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Resilience-based approach to maintenance asset and operational cost planning

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ABSTRACT

Reliability-based and risk-based methods for directing maintenance activities play a critical role in ensuring system safety and reducing unnecessary downtime. Those methods focus on preventive maintenance to avoid component failures and are applicable before unexpected disruptions occur. However, when disruptions are unavoidable, more attention should be paid to systems' recovery from unwanted changes. As a remedy of preventive maintenance, improving system restoration capacity of resilience through optimizing the system's maintenance asset and operational cost is an efficient way to help system restore from disruption conditions within an optimal cost. In this paper, a resilience-based approach is proposed to optimize maintenance asset and operational cost. A novel resilience metric is developed and utilized to quantify system resilience under various restoration capacities. The minimal acceptable resilience level (MARL) and maximal acceptable restoration time (MART) are proposed to determine the optimal maintenance cost. The proposed approach is applied to the Chevron Richmond refinery crude unit and its upstream process. The results show that it can help practitioners identify the optimal cost to ensure a system is resilient to respond to uncertain disruptions and provide a dynamic resilience profile to support decision-making.

1. Introduction

Chemical process systems play an essential role in meeting people's daily energy and materials demands. To enhance productivity, modern electromechanical process systems become more automated and complex so that non-linear interdependencies, tight couplings, and possibly dysfunctional components failure may exhibit more frequently (Khan et al., 2020; Mamudu et al., 2021; Misuri et al., 2021; Landucci et al., 2017; Yang, 2018). Ensuing uncertainty, complex interaction, and interdependence between components (e.g., human, technical, and organizational elements) have become prominent and less graspable risk factors in process systems. This makes systems vulnerable to uncertain disruptions.

Preventive maintenance aims to keep equipment and asset operating normally and avoid costly downtime from unexpected failures (Zhen et al., 2021; Han et al., 2019; Abubakirov et al., 2020; Schmitz et al., 2020). These methods are developed based on reliability, vulnerability, and risk metrics (Xiao et al., 2022). They focus on measuring the probability of failure or failure rate based on degradation models and historical data. Nevertheless, to ensure system safety, we may need to shift the focus to analyzing a system's ability to handle uncertain disruptions under varying conditions. When internal (e.g., component failure, human error, etc.) or external disruptions (e.g., cyber-attack, internal or external attack, intentional attack, natural disasters, etc.) cannot be avoided and accurately predicted, improving the system restoration capacity is a remedy (Chen et al., 2021; Jain et al., 2018a). Since restoration is an essential

Abbreviations: MARL, minimal acceptable resilience level; MART, maximal acceptable restoration time; C, maintenance cost; M_a, maintenance asset; O_c, operational cost; DBN, dynamic Bayesian network; PRF, performance response function; R_0, initial resilience of a system at T_0; R_1, the minimal resilience at T_1; R_2, the system resilience after adaptation at T_2; P_0, initial performance of a system at t_0; P_1, the minimal performance at t_1; P_2, the system performance at t_2; P_3, the performance at t_3; f_1t, the function of system performance decreases after disruptions; f_2t, the function of system performance increase with adaptation measures; f_3t, the function of system performance caused by maintenance activities; RT, response time; T_D, fault diagnosis time; T_{RA}, resource allocation time; R_S, system resilience; n,, number of emergency teams; t, the required time for maintenance activities; C_1, the money needed to assemble an emergency team and required facilities; C_2, the money consumed per maintenance team per hour during maintenance activities

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part of system resilience, it is natural to adopt resilience measures in maintenance planning.

Resilience plays a vital role in ensuring system safety and mitigating functionality loss; it minimizes system vulnerability for any disruption. Due to uncertain disruptions, installing resilience strengthening measures is a potential way to reduce system performance loss and enhance system safety. Unlike risk assessment, resilience extends, covering the pre-disturbance and post-accident phases. Resilience as a novel paradigm has attracted the attention of scholars (Hosseini et al., 2016; Qi et al., 2021; Pramoth et al., 2020; JesúsNúñez-López et al., 2021; Jamaluddin et al., 2018; Sun et al., 2021). Zhang et al. (2022) proposed a resilience-based approach, considering resilience efficiency importance measure (REIM) and maintenance efficiency measure (MEM), to determine the optimal maintenance strategy for a horizontal subsea Christmas tree system. Okoh and Heagen (2015) examined what robustness and resilience exist in maintenance activities and how to enhance them, and thus reinforce the resilience of process systems. Azadeh et al. (2017) developed a comprehensive method, including analytical hierarchy process (AHP), k-means clustering, and data envelopment analysis (DEA), to assess the resilience of maintenance organizations. Besides, to determine the performance factors, a questionnaire is designed to obtain the relevant data. Jain et al. (2019) proposed a data-driven-based approach, considering energy consumption, maintenance costs, to assess a model for survival of a process system under disruptive situations by utilizing the Process Resilience Analysis Framework. Ghaffarpour et al. (2018) presented a resilience-based approach to improve the resilience of the water and energy hub scheduling system to address disruptions and maintenance programs. Tong et al. (2020) proposed a probabilistic indicator-based approach that separately identifies the indicators of absorption (e.g., redundancy), adaptation (e.g., flexibility), and restoration capacities (e.g., safety culture), respectively, to assess the system resilience. However, the basis of the indicator-based approach is to identify the indicators for each capacity. This inevitably introduces subjective factors, leading to uncertainty in the results. Thus, in the proposed methodology, the performance-based method models the system based on its structure, which can reduce uncertainty. The availability is employed to represent the system performance. Besides, a new resilience metric is proposed in the developed methodology to assess the system resilience. Moreover, the focus of the proposed approach is on restoring the system to a safe range with an optimal maintenance cost C. This study focuses on the maintenance cost optimization problem; while Tong et al. (2020) was concerned with quantifying the system resilience using a probabilistic indicator-based approach.

