies among the events. In the future, more advanced models, such as Bayesian Networks, can be integrated into the framework to more realistically model some aspects of the business continuity. A framework can also be developed to identify major contributors to business continuity and determine optimal design solutions, so that the required business continuity can be achieved under the constraint of time and resources.

REFERENCES

[1] E. Zio, "Challenges in the vulnerability and risk analysis of critical infrastructures," *Reliability Engineering and System Safety*, vol. 152, pp. 137–150, 2016.

[2] A. Hameed, F. Khan, and S. Ahmed, "A risk-based shutdown inspection and maintenance interval estimation considering human error," *PROCESS SAFETY AND ENVIRONMENTAL PROTECTION*, vol. 100, pp. 9–21, MAR 2016.

[3] Y. Meng, C. Lu, Y. Yan, L. Shi, and J. Liu, "Method to analyze the regional life loss risk by airborne chemicals released after devastating earthquakes: A simulation approach," *PROCESS SAFETY AND ENVIRONMENTAL PROTECTION*, vol. 94, pp. 366–379, MAR 2015.

[4] G. L. L. Reniers and A. Audenaert, "Preparing for major terrorist attacks against chemical clusters: Intelligently planning protection measures w.r.t. domino effects," *PROCESS SAFETY AND ENVIRONMENTAL PROTECTION*, vol. 92, pp. 583–589, NOV 2014.

[5] T. Aven and L. A. Cox, "National and global risk studies: How can the field of risk analysis contribute?," *Risk Analysis*, vol. 36, no. 2, pp. 186–190, 2016.

[6] E. Zio, "Critical infrastructures vulnerability and risk analysis," *European Journal for Security Research*, pp. 1–18, 2016.

[7] M. Yang, F. Khan, L. Lye, and P. Amyotte, "Risk assessment of rare events," *PROCESS SAFETY AND ENVIRONMENTAL PROTECTION*, vol. 98, pp. 102–108, NOV 2015.

[8] M. Yang, F. Khan, and P. Amyotte, "Operational risk assessment: A case of the Bhopal disaster," *PROCESS SAFETY AND ENVIRONMENTAL PROTECTION*, vol. 97, pp. 70–79, SEP 2015.

[9] F. Khan, S. Rathnayaka, and S. Ahmed, "Methods and models in process safety and risk management: Past, present and future," *PROCESS SAFETY AND ENVIRONMENTAL PROTECTION*, vol. 98, pp. 116–147, NOV 2015.

[10] T. Bjerga and T. Aven, "Some perspectives on risk management: A security case study from the oil and gas industry," *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 2016.

[11] "Costs and scope of unplanned outages." http://http://www.evolven.com/blog/costs-and-scope-of-unplanned-outages.html.

[12] "Downtime, outages and failures - understanding their true costs." http://http://www.evolven.com/blog/downtime-outages-and-failures-understanding-their-true-costs.html.

[13] V. Cerullo and M. J. Cerullo, "Business continuity planning: a comprehensive approach," *Information Systems Management*, vol. 21, no. 3, pp. 70–78, 2004.

[14] International Organization for Standardization (ISO), "Societal security – business continuity management systems," 2012.

[15] B. Herbane, "The evolution of business continuity management: A historical review of practices and drivers," *Business history*, vol. 52, no. 6, pp. 978–1002, 2010.

[16] G. A. Zsidisin, S. A. Melnyk, and G. L. Ragatz, "An institutional theory perspective of business continuity planning for purchasing and supply management," *International journal of production research*, vol. 43, no. 16, pp. 3401–3420, 2005.

[17] C. Castillo, "Disaster preparedness and business continuity planning at boeingan integrated model," *Journal of Facilities Management*, vol. 3, no. 1, pp. 8–26, 2005.

[18] F. Gibb and S. Buchanan, "A framework for business continuity management," *International Journal of Information Management*, vol. 26, no. 2, pp. 128–141, 2006.

[19] S. Snedaker, *Business continuity and disaster recovery planning for IT professionals*. Newnes, 2013.

[20] K. Randeree, A. Mahal, and A. Narwani, "A business continuity management maturity model for the uae banking sector," *Business Process Management Journal*, vol. 18, no. 3, pp. 472–492, 2012.

[21] D. Faertes, "Reliability of supply chains and business continuity management," *Procedia Computer Science*, vol. 55, pp. 1400–1409, 2015.

[22] N. Sahebjamnia, S. A. Torabi, and S. A. Mansouri, "Integrated business continuity and disaster recovery planning: Towards organizational resilience," *European Journal of Operational Research*, vol. 242, no. 1, pp. 261–273, 2015.

[23] G. Parise, E. Hesla, L. Parise, and R. Pennacchia, "Switching procedures and business continuity management: The flock logic of multiple source systems," *IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS*, vol. 52, no. 1, pp. 60–66, 2016.

[24] S. A. Torabi, R. Giahi, and N. Sahebjamnia, "An enhanced risk assessment framework for business continuity management systems," *Safety Science*, vol. 89, pp. 201–218, 2016.

[25] M. Rabbani, H. R. Soufi, and S. A. Torabi, "Developing a two-step fuzzy costbenefit analysis for strategies to continuity management and disaster recovery," *Safety Science*, vol. 85, pp. 9–22, 2016.

