A Resilience-Based Approach for the Prevention and Mitigation of Domino Effects

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Chapter 7
A Resilience-Based Approach for the Prevention and Mitigation of Domino Effects

7.1 Introduction

The chemical industry is pivotal for welfare, industrial production and daily life by providing various chemical products such as gasoline, benzene, and natural gas.[1] Most of these chemical products are usually flammable, combustible, and toxic, and are stored, transferred, and processed via different equipment and installations within a chemical plant. These hazardous materials make process plants vulnerable to disruptions, with the possibility of major accidents such as fire, explosion, and/or hazardous release [3–8].

Several types of disruptions are possible: unintentional accidents, natural disasters, and intentional attacks [3, 9, 10]. Unplanned disruptions are induced by unintentional events such as mechanical failure, corrosion, fatigue, and human errors. For instance, the Intercontinental Terminal Company Tank Fire in March 2019 at Deer Park in the US was triggered by an unloading operation [11]. Compared with accidental disruptions, natural hazard-related disasters may lead to more severe consequences due to the damage of multiple chemical facilities at once, safety barriers, and other emergency response infrastructures. The damage to industrial facilities induced by natural disasters is called the "Natech event" [12, 13]. For example, Hurricane Harvey in 2017 led to the release of the contents of at least 18 hazardous storage tanks in Texas [14, 15]. Both accidental disruptions and the disruptions caused by natural hazards are unintentional, while intentional attacks may aim to cause damage to chemical facilities deliberately. For instance, on June 26, 2015, two tanks in a France chemical plant were damaged due to an intentional attack by using explosive devices [16].

Many studies dealing with unintentional and intentional disruptions have been conducted. Types of various measures were explored w.r.t. disruptions such as

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[1] This chapter is mainly based on two publications: Chen et al. [1, 2].

C. Chen et al., *Integrating Safety and Security Management to Protect Chemical Industrial Areas from Domino Effects*, Springer Series in Reliability Engineering,
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inherent safety [17–21], hazard identification [22, 23], safety risk assessment [24–27], Natech risk assessment [10, 28, 29], security risk assessment [30–33], safety barrier management [34–36], security measure management [37–39], emergency response [40–42], integrated safety and security management [43–45], etc. No matter what the disruption is, the primary undesired scenario caused by the disruption may escalate to installations nearby, leading to a chain of accidents, resulting in the overall consequences more severe than the primary event, the so-called "domino effects" [46]. Chapters 2, 3, 4 and 5 provide models for assessing domino effects, and Chaps. 5, 6 develop an approach to manage escalation effects using safety and security measures. Safety and security management aims to reduce the likelihood and consequences caused by undesired events for avoiding and mitigating human loss, economic loss, environmental loss, etc. However, domino effects caused by intentional attacks or natural disasters may be unpredictable and unpreventable due to the simultaneous failure of multiple installations. Only considering safety and security measures may not be sufficient to deal with unpredictable or unpreventable domino effects. This chapter thus provides a resilience approach to manage domino effects, considering safety measures, security measures as well as adaptation measures, and restoration measures. In this chapter, a methodology for quantifying the resilience of chemical plants, considering the dynamic stochastic evolution of disruptions due to domino effects, adaptation performance, and the dynamic restoration process. This chapter is organized as follows: Sect. 7.2 introduces the concept of resilience and defines chemical plant resilience, and introduces the possible measures to enhance the resilience of chemical plants. A stochastic dynamic methodology for quantifying the chemical plant resilience is elaborated in Sect. 7.3. Section 7.4 develops an algorithm to obtain chemical resilience. Finally, the conclusions drawn from this study are present in Sect. 7.5.

7.2 Chemical Plant Resilience

7.2.1 Resilience Concept

The term "resilience" originated from the Latin word "resiliere" which refers to the bounce back from disruptions [47]. Based on the original meaning of "resiliere", a narrow definition of resilience can be obtained: "the ability of a system to recover to a normal condition or a new stable equilibrium after an event disrupts from its original state" [48]. Unlike the concept focusing on the recovery capability of a system, Holling [49] defined resilience as "the ability to absorb disruptions without dramatic change. The definition thus focuses more on the ability of a system to withstand disruptions and maintain its functions". Integrating the elements in the above two definitions, National Infrastructure Advisory Council [50] defined a more comprehensive definition: the ability to predict, absorb, adapt, and/or quickly recover from disruptions. Many other definitions of resilience are also available in the literature

[6, 47, 48], but no identical definition of resilience exists in the academic domain [47]. According to these definitions, the abilities (metrics) of a resilient system for responding to unexpected disruptions can be summarized as follows [51–53]:

- Absorptive ability: the ability of a system to resist, absorb, or withstand the impact of disruptive events;
- Adaptive ability: the ability of a system to adapt itself to maintain its operational performance after disruptions without any recovery activity;
- Recovery ability: the capability of a system to repair or restore damages from a disruption to recover the loss performance of the system, making the system reach a new stable equilibrium.

In recent years, resilience is becoming a more active and substantial research topic in the safety and security domain. Resilience engineering aims to enhance a system's capabilities to absorb, adapt, and recover from a disruption, and reduce the impacts of the disruptions on the system's performance. Safety and security management may be used to enhance absorption capability while has no direct impacts on adaption and recovery capabilities. Safety and security management is not as wide as that of resilience management/engineering. In terms of unpredictable or indefensible threats (e.g., terrorist attacks and natural disasters), enhancing the resilience capability is an ideal approach to reduce the losses caused by disruptions and to quickly recover a system's performance. [54].