Most of the current models for assessing the resilience of complex systems assume that the resilience of the system will recover to or exceed its original state after disruptions. Few studies considered the influence of limited maintenance cost Con system resilience for a given absorption and adaptive capacity. Maintenance cost C is composed of two parts: maintenance asset M_a and operational cost O_c. Maintenance asset M_a refers to manpower, facilities, equipment, and other non-consumable materials (Xiao et al., 2022); Operational cost O_c indicates materials, money, and other consumables consumed during maintenance activities. When it is challenging to increase absorption capacity and adaptation capacity of system resilience by improving the system structure, it becomes essential to enhance system restoration capacity within an optimal maintenance cost C to strengthen system resilience. Hence, a resilience-based approach is proposed to address this important missing area for chemical process systems.

The developed methodology aims to improve restoration capacity of system resilience through optimizing the system's maintenance cost C to ensure that a system can restore to the minimal acceptable resilience level (MARL) within an optimal maintenance cost C. The remainder of this paper is organized as follows. The introduction of resilience is presented in Section 2. A brief description of the proposed method, including the dynamic Bayesian network (DBN), how to determine the performance response function (PRF) of the system, and how to determine the optimal maintenance cost based on system resilience, is given in Section 3. An illustrative example of a chemical process system is conducted in Section 4, and the corresponding results and discussions are provided in Section 5. Finally, Section 6 is a brief conclusion along with future work.

2. Resilience

Resilience comprises three primary capacities: absorption, adaptation, and restoration (Tong et al., 2020; Cai et al., 2021; Jain et al., 2018b). Absorption is the intrinsic capacity of a system to withstand and resist a disruption. It can absorb the influence and mitigate the consequence caused by disruptions. Under constant disturbance intensity, the absorption capacity of different systems is different. The strength of absorption capacity depends on the design of the system, e.g., the system structure. Absorption reduces the rate of system performance degradation when disruption is unavoidable. More specifically, greater absorption capacity reduces the performance loss of a system and therefore requires less effort and resources after a disruption. Adaptation is an inherent ability of a system to adapt to a disruptive situation. It allows recovering a certain amount of lost performance without external maintenance activities. In other words, greater adaptation represents higher performance levels after a disruption. Restoration ability is a manifestation of system maintenance capabilities. The lost performance of a system can be restored to a new equilibrium state through external maintenance activities and measures. It is worth noting that the new equilibrium state may be lower, equal, or greater than the initial state of the system, which is dependent on restoration capacity. The absorption and adaptation capacities are considered as intrinsic properties: unlike restoration capacity, it is not reactive but an inherent property of the system (Patriarca et al., 2021).

According to the aforementioned descriptions, it can be seen that the absorption and adaptation capacity of a system is a constant value if the internal structure (e.g., human-technical-organizational factors) and the external environment of the system remain unchanged. Therefore, when the structure of a system is difficult to change and improve, the system resilience strength depends on the restoration capacity rather than absorption and adaptation capacities. The resilience behavior of a system under a disruptive condition is shown in Fig. 1.

It can be seen from Fig. 1 that the initial resilience of a system is R_0. When a disruption occurs at the system at T_0, the system

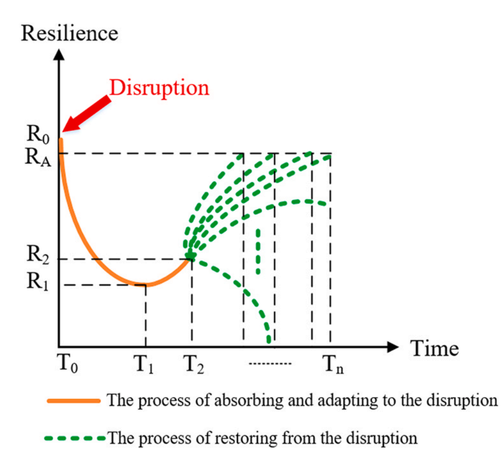

Fig. 1. The resilience behavior of a system subject to disruption.

resilience drops suddenly to the minimal value R_1 at T_1. The magnitude of R_1 is determined by the absorption capacity of the system. The stronger the absorption capacity, the greater the R_1. After this, the system resilience increases gradually to R_2 at T_2. The magnitude of R_2 depends on the adaptation capacity of the system. Moreover, the stronger the adaptation capacity, the smaller the T_2. In other words, if a system has a strong absorption and adaptation capacity, the system resilience can recover to a large value in a short time. However, it is difficult to optimize the system structure for an established system. Therefore, more attention should be paid to restoration capacity. Different restoration capacity determines different resilience of the system, which is shown as the green dotted lines. More specifically, what level of system resilience can be recovered and how long it takes to recover to this level depend on the system's restoration capacity. The green dotted lines represent different resilience curves resulting from various restoration capacities. In practice, the restoration capacity is dependent on maintenance asset M_a and operational cost O_c, which is discussed in the following section. The more M_a and O_c available for maintenance activities, the stronger the restoration capacity, the more resilient the system. However, maintenance asset M_a and operational cost O_c are practically limited. Therefore, it is indispensable to develop a resilience-based approach to help systems determine the optimal solution between M_a and O_c, which can be used to ensure systems restore to the minimal acceptable resilience level (MARL) within an optimal cost C. The specific process of the proposed methodology will be discussed in the following sections.