[26] W. Boehmer, C. Brandt, and J. F. Groote, "Evaluation of a business continuity plan using process algebra and modal logic," in *Science and Technology for Humanity (TIC-STH), 2009 IEEE Toronto International Conference*, Science and Technology for Humanity (TIC-STH), 2009 IEEE Toronto International Conference, pp. 147–152, IEEE, 2009.

[27] C. Brandt, F. Hermann, and T. Engel, "Modeling and reconfiguration of critical business processes for the purpose of a business continuity management respecting security, risk and compliance requirements at credit suisse using algebraic graph transformation," in *Enterprise Distributed Object Computing Conference Workshops, 2009. EDOCW 2009. 13th*, Enterprise Distributed Object Computing Conference Workshops, 2009. EDOCW 2009. 13th, pp. 64–71, IEEE, 2009.

[28] Y. Asnar and P. Giorgini, "Analyzing business continuity through a multi-layers model," in *Business Process Management*, Business Process Management, pp. 212–227, Springer, 2008.

[29] E. C. Bonafede, P. Cerchiello, and P. Giudici, "Statistical models for business continuity management," *Journal of Operational Risk*, vol. 2, no. 4, pp. 79–96, 2007.

[30] Y. Tan and S. Takakuwa, "Use of simulation in a factory for business continuity planning," *International Journal of Simulation Modelling*, vol. 10, no. 1, pp. 17–26, 2011.

[31] J. I. Chang and C.-C. Lin, "A study of storage tank accidents," *Journal of loss prevention in the process industries*, vol. 19, no. 1, pp. 51–59, 2006.

[32] A. Necci, F. Argenti, G. Landucci, and V. Cozzani, "Accident scenarios triggered by lightning strike on atmospheric storage tanks," *Reliability Engineering and System Safety*, vol. 127, pp. 30–46, 2014.

[33] A. Necci, G. Antonioni, V. Cozzani, E. Krausmann, A. Borghetti, and C. Alberto Nucci, "A model for process equipment damage probability assessment due to lightning," *Reliability Engineering and System Safety*, vol. 115, pp. 91–99, 2013.

[34] D. Wu and Z. Chen, "Quantitative risk assessment of fire accidents of large-scale oil tanks triggered by lightning," *Engineering Failure Analysis*, vol. 63, pp. 172–181, 2016.

[35] M. Bruneau, S. E. Chang, R. T. Eguchi, G. C. Lee, T. D. O'Rourke, A. M. Reinhorn, M. Shinozuka, K. Tierney, W. A. Wallace, and D. von Winterfeldt, "A framework to quantitatively assess and enhance the seismic resilience of communities," *Earthquake spectra*, vol. 19, no. 4, pp. 733–752, 2003.

[36] E. Zio, *An introduction to the basics of reliability and risk analysis*, vol. 13. World scientific, 2007.

[37] J. Zhou, G. Reniers, and N. Khakzad, "Application of event sequence diagram to evaluate emergency response actions during fire-induced domino effects," *Reliability Engineering and System Safety*, vol. 150, pp. 202–209, 2016.

[38] M. Compare, F. Martini, S. Mattafirri, F. Carlevaro, and E. Zio, "Semi-markov model for the oxidation degradation mechanism in gas turbine nozzles," *IEEE Transactions on Reliability*, vol. 65, no. 2, pp. 574–581, 2016.

[39] S. M. Ross, *Introduction to probability models*. Academic press, 2014.

[40] A. Necci, V. Cozzani, G. Spadoni, and F. Khan, "Assessment of domino effect: State of the art and research needs," *Reliability Engineering and System Safety*, vol. 143, pp. 3–18, 2015.

[41] B. Abdolhamidzadeh, C. R. C. Hassan, M. D. Hamid, S. FarrokhMehr, N. Badri, and D. Rashtchian, "Anatomy of a domino accident: Roots, triggers and lessons learnt," *Process Safety and Environmental Protection*, vol. 90, no. 5, pp. 424–429, 2012.

[42] S. Swaminathan and C. Smidts, "The event sequence diagram framework for dynamic probabilistic risk assessment," *Reliability Engineering and System Safety*, vol. 63, no. 1, pp. 73–90, 1999.

[43] E. Zio, *The Monte Carlo simulation method for system reliability and risk analysis*. Springer, 2013.

[44] E. Renni, E. Krausmann, and V. Cozzani, "Industrial accidents triggered by lightning," *Journal of Hazardous Materials*, vol. 184, no. 1-3, pp. 42–48, 2010.

[45] International Electrotechnical Commission (IEC), "Protection against lightning," 2010.

[46] A. Necci, G. Antonioni, V. Cozzani, A. Borghetti, and C. A. Necci, "Reduction of natech risk due to lightning by the use of protection systems," *Chemical Engineering Transactions*, 2014.

[47] A. Necci, G. Antonioni, V. Cozzani, A. Borghetti, and C. A. Nucci, "Quantification of risk reduction due to the installation of different lightning protection solutions for large atmospheric storage tanks," *Chemical Engineering Transactions*, 2013.

[48] DEHN, "Lightening protection guide, 2nd edition," 2014.

[49] V. Cozzani, G. Gubinelli, G. Antonioni, G. Spadoni, and S. Zanelli, "The assessment of risk caused by domino effect in quantitative area risk analysis," *Journal of hazardous Materials*, vol. 127, no. 1, pp. 14–30, 2005.

[50] P. Chen, "The statistics law of fire response time and its correlation with the scale of urban fire," *University of Science and Technology of China*, 2010.