The advancements of resilience engineering can considerably contribute to process safety and security [7, 53, 55–57]. Past research attempts on resilience in the process industry identified process resilience influence factors [57, 58], resilience hazards [59–61], and hired quantification of process resilience using Bayesian network [6, 54, 62]. However, little attention has been paid to chemical plant resilience in which escalation effects may play an essential role [53, 63]. Consequently, a new definition of chemical plant resilience will be provided in this chapter.

7.2.2 A Definition of Chemical Plant Resilience

Resilience has been used in various industries and systems, such as ecological systems [49], communities [64], and container terminals [65]. In light of possible catastrophic effects in the chemical and process industry, we define chemical plant resilience as the ability of a chemical plant to resist, mitigate, adapt and recover from undesired events to maintain its operation. Unlike safety and security in the process and chemical industry that aims to prevent and mitigate undesired events, chemical plant resilience intends to enhance a system's capability to anticipate and prepare for disruption and its ability to adapt and recover from the disruption. In other words, chemical plant resilience aims to prevent disruptions, withstand and mitigate their consequences during the evolution of disruptions and quickly recover their functions after disruptions. To enhance chemical plant resilience, Resilience measures may be

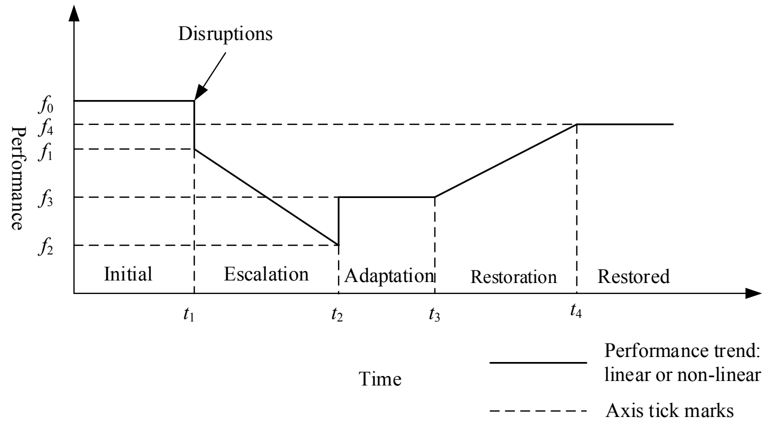


Fig. 7.1 Chemical plant performance varies over time (adapted from Henry and Emmanuel Ramirez-Marquez [66])

implemented in different stages to resist the impacts of an undesired event, mitigate the consequences by preventing possible domino effects, and adjust operation strategies to improve the operation performance before recovery and to rapidly recover the plants. Figure 7.1 shows the chemical plant performance response to a disruption.

As shown in Fig. 7.1, the chemical plant performance evolves, and the entire process from a disruption to restoration is called a resilience evolution scenario. For a disruption event, there may be multiple resilience evolution scenarios since the uncertainties in the vulnerability of installations, hazardous scenario escalation, emergency response, adaptation strategies, and restoration strategies. A resilience evolution scenario of a chemical plant can be divided into six stages: initial stage, disruption stage, escalation stage, adaptation stage, restoration stage, and restored stage. The chemical plant performance decreases in the disruption stage and the escalation stage while increasing in the adaptation and restoration stage. Before the occurrence of a disruption event, the chemical plant is in the initial stage in which the performance is the initial value f_0. When a disruption occurs, the chemical plant performance may decrease immediately and cause major accident scenarios due to the damage to one or more hazardous facilities. Primary major accident scenarios may trigger secondary and higher-order major accident scenarios, the so-called domino effects, damaging the installations nearby and further decreasing the performance of the chemical plant. When the escalation of domino effects ends at t_2, the residual performance reduces to the minimum value f_2. Then, the chemical plant may change its operation strategies to adapt to the new state and thus improve its performance. For instance, a chemical plant may utilize reserve equipment or adjust production processes to partly or fully offset the reduced performance. The last resilience stage is restoration, in which the performance of the chemical plant is recovered by repairing or rebuilding the damaged installations ($t_3 \sim t_4$). In Fig. 7.1 the performance is not fully recovered after the restoration stage at t_4. In general, the performance at the end of the restoration stage may be in three possible states: the recovered performance is equal to the initial performance (fully recovered), the recovered performance is less than the initial performance (partly recovered, usually, this is the case in industrial practice, see also Fig. 7.1), and the recovered performance is greater than the initial performance (overly recovered). In real cases, the performance of a recovered chemical plant may then be different from the plant in the initial stage.

7.2.3 Resilience Metrics

According to the definition of chemical plant resilience, resilience metrics should characterize the ability to withstand and resist disruptions, the ability to prevent the escalation of a disruption event, the ability to adapt to the disrupted condition, and the ability to quickly recover from the disruption. Combining the definition and the performance curve in Fig. 7.1, it can be demonstrated that the resilience of chemical plants mainly depends on two factors: chemical plant performance and evolution time. As a result, the essential step to quantify chemical plant resilience is to quantify the change of chemical plant performance over time during a resilience evolution scenario. Based on the resilience framework proposed by Bruneau et al. [64], the expected resilience loss of a chemical plant can be expressed as the expected degradation in performance over time, and resilience thus can be represented by the expected resilience loss divided by the planned resilience. Therefore, we define the chemical plant resilience as a dimensionless ratio, as follows:

$$R = \frac{\int_{t_1}^{t_4} f(t)}{f(t_0)(t_4 - t_1)} \tag{7.1}$$

$f(t)$ is the chemical plant performance function which depends on resilience evolution time (t); $f(t_0)$ is the performance at the initial stage (planned performance). The numerator of Eq. (7.1) represents the accumulation of chemical plant performance $f(t)$ during a resilience evolution process (between t_1 (disruption) and t_4 (fully recovered)). The denominator represents the accumulation of the planned performance $f(t_0)$ from t_1 to t_4.