3. The proposed methodology

Several aspects need to be considered holistically to optimize a system as a whole. (i) Comprehensive consideration of possible disruptions based on system characteristics, including internal disruptions (e.g., component failure, human error, etc.) and external disruptions (e.g., cyber-attack, internal or external attack, intentional attack, natural disasters, etc.); (ii) Calculating the probability distribution for each type of disruption; (iii) Quantifying the impact of each disruption type on system performance; (iv) Determining the system resilience according to the proposed resilience metric; (v) Optimizing the system resilience (i.e., absorption, adaptation, and restoration capacities) through reinforcing equipment, organization, employee competence, etc.; (vi) Judging whether the optimized system resilience meets the requirements based on expert judgments. The relevant measures can be implemented according to the results if the requirements are met. If not, the system structure needs to be re-optimized to improve the system resilience. The specific procedure for optimizing system resilience is shown in Fig. 2.

However, comprehensive system optimization requires extensive work. Thus, the proposed method is based on the following assumptions: (i) Only one type of disruption to the system is considered; (ii) We assume that the disruption is inevitable, so the probability distribution of the interruption is not considered; (iii) System optimization is based on restoration capacity. In practice, optimizing the system's resilience can be achieved in three ways: enhancing absorption capacity, reinforcing adaptation capacity, and improving restorations. The study focuses on maintenance activities. Therefore, only restoration capacity is taken into account.

A resilience-based approach is developed to optimize the maintenance cost, including the maintenance asset M_a and operational cost O_c. Firstly, the dynamic Bayesian network (DBN) is employed to model the structure of the system. After this, parameter modeling in different processes is conducted to determine the corresponding performance curves (i.e., $f_1(t)$, $f_2(t)$, and $f_3(t)$). Based on this, the system resilience is determined by the proposed resilience metric. Finally, the optimal solution between maintenance asset M_a and

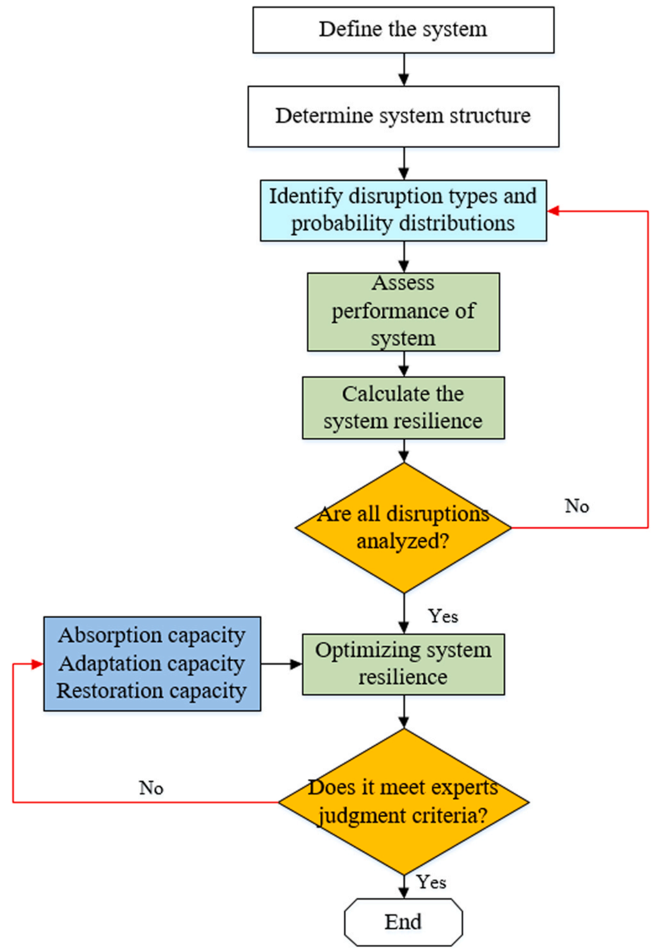

Fig. 2. The procedure for optimizing system resilience.

operational cost O_c is determined through resilience curve, MARL, and maximal acceptable restoration time (MART). The specific information of the proposed methodology for resilience assessment is illustrated in Fig. 3.

3.1. Dynamic Bayesian network (DBN)

Dynamic Bayesian network (BN) is a type of directed acyclic graph comprising two parts, namely structure modeling, and parameter modeling. Structure modeling consists of nodes and directed arcs. Nodes, including parent nodes, child nodes, and root nodes, indicate the components of a system. Directed arcs from parent nodes to child nodes stand for the qualitative relationship among nodes. DBN can be determined by the relationship between nodes. For instance, system A contains two subsystems B and C, and each subsystem is composed of two components, then the DBN model can be represented as Fig. 4.