Equation (7.1) only addresses one resilience evolution scenario. Due to the uncertainties in resilience evolution, there may be many resilience evolution scenarios that can be seen as different performance curves. Considering a total of X resilience evolution scenarios and the maximum value of t_4 of all the scenarios being $t_{\max}$, the resilience metrics considering uncertainties can be obtained, as follows:

$$R = \frac{1}{X}\sum_{i=1}^{X} \frac{\int_{t_1}^{t_{\max}} f(t)}{f(t_0)(t_{\max} - t_1)} \tag{7.2}$$

In Eq. 7.2, t_4 is substituted with $t_{\max}$ to unify the integration interval and avoid overestimating the resilience evolution scenarios with longer resilience evolution time or underestimating the resilience evolution scenarios with shorter resilience evolution time. According to Eq. 7.2, the most resilient chemical plant (R is equal to 1) is an ideal condition in which a disruption event does not lead to any performance degradation. In such case, the impact of the disruption on the chemical plant is fully absorbed, and the chemical plant continuously maintains its initial performance. On the contrary, R is equal to zero when the chemical plant is damaged by the disruption, the performance immediately drops to zero, and adaptation and recovery are impossible. Usually, the resilience value of R is between 0 and 1. It should be marked that t_4 is the time the system is fully recovered if the performance at the end of the restoration exceeds the initial performance. In that case, the maximum recovered performance at t_4 can not exceed its initial performance, and R is no more than 1. Although the resilience metrics is established by the case of chemical plants, it may be applied to other infrastructure systems with catastrophic effects by substituting infrastructure system performance functions for the chemical plant performance function $f(t)$.

7.2.4 Capabilities of Chemical Plant Resilience

According to the performance evolution curve shown in Fig. 7.2 and the resilience metrics shown in Eq. (7.2), chemical plant resilience capabilities consist of resistance capability, mitigation capability, adaptation capability, and restoration capability. Therefore, the resilience of a chemical plant can be improved by resistance measures,

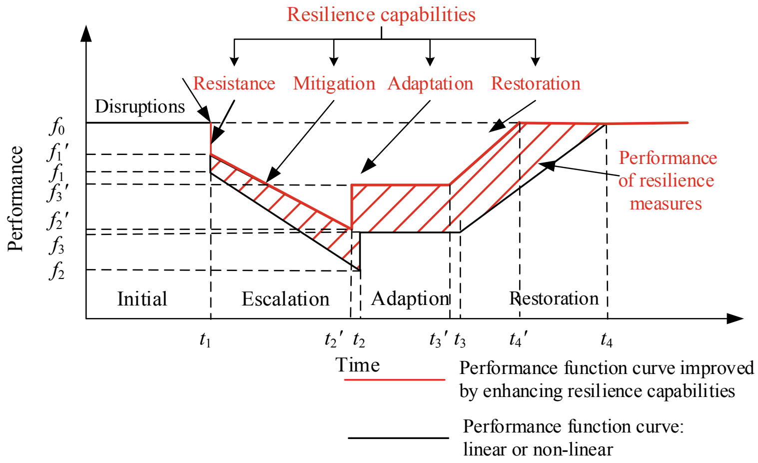


Fig. 7.2 Chemical plant performance improved by resilience capabilities (Chen et al. [1])

mitigation resilience, adaptation measures and restoration measures, as shown in Fig. 7.2.

(1) Resilience capability

Resistance capability is the capability to withstand disruption events, avoid failure of installations, and maintain performance. Similar to the prevention capability in safety and security management, various measures can improve resistance capability, and different measures may be taken for tackling different disruptions. For instance, installing lightning masts around installations and installing air terminals on the installations can prevent the damage of installations caused by lightning strikes [5, 67]; while detection measures such as closed-circuit television (CCTV) cameras can be used to detect illegal invasions and accidental scenarios [16, 38]. By implementing resistance measures, resistance capability can be improved and thus increase the value of f_1 in Fig. 7.2, enhancing resilience.

(2) Mitigation capability

Mitigation capability is the capability to prevent the escalation of possible major accident scenarios caused by disruptions. Mitigation capability is essential for chemical plants with many hazardous infrastructures due to possible domino effects. In this chapter, the mitigation capability only refers to the capability to prevent and mitigate domino effects. In contrast, the capability to mitigate the performance loss in the disruption stage is considered in resistance capability. As a result, any measures that can be used to prevent and mitigate domino effects can be applied to enhance mitigation capability, such as active measures (e.g., fire sprinkler system), passive measures (e.g., fireproof coating), procedural and emergency response (e.g., firefighting) [3, 68, 69]. Under the protection of mitigation capability, possible domino effects may be prevented or mitigated, leading to a higher value of f_2 and a shorter time between t_1 and t_2, thus reducing the performance degradation and improving the resilience.

(3) Adaptation capability

Adaptation capability is the capability to adapt to a new operation state to wholly or partly recover the chemical plant performance before restoration. At the end of the escalation stage, chemical plants may adjust operation strategies (e.g., utilizing reserve equipment and speeding inventory turnover ratio) to partly or fully recover the chemical plant performance. To enhance adaptation capability, a chemical plant can provide reserve equipment and prepare multiple operation strategies under the lack of installations. By using these measures, the adaptation capability can be enhanced, and the value of f_3 in Fig. 7.2 can be increased, resulting in the increase of chemical plant performance before the restoration of the chemical plant.

(4) Restoration capability

Restoration capability refers to the capability to quickly repair or rebuild the damaged installations to recover the chemical plant performance. The restoration capability mainly depends on the time to fully recover (*TTR*). Therefore, shortening the *TTR* (t_3–t_4) can effectively reduce the lost performance and achieve a more resilient chemical plant. To shorten the restoration time, a chemical plant may formulate restoration plans, establish a maintenance team, or reach contact with construction companies. Once a disruption occurs, these precautions can help the chemical company to save time and obtain a quick recovery.

7.3 A Quantification Framework of Chemical Plant Resilience

Chemical plants are industrial infrastructures that manufacture, process, and storage chemical materials. The performance of a chemical plant mainly depends on its operation and products. For instance, hazardous material storage plants are industrial facilities for storing hazardous chemicals such as petroleum, benzene, and other chemical products. These products are delivered to end-users, process facilities, and other storage facilities. As a result, the total storage volume of the plant or the average daily chemical flow rate at the initial stage of a hazardous material storage plant can be used to represent the chemical plant performance. According to the chemical plant performance, the performance function $f(\mathrm{t})$ can be established by quantified the capability of resistance, mitigation, adaptation, and restoration.

Based on the description of chemical plant resilience capability, the next section is to develop a framework to quantify the resilience metrics by modeling these resilience capabilities. Modeling the resilience capabilities based on the performance curve is the crucial step to quantify the resilience of a chemical plant.

7.3.1 Resistance Modeling

Resistance is the capability to withstand disruptions, avoid being damaged and retain performance [52]. From the perspective of safety and security management, resistance may be deemed the antonym of vulnerability which represents the inability of an installation to withstand disruptions and the consequent failures [70]. The vulnerability of installations is usually characterized by the failure probability of installations exposed to disruption events. Therefore, the resistance capability of an installation can be represented by the probability that an installation successfully resistant to a disruption event, as follows:

$$C_r = 1 - P_f \tag{7.3}$$

C_r represents the resistance capability of the installation exposed to a disruption event, P_f represents the failure probability of an installation exposed to the disruption. In a chemical plant, there are usually multiple installations situated nearby. A disruption event such as an explosion [16] or a natural disaster may lead to simultaneous failure of multiple installations, resulting in a sudden degradation of chemical plant performance (from f_0 to f_1). f_1 is the performance of the chemical plant with undamaged installations, as shown in Fig. 7.1. According to *Cr,* the damaged installations in the disruption stage of each resilience evolution scenario can be determined by sampling random numbers based on Monte Carlo simulation. Consequently, the total performance at t_1 (f_1) can be obtained according to the damaged performance in the disruption stage (f_{di}), as follows:

$$f_1 = f_0 - f_{di} \tag{7.4}$$

To determine the failure probability of an installation, we need to conduct a vulnerability assessment for all the installations. For a specific installation, the vulnerability of an installation depends on the type and intensity of disruptions.

7.3.2 Mitigation Modeling

Domino effects are a discriminate phenomenon within the process and chemical industry whereby many hazardous installations are usually located nearby. Domino effects may occur due to the escalation of accident scenarios (e.g., fire and explosion) caused by disruptions. The spatial–temporal evolution of domino effects can lead to consequences more severe than the primary disruption. The mitigation ability of chemical plants thus refers to preventing and mitigating the escalation of major accident scenarios. When one or more hazardous installations are damaged and leads to loss of containment of hazardous materials, major hazards such as fire and explosion can occur, resulting in the nearby installations exposed to escalation vectors such as heat radiation and overpressure. Once the escalation vectors damage the nearby installations, the major accident scenarios may propagate, resulting in a chain of accidents and decreased performance. To avoid the failure of installations caused by domino effects, safety barriers such as passive barriers, active barriers, and emergency response barriers may be implemented [68, 69]. Passive fire protection measures refer to these safety measures that do not need external activation to trigger the protection functions for controlling fire or delaying fire escalation, such as fireproof coating and pressure safety valves. These barriers are based on different mechanisms and thus have different performances for improving mitigation capability. In terms of active protection measures, external activations are needed to trigger the protection function, such as the water spray system (WSS) and relief valves. The third safety barrier is emergency response actions. Emergency response actions such as firefighting teams are essential to prevent domino effects while a time-lapse is needed for the emergency response team to arrive. The emergency response measures can be considered a socio-technical system with some uncertainties since the procedural events depend on human behavior. The performance of these safety barriers has been illustrated in Chap. 5. Applying the Domino Evolution Graph (DEG) model in this study, we can obtain the time t_2 (at the end of the escalation stage) and the failure likelihood of installations due to domino effects. Based on the failure probability, random numbers should be sampled again to determine the failure installations in one resilience evolution scenario. Then the total performance (f_2) can be obtained according to the damaged installations in the disruption and escalation stages, as follows:

$$f_2 = f_1 - f_{es} \tag{7.5}$$

f_2 denotes the chemical plant performance at the end of the escalation stage, and f_{es} represents the performance loss due to the escalation of domino effects. Enhancing the mitigation capability can raise f_2 and/or decrease t_2, thus improving chemical plant resilience.

7.3.3 Adaptation Modeling

In the chapter, adaptation capability refers to operation adjustments, which can lead to improved chemical plant performance. These operation strategies include utilizing reserve installations, speeding inventory turnover ratio, adjusting chemical production strategies, etc. The first operation adjustment needs to add reserve ones for vulnerable installations. Once an installation is damaged, the reserve installation can quickly replace the damaged installations and thus increase the chemical plant performance. Speeding the inventory turnover ratio can increase the daily chemical flow rate and thus reduce the effect of damaged installations on the chemical plant performance. Adjusting chemical production strategies may decrease the dependence of operation on damaged installation. These adaptation strategies can be used alone or in combination according to the adaptation capabilities of chemical plants. To increase the adjustment strategies, adaptation measures should be taken in advance. By the available adaptation strategies, the loss of chemical plant performance caused by the disruption and the sequential cascading effect may be partially or fully recovered, as follows:

$$f_3 = f_2 + f_{ad} \tag{7.6}$$

f_3 represents the chemical plant performance after adaptation; f_{ad} denotes the increased performance induced by adaptation strategies.