Parameter modeling includes intra parameters (e.g., prior probability, conditional probability tables (CPTs)) and inter parameters (i.e., the transition probability for different time slices). The intra-slice arcs can be quantified by CPTs, which are the quantitative relationship among nodes and can be determined by logic gates and expert knowledge. The inter-slice arcs can be quantified through transition probability, which reflects the transition of a component or system state at different times. Transition probabilities can be determined by failure rate λ and repair rate μ. The probability is determined through a Markov-state transition relationship and is expressed as follows (Cai et al., 2018):

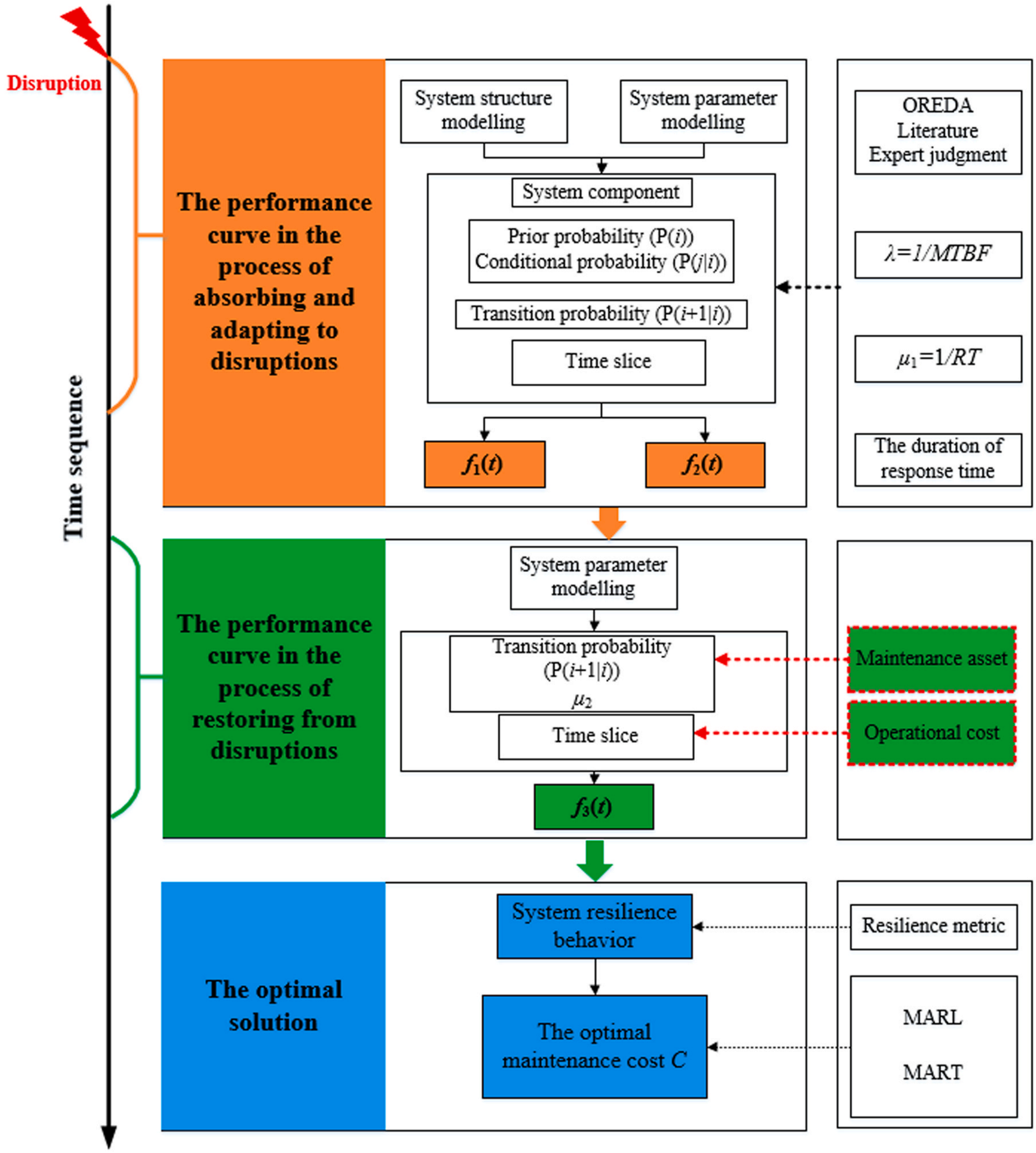

Fig. 3. The proposed methodology for assessing the system resilience.

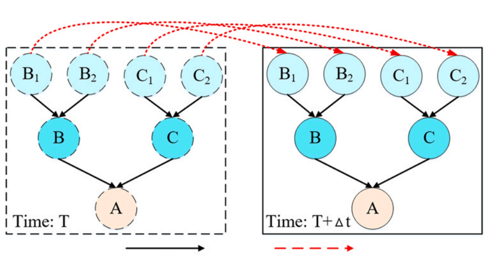

Fig. 4. Structure model of DBN.

$$p(X_{t+\Delta t} = work|X_t = work) = e^{-\lambda\Delta t} \quad (1)$$

$$p(X_{t+\Delta t} = fail|X_t = work) = 1 - e^{-\lambda\Delta t} \quad (2)$$

$$p(X_{t+\Delta t} = fail|X_t = fail) = e^{-\mu\Delta t} \quad (3)$$

$$p(X_{t+\Delta t} = work|X_t = fail) = 1 - e^{-\mu\Delta t} \quad (4)$$

The DBN model is employed to model the system in this study. Parameter modeling is then conducted to determine performance curves in different processes (i.e., $f_1(t)$, $f_2(t)$, and $f_3(t)$ in Fig. 5). The state transition, shown in Fig. 6, depends on two main parameters: the initial performance P_0 and the corresponding transition probabilities (i.e., λ, μ_1, and μ_2) in different processes. The quantification of the system resilience is based on the system performance curve. The system performance changes over time under a disruption condition is shown in Fig. 5. The following sections describe details of the main steps for the proposed methodology.