7.3.4 Restoration Modeling

The degradation of performance may be partly, fully, or overly recovered by restoring the damaged chemical plant. In this chapter, all the damaged installations are considered to be reconstructed. In this stage, the key indicator to character the restoration capability is the time to full recovery (TTR) since the reconstruction of installations is a complex and time-consuming process. The restoration capability increases with decreasing the construction time. For instance, the construction of a hazardous material storage tank includes many steps: installing the tank bottom, installing the hydraulic jacking system, installing the tank roof, assembling and lifting the first ring (top) of the tank wall, assembling and lifting the second ring of the tank wall, installing the accessories. Each step of the construction needs several days. The total construction time depends on many factors, such as the construction method, the number of people, and resources invested in the construction. Besides, the restoration sequence may also influence the TTR if multiple installations are damaged. To shorten the restoration time, a company can invest in restoration capability such as formulating restoration plans, establishing a maintenance department, and reach cooperation with reliable construction companies. After restoration, the chemical plant performance can be expressed as follows:

$$f_4 = f_3 + f_{re} \tag{7.7}$$

f_4 represents the chemical plant performance after adaptation; f_{re} denotes the increased performance induced by restoration. In this chapter,f_4 is assumed to equal tof_1.

7.4 Simulation Algorithm

Based on the quantification framework illustrated in Sect. 7.3, this section develops an algorithm to obtain the resilience of chemical plants exposed to disruptions. Due to the uncertainties in the disruption stage and the escalation stage, dynamic Monte Carlo is employed to generate resilience evolution scenarios. Figure 7.3 shows the flow diagram of the dynamic-stochastic algorithm. Firstly, initial parameters need to be inputted in the program, such as the number of iterations N, the disruption time $t_1 = 0$, the initial iteration $n = 1$. Besides, the needed information and data related to the chemical plant are also required, such as the performance of the chemical plant, the installations, and the layout of the chemical plant. Given a disruption, vulnerability analysis will be conducted by using the method illustrated in Sect. 7.3.1. Based on the vulnerability analysis, we can obtain the failure probability of installations exposed to the disruption. According to the failure probabilities, a set of random data (between 0 and 1) is sampled to determine the damaged installations. Each installation is assigned a random value. If the random value is less than the failure

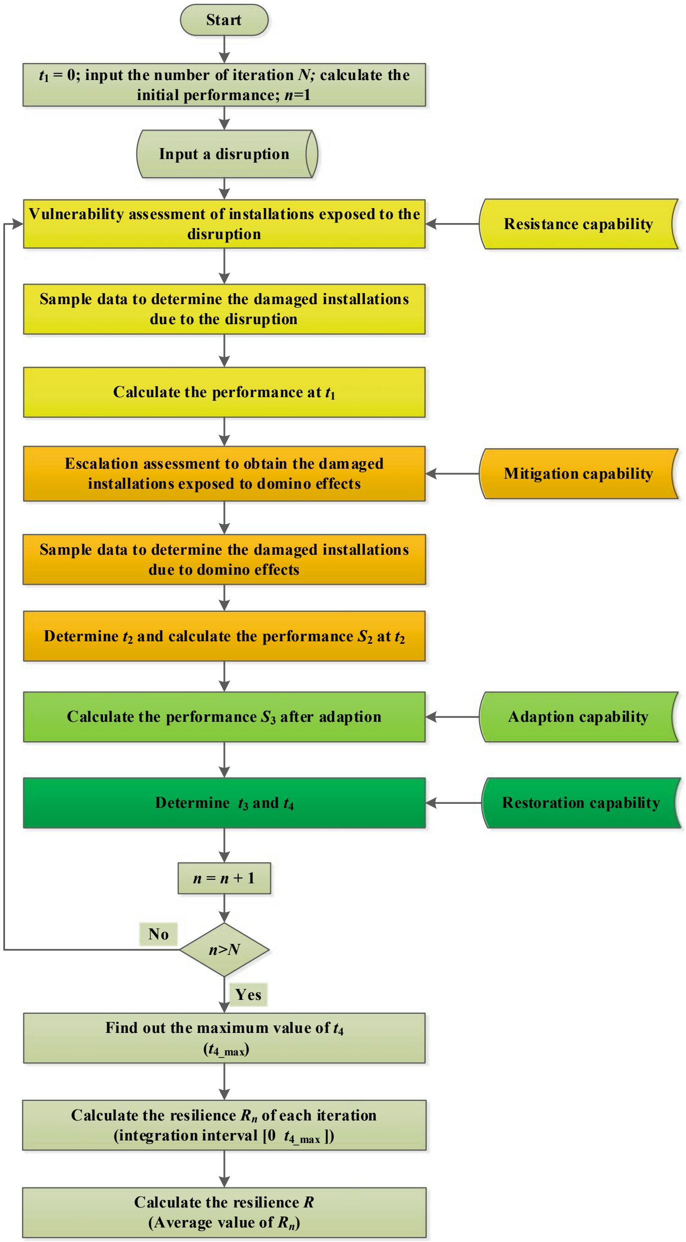


Fig. 7.3 Flow diagram of the algorithm for obtaining chemical plant resilience (Chen et al. [1])

probability, the installation is considered damaged; otherwise, the installation is not damaged. The chemical plant performance should then be updated by subtracting the performance delegation caused by the damaged installations. Next, the possible escalation is assessed using the escalation assessment method illustrated in chapter 2. By the escalation analysis, the failure probability of installations caused by domino effects and the time at the end of the escalation stage can be obtained. According to the results of the escalation analysis, the chemical plant performance at the end of the escalation stage can be calculated. Thirdly, possible adaptation strategies will be determined, and the improved performance induced by the implementation of adaptation measures needs to be determined. Following the adaptation strategy, the restoration strategy should be determined to obtain the start time (t_3) and end time (t_4) of restoration. In that case, a resilience evolution scenario represented by a performance curve (t_1–t_4) can be obtained. The above steps will be repeated until n exceeds N. When the loop ends, we can obtain a total of N resilience evolution scenarios. The maximum value of t_4 ($t_{\max}$) of all the evolution scenarios will be regarded as the upper limit of the integral interval for calculating the resilience value of each scenario. According to the integral interval $[0, t_{\max}]$ and the resilience metrics illustrated in Sect. 7.2.3, the resilience value of each scenario can be obtained. Finally, the resilience can be obtained according to Eq. (7.2), considering the dynamic resilience evolution process and uncertainties in the disruption and escalation stages.

7.5 Case Study

In this section, the procedures of the developed resilience approach are illustrated by a case of a chemical storage plant. There are two fuels (gasoline and diesel) in 14 storage tanks (numbering T1–T14). Figure 7.4 shows the layout of the chemical storage plant and Table 7.1 lists the characteristics of the 14 storage tanks. The total storage volume in the initial stage (initial) is 30500 m^3. The flow rate of gasoline and diesel is 1088.6 m^3/d (3×10^8 kg/y) and 658.6 m^3/d (2×10^8 kg/y), respectively. The inventory turnover ratio of the storage farm is 20.9. Assuming that the average value of *TER* (μ) is 15 min and the variance (σ) is 5 min.

Assume that a disruption of an intentional explosion occurs in the chemical storage plant, represented by a red asterisk in Fig. 7.4. The attack is induced by a suitcase bomb with an improvised explosive device (IED) and the explosion is assumed to be equivalent to 23 kg TNT [71]. Once the attack results in tank damage, a suspended time (t_2–t_3) of 30 days is assumed for incident investigation, preparation for restoration. In the restoration stage, the damaged tanks are sequentially rebuilt according to the tank volume (descending order). According to the illustrated information and data. steps to assess the resilience of the chemical storage plant will be illustrated below.

Fig. 7.4 Layout of the oil tank farm (Chen et al. [1])

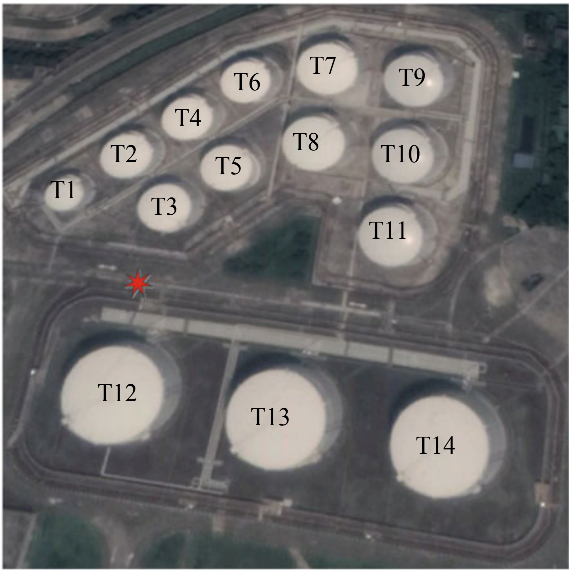


Table 7.1 Characteristics of storage tanks

Tank	Type	Dimensions (m)	Volume (m^3)	Material	Density (kg/m^3)	Restoration time (day)
T1	Atmospheric, fixed-roof	8.9 × 8.0	500	Diesel	832	15
T2–T5	Atmospheric, floating-roof	11.5 × 12.0	1000	Gasoline	755	30
T6	Atmospheric, fixed-roof	11.5 × 9.6	1000	Diesel	832	30
T7–T11	Atmospheric, fixed-roof	15.7 × 10.4	2000	Diesel	832	60
T12–T14	Atmospheric, floating-roof	21.7 × 16.0	5000	Gasoline	755	150

7.5.1 Resistance Analysis

According to the resilience-based approach, the first step is to analyze the resistance capability to a disruption. The failure probability of tanks exposed to the explosion can be obtained by using the TNT equivalency method and probit models illustrated in Chap. 3. Figure 7.5 shows the damage probability of tanks exposed to the explosion disruption.

As shown in Fig. 7.5, the tanks (T3 and T12) close to the explosion point have much higher damage probabilities than other tanks. In other words, T3 and T12 are more likely to be directly damaged by the explosion while other tanks have a high

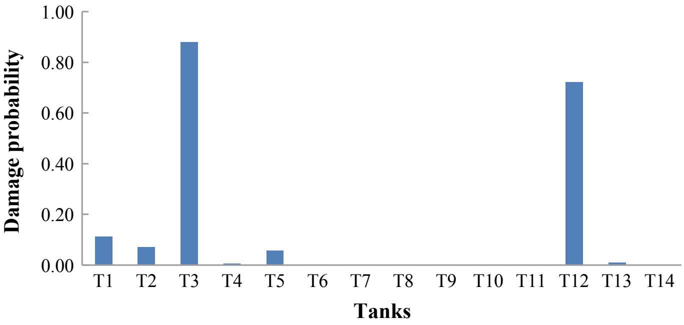


Fig. 7.5 Damage probability of tanks exposed to an IED

probability to survive in the disruption stage. According to the developed algorithm, in a resilience evolution scenario, the damaged tanks can be obtained by sampling 14 random numbers (between 0 and 1) and comparing the random numbers with the damage probabilities, respectively. Given a resilience evolution scenario that only T12 is damaged by the explosion, the total storage capability decreases from 30,500 to 25,500 m^3.