3.2. System performance curve f(t)

The change of system performance curve can be divided into three parts. (i): The curve of the performance degradation process

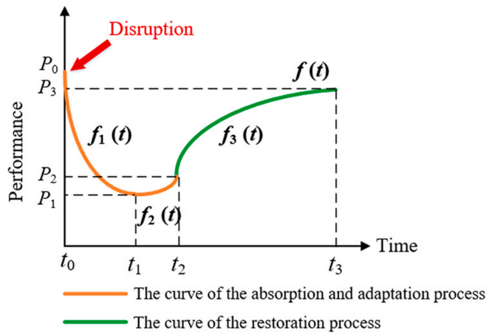

Fig. 5. The performance curve of a system subject to disruption.

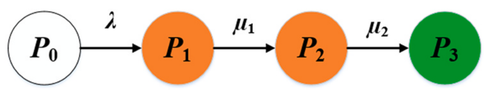

Fig. 6. Markov chain model for the process of performance change over time.

caused by a disruption is defined as $f_1(t)$. In this process, the system performance decreases from P_0 at t_0 to the minimal value P_1 at t_1. (ii): The curve of the performance increase process without external maintenance is regarded as $f_2(t)$. In this part, the system performance increases from P_1 at t_1 to P_2 at t_2. The recovered performance in this part depends on the adaptation capacity of the system. (iii): The curve of the performance increase process with external maintenance activities is considered as $f_3(t)$. In this process, the system resilience is enhanced through external maintenance activities and measures, dependent on restoration capacity.

In the light of the abovementioned descriptions in Section 2, as long as the internal structure and external environment of the system stay the same, the absorption and adaptation capacity of the system remains unchanged, so the corresponding system performance curve (i.e., $f_1(t)$ and $f_2(t)$) also remains the same.

The development process of the three curves involves the transformation between four states of the system, namely, P_0, P_1, P_2, and P_3. In the process of transiting from state P_0 to state P_1, due to the impact of the disruption, the failure rate λ of system components is increased. Therefore, the system performance drops rapidly from P_0 to the minimal performance P_1. Due to adaptation capacity, the system performance increases gradually from P_1 to P_2. In this process, the transition probability of each component depends on μ_1. Moreover, when external maintenance activities are taken, the system performance will be strengthened over time. The increase rate is dependent on μ_2. The detailed information is illustrated in Fig. 6. To determine the optimal solution between maintenance asset M_a and operational cost O_c based on system resilience, the λ, μ_1, and μ_2 should be identified first.

(1) The quantification of $f_1(t)$ and $f_2(t)$.

During the process of state transition from P_0 to P_1, the corresponding performance curve $f_1(t)$ is dependent on the failure rate λ of each component. Before the disruption occurs, the initial failure rate λ_0 can be determined by *MTBF* (mean time between failure). The relationship between λ_0 and *MTBF* can be expressed as $\lambda_0 = 1/MTBF$, which means that the greater the *MTBF*, the lower the failure rate of the components. However, the *MTBF* is reduced by the disruption, leading to an increase from λ_0 to λ. This is why P_0 drops to P_1 rapidly in the period of t_0 to t_1. The λ can be determined by historical data (i.e., *MTBF* after disruption) of plant accident reports and expert judgment (Tong et al., 2020). After this, due to the effect of adaptation capacity, the system performance increases gradually from P_1 to P_2. The corresponding performance curve $f_2(t)$ can be determined by μ_1 of each component. The duration of the adaptation process (i.e., t_1 to t_2) is defined as the response time (*RT*) (Tong et al., 2020). Their relationship can be expressed as Eq. (5). Besides, *RT* consists of two elements, fault diagnosis time T_D and resource allocation time T_{RA}, which can be defined as Eq. (6). The shorter the *RT*, the larger the μ_1. For example, the time period from when the main feed pump is inoperative to the backup feed pump is activated can be regarded as the *RT*, which can be obtained from historical data of plants reports. Once these parameters are determined, $f_1(t)$ and $f_2(t)$ can be quantified.

$$\mu_1 = \frac{1}{RT} \tag{5}$$

$$RT = T_D + T_{RA} \tag{6}$$

(2) The quantification of $f_3(t)$.

External maintenance can be taken to recover and increase the system performance from P_2 to P_3. In this process, the system performance curve $f_3(t)$ can be determined by the transition probability of each component, i.e., repair rate μ_2. The magnitude of P_3 depends on the restoration capacity of the system. Besides, restoration capacity is dependent on maintenance asset M_a and operational cost O_c.

Maintenance asset M_a refers to manpower, facilities, equipment, and other non-consumable materials (Xiao et al., 2022). In other words, M_a consists of a certain number of emergency maintenance teams, which possess required non-consumable materials. It is worth noting that the annual costs related to maintain the stand-by of reliable emergency teams during normal operation are not considered. This is because when a major disruption occurs, an enterprise's maintenance capacity may not be sufficient to cope with the disruption. At this time, the maintenance power of other enterprises in the same plant cluster can be paid to be used. Maintenance assets determine the recovery rate of the system. Under a normal condition, μ_0 can be expressed as Eq. (7). Mean time to repair (*MTTR*) stands for the time from the start of repair to its end, a constant value that can be determined by historical data (OREDA, 2002; Khakzad et al., 2013).

$$\mu_0 = \frac{1}{MTTR} \tag{7}$$

In real-world situations, the emergency department in a plant comprises several emergency maintenance teams. Each team possesses the required manpower, facilities, equipment, etc. When the number of maintenance teams increases, the required maintenance time will be decreased. Assume that each maintenance team has the same maintenance capacity.