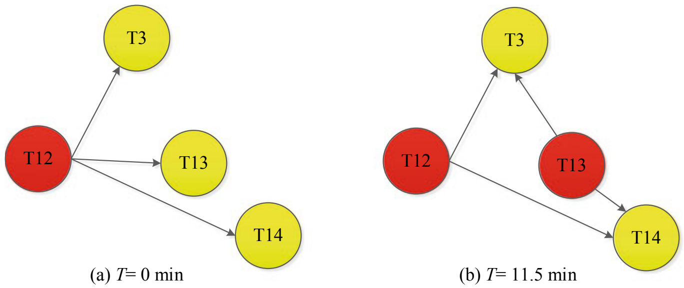
7.5.2 *Mitigation Analysis*

Although only T3 and T12 have a high damage probability (>0.5) in the disruption stage while other tanks may be damaged by domino effects in the escalation stage. The explosion may induce fire on the damaged tanks and the heat radiation generated by the damaged tank to other tanks is obtained by using the ALOHA software [72], as shown in Table 7.2.

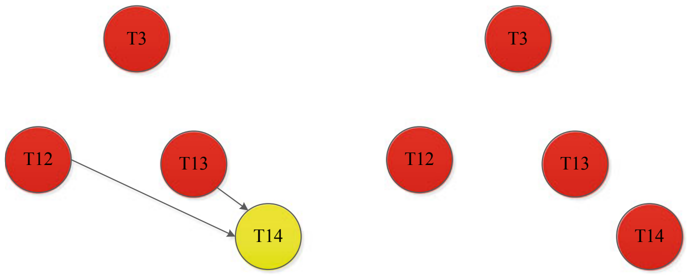
According to the potential heat radiation intensities, fire-escalation can be analyzed using the dynamic graph approach developed in Chap. 2. For instance, if only T12 in a resilience evolution scenario is damaged in the disruption stage according to the developed algorithm, then the following fire on T12 may trigger a fire scenario on T13 and subsequently leads to fires on T3 and T14, as shown in Fig. 7.6. T12 is damaged by the explosion, resulting in a fire on T12 at $T = 0$ min. Then, the heat radiation generated by T12 leads to a fire on T13 at $T = 11.5$ min, followed by T3 at $T = 16.5$ min and T14 at $T = 19.9$ min. Due to possible domino effects, the storage performance may further decrease. Given the instance shown in Fig. 7.6, the storage capacity decreases from 25,500 to 14,500 m^3.

Table 7.2 The heat radiation (kW/m^2) from installation *i* to installation *j* (Chen et al. [1])

Tank *i*, *j*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0	11	6	0	0	0	0	0	0	0	0	0	0	0
2	19	0	18	18	11	6	0	0	0	0	0	0	0	0
3	11	18	0	11	18	0	0	0	0	0	0	0	0	0
4	6	18	11	0	18	18	6	7	0	0	0	0	0	0
5	0	11	19	19	0	11	5	13	0	0	0	0	0	0
6	0	0	0	15	9	0	13	13	0	0	0	0	0	0
7	0	0	0	8	8	21	0	18	18	11	0	0	0	0
8	0	5	7	10	18	21	18	0	11	17	11	0	0	0
9	0	0	0	0	0	6	18	11	0	17	5	0	0	0
10	0	0	0	0	6	5.5	11	17	17	0	18	0	0	0
11	0	0	0	0	6	0	0	11	5	18	0	0	0	0
12	9	7	12	5	7	0	0	0	0	0	5	0	17	5
13	0	0	8	0	6.3	0	0	5	0	5	10	17	0	18
14	0	0	0	0	0	0	0	0	0	5	10	5	18	0



(a) *T*= 0 min (b) *T*= 11.5 min



(c) *T*= 16.5 min (d) *T*= 19.9 min

Fig. 7.6 A domino effect caused by the damage of T12 (Chen et al. [1])

7.5.3 Adaptation Analysis

Adaption measures such as utilizing reserve tanks and speeding inventory turnover ratio can compensate for the performance loss caused by a disruption before the storage plant is restored. However, the adaption capability is limited by the storage equipment (reserve tanks), loading, and unloading facilities. The performance loss may not be fully restored by using adaptation strategies. In this case study, the inventory turnover is assumed to be increased by 20% after the escalation stage. Following the instance in Sect. 7.5.2, the storage capacity increases from 14,500 to 17,400 m^3 by speeding the inventory turnover ratio.

7.5.4 Restoration Analysis

Restoration is the final stage of a resilience evolution scenario. According to the restoration time of different tanks shown in Table 7.1, we can obtain the entire performance curve of a resilience evolution scenario, as shown in Fig. 7.7. The storage plant's storage performance decreases from 30,500 to 25,500 m^3 due to the damage of T12 exposed to the explosion at $T = 0$ min. In the escalation stage, the storage performance further decreases from 25,500 to 14,500 m^3 since T13, T3, and T14 are sequentially damaged by the domino effect. At the end of the escalation stage, an adaptation strategy is used, resulting in an increase of storage performance from 14,500 to 17,400 m^3. Finally, T12, T13, T14, and T3 are sequentially restored, leading to a recovery of storage performance.