In practice, failure categories should be classified. Thus, mean time to repair (*MTTR*) can be divided into the different categories, e.g., *MTTR* under normal conditions (*MTTRN*) and *MTTR* under disruptive conditions (*MTTRD*). Besides, *MTTRD* can also be divided into various categories according to different types of disruptions (e.g., cyber-attack, natural disasters, etc.). In this way, the recorded data *MTTRD* can be used to determine the relationship between maintenance teams n and μ_2, so that to quantify $f_3(t)$. However, few plants record and classify this type of data. Therefore, we assume that the maintenance rate under disruptive conditions μ_2 is related to the number of maintenance teams n and the maintenance rate under normal conditions μ_0. When practitioners choose the proposed approach, the specific data recorded under disruptive conditions in their plant can be used to determine μ_2. Besides, the μ can also be obtained by expert judgment based on the characteristics of disruption. When the number of maintenance team is 1 unit, $\mu_2 = 1/MTTR$. While, when the number of emergency team is 2 units, $\mu_2 = 1/(0.5 \times MTTR) = 2/MTTR$. Therefore, the relationship between the number of emergency team n and μ_2 can be illustrated by Eq. (8).

$$\mu_2 = \frac{n}{MTTR} \tag{8}$$

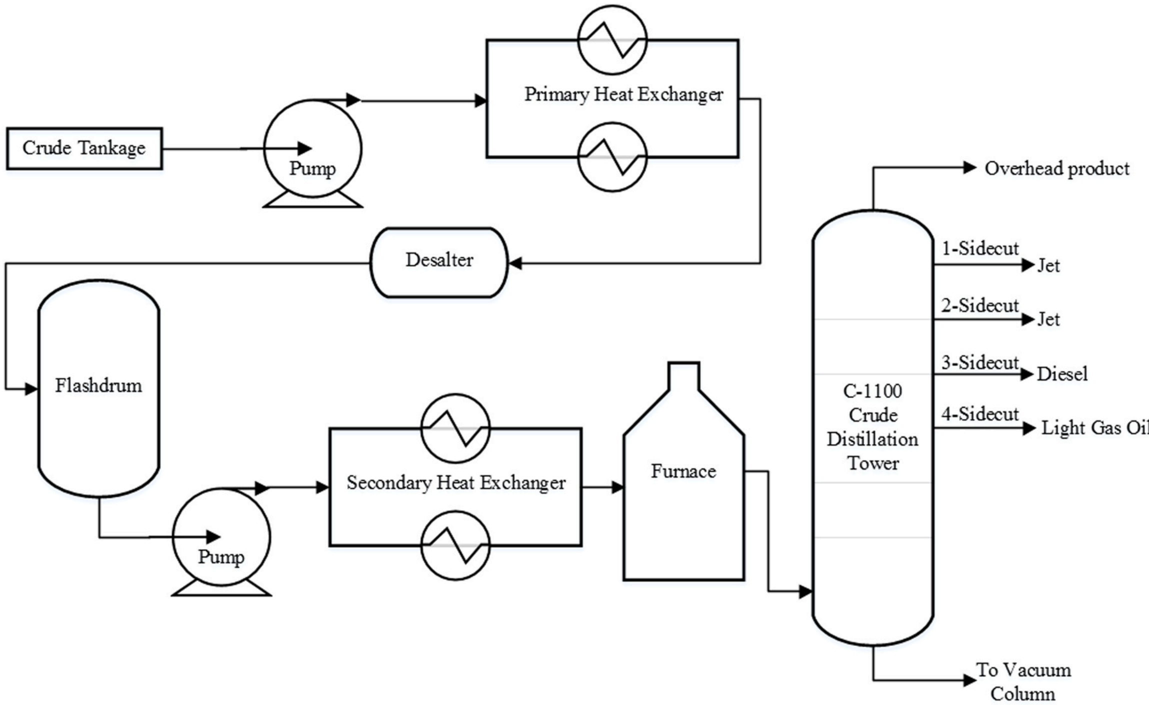

Fig. 7. Schematic diagram of the Chevron Richmond refinery crude unit.

Operational cost O_c indicates materials, money, and other consumables consumed during maintenance activities. Hence, these two factors (i.e., maintenance asset M_a and operational cost O_c) together determine whether system resilience will be restored to the MARL within the specified time MART. There is an optimal solution between maintenance asset M_a and operational cost O_c.

3.3. The optimal solution between maintenance asset and operational cost

The performance curve can be obtained by integrating $f_1(t)$, $f_2(t)$, and $f_3(t)$, which is determined by the DBN models of the absorption, adaptation, and restoration process. The system performance curve is presented in Fig. 5. As aforementioned above, the system resilience can be determined by the proposed resilience metric. In the present study, the system resilience is the ratio of the sum of area under the $f_1(t)$, $f_2(t)$, and $f_3(t)$ to the total area, i.e., $P_0 \times (t_3\text{-}t_0)$ in Fig. 5. The system resilience R_S can be expressed as Eq. (9) (Sun et al., 2022).

$$R_S = \frac{\int_{t_0}^{t_x} f(t)}{P_0 \times (t_x - t_0)} \tag{9}$$

where t_x is greater than t_0 and less than t_3.

However, due to the limitation of the total maintenance cost C, the system resilience varies for different combinations of M_a and O_c. To determine the optimal solution, the minimal acceptable resilience level (MARL) and maximal acceptable restoration time (MART) are defined. To ensure that the repaired system is within a safe range, it is assumed that the resilience of the system is restored to at least 90% of the lost resilience, i.e., R_A in Fig. 1. The MARL (R_A) can be determined by Eq. (10) (Tong et al., 2020). In other words, as long as the system resilience is restored to 90% of its loss, the system resilience is considered sufficient to ensure system safety.

$$R_A = R_1 + (R_0 - R_1) \times 90\% \tag{10}$$

The duration of maintenance activities is also a critical parameter for a system. The shorter the time taken to reach MARL, the higher the restoration capability of the system. Therefore, other than the total cost C, the time factor should also be considered when determining the optimal solution. In other words, other than the MARL, the maximal acceptable restoration time (MART) should be defined to represent the acceptable time for a system to restore to the MARL. It is considered unacceptable if the system resilience restores to MARL longer than MART. In practice, the MART can be determined by the requirement of systems. The MARL and MART are employed to help identify the optimal resolution between M_a and O_c.

To determine the optimal solution of M_a and O_c, the total cost C is defined as Eq. (11) to represent the sum of the money spent to set up the maintenance teams (i.e., maintenance asset M_a) and the money spent on maintenance activities (i.e., operational cost O_c).

$$C = M_a + O_c = n \times C_1 + n \times t \times C_2 \tag{11}$$

where n stands for the number of emergency teams, t indicates the required time for system resilience to restore to the 90% of the lost resilience, C_1 refers to the money needed to assemble an emergency team and required facilities, C_2 is the money consumed per maintenance team per hour during maintenance activities.

According to the system resilience obtained by various combinations of M_a and O_c, the optimal solution can be identified to optimize the maintenance cost C. In this way, the resilience of the system can be restored to a safe state within an optimal cost C.

3.4. Application of the proposed methodology

On August 6, 2012, a leakage accident originated from a pipe rupture in a crude distillation unit in the Chevron Richmond refinery occurred, resulting in a fire accident eventually. Fortunately, no one was injured in the accident (CSB, 2014). The fire accident resulted from the "4-side cut" leaving the Richmond refinery's C- 1100 Crude unit atmospheric column (Adedigba et al., 2018), causing flammable light oil released at the rate of 10,800 barrels per day (CSB, 2014). The specific information regarding the Richmond refinery accident can be found in the CSB investigation report (CSB, 2014). The process

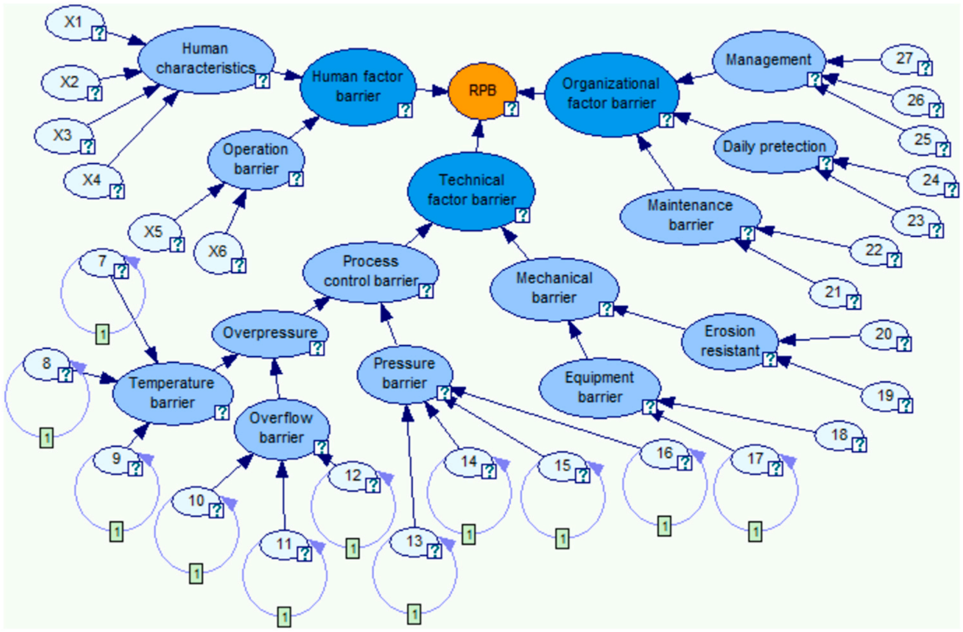

Fig. 8. The DBN model for the RPB of Chevron Richmond refinery crude unit.

of the Chevron Richmond refinery crude unit and its associated upstream process is shown in Fig. 7.

To prevent the release accident, the release prevention barrier (RPB) of the Chevron Richmond refinery crude unit is used to demonstrate the proposed methodology. According to the information provided by CSB (2014), the DBN model is developed, which is illustrated in Fig. 8. The RPB comprises three main secondary barriers, i.e., human, technical, and organizational barriers. The basic nodes and corresponding descriptions are illustrated in Table 1. The prior probability, initial failure rate $\lambda_{0,}$ and initial repair rate μ_0 under normal conditions of each node are obtained by historical data and expert judgment (Cai et al., 2018; OREDA, 2002; Zarei et al., 2017). The μ_1 and μ_2 can be obtained by Eq. (5), Eq. (6), and Eq. (8). For the inter slice parameter model, the Markov state transition relationship, shown in Fig. 6, is used to determine the dynamic degradation process $f_1(t)$, system response process $f_2(t)$, and repair process $f_3(t)$. Note that the structure of the DBN model remains the same during these three different processes. In the light of structure modeling and parameter modeling, the system performance curves (i.e., $f_1(t)$, $f_2(t)$, and $f_3(t)$) are ascertained by the availability of RPB and employed to calculate system resilience. According to the various restoration capacity, the MARL, and the MART, the optimal solution between maintenance assets M_a and operational cost O_c can be determined.