Figure 7.7 only shows one possible resilience scenario. Applying the developed algorithm in this chapter, we can obtain many evolution scenarios due to uncertainties in resilience. Then, according to Eq. (7.2), we can obtain the chemical storage plant's resilience value of 0.85.

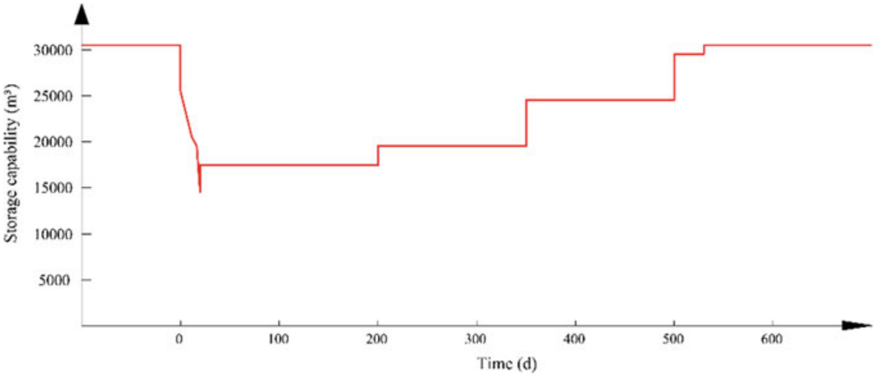


Fig. 7.7 Performance curve of a resilience evolution scenario (Chen et al. [1])

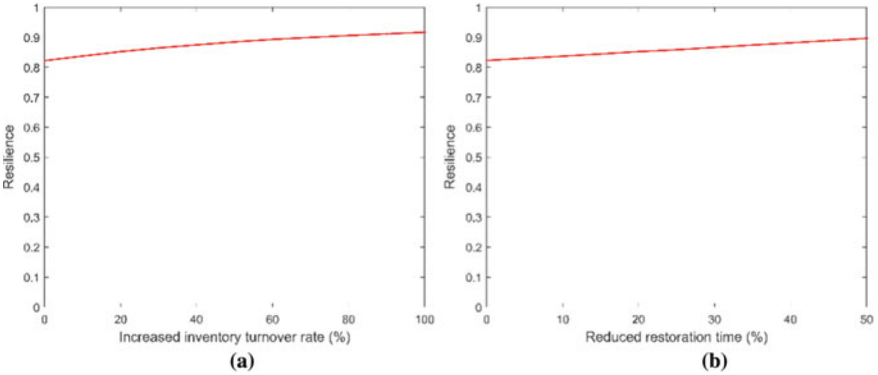


Fig. 7.8 Resilience performance of **a** speeding inventory turnover ratio and **b** reducing restoration time

7.5.5 *Resilience Measure Performance*

According to the resilience-based approach developed in this chapter, the performance of different resilience measures can be quantified to support resilience management. Figure 7.8 shows the performance of (a) speeding inventory turnover ratio and (b) reducing restoration time on the chemical storage plant's resilience. The resilience increases with increasing the inventory turnover ratio and with decreasing restoration time. Besides adaptation restoration measures, safety barriers can also be used to enhancing resilience by preventing and mitigating domino effects. Figure 7.9 shows the resilience performance of a safety barrier (emergency response). The resilience increases with the reduction of the mean value of the time needed for emergency response (u).

7.6 Conclusions

This chapter proposes a dynamic stochastic approach to quantify the resilience of chemical plants, considering possible escalation effects, adaptation strategies, and the recovery of damaged chemical plants. In this approach, a dynamic stochastic resilience process (called a resilience evolution scenario) is divided into four stages: disruption, escalation, adaption, and restoration stages. The uncertainties in the vulnerability of installations exposed to disruptions, major accident escalations, and emergency response are considered. A dynamic Monte Carlo method is used to generate possible resilience evolution scenarios and obtain chemical plant resilience. Compared with traditional safety and security management methods, the resilience-based method highlights the roles of adaptation capability and restoration capability in tackling unpredictable and unpreventable disruptions. According to the developed approach, the uncertainties in the resilience process cannot be ignored; domino

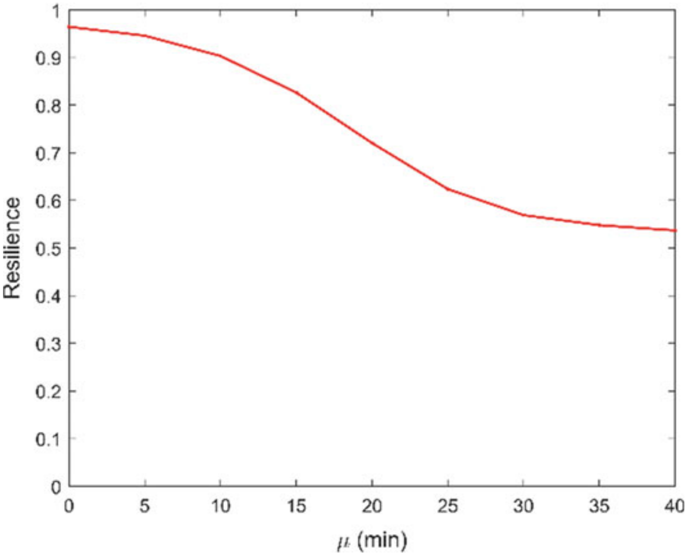


Fig. 7.9 Resilience performance of enhancing emergency response capability

effects play an essential role in chemical plant resilience; All the resilience measures, such as safety barriers used in the escalation stage, speeding inventory turnover in the adaptation stage, and shortening the restoration time in the restoration stage is effective for dealing with domino effects.

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