Table 1
The information of each node in the DBN model.

Node	Description	Failure rate λ_0	Repair rate μ_0	μ_1	Prior probability
X_1	Supervision	–	–	–	1.00 × 10–3
X_2	Skill	–	–	–	1.00 × 10–3
X_3	Experience	–	–	–	1.00 × 10–3
X_4	Knowledge	–	–	–	1.00 × 10–3
X_5	Work permit	–	–	–	7.00 × 10–3
X_6	Work procedure	–	–	–	5.00 × 10–3
X_7	Temperature controller	5.72 × 10–5	0.020	0.100	1.98 × 10–3
X_8	Temperature sensor	4.66 × 10–5	0.023	0.100	1.46 × 10–3
X_9	Over temperature alarm	4.86 × 10–5	0.019	0.100	1.58 × 10–3
X_{10}	Overflow alarm	6.54 × 10–5	0.022	0.100	2.36 × 10–3
X_{11}	Flow control valve	4.97 × 10–5	0.013	0.100	1.78 × 10–3
X_{12}	Pump	4.05 × 10–5	0.014	0.100	1.32 × 10–3
X_{13}	Pressure controller	4.13 × 10–5	0.013	0.100	1.39 × 10–3
X_{14}	Pressure sensor	6.58 × 10–5	0.018	0.100	2.42 × 10–3
X_{15}	Overpressure alarm	5.07 × 10–5	0.022	0.100	1.67 × 10–3
X_{16}	Safety valve	6.13 × 10–5	0.021	0.100	2.15 × 10–3
X_{17}	Compressor	6.14 × 10–5	0.020	0.100	2.25 × 10–3
X_{18}	Flange	–	–	–	3.24 × 10–4
X_{19}	Protective coating	–	–	–	6.20 × 10–4
X_{20}	Cathodic protection	–	–	–	5.30 × 10–4
X_{21}	Maintenance procedure	–	–	–	5.00 × 10–3
X_{22}	Maintenance method	–	–	–	5.00 × 10–3
X_{23}	Testing	–	–	–	3.00 × 10–3
X_{24}	Routing inspection	–	–	–	5.00 × 10–3
X_{25}	Education	–	–	–	4.00 × 10–4
X_{26}	Training	–	–	–	4.00 × 10–4
X_{27}	Safety culture	–	–	–	5.00 × 10–3

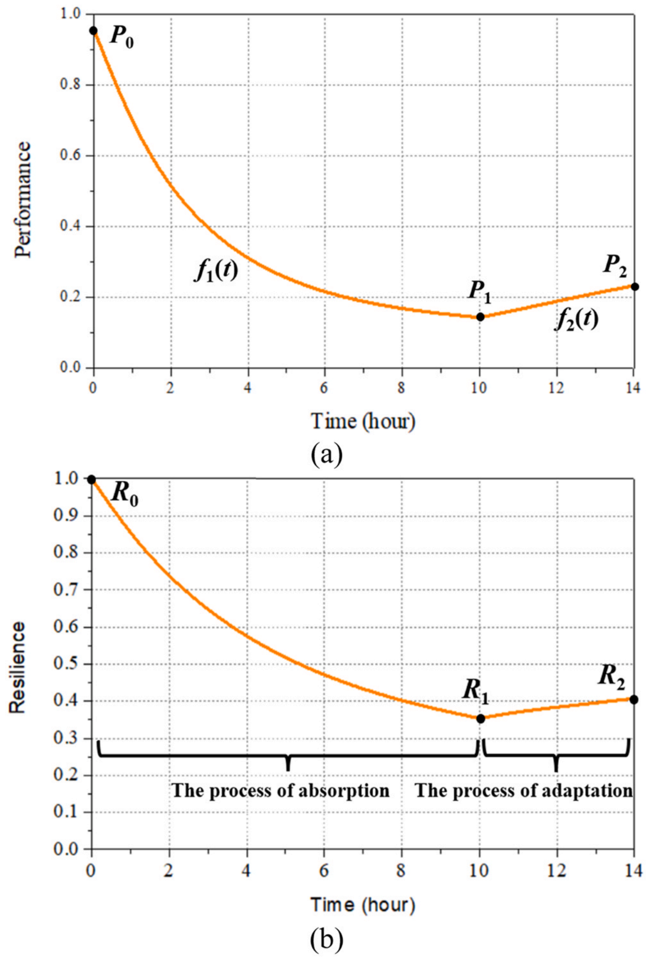

Fig. 9. (a) The $f_1(t)$ and $f_2(t)$ of the system, (b) The system resilience behavior in the process of absorption and adaptation.

4. Results and discussions

In accordance with the developed DBN model and data in Table 1, $f_1(t)$ and $f_2(t)$ can be determined, which is illustrated in Fig. 9(a). It can be seen from Fig. 9(a) the system performance drops from P_0 to P_1 over a time span of 0–10 h. P_1 is the minimal value of the system performance, which is determined by the system absorption capacity. The stronger the absorption capacity, the greater the P_1. After this, the system performance increases gradually from P_1 to P_2 over time span of 10–14 h. P_2 is dependent on the adaptation capacity of the system. The stronger the adaptation capacity, the greater the P_2. As discussed above, system resilience can be promoted by increasing the absorption and adaptation capacity. If these two capabilities are large enough, the system can reach MARL (i.e., a high-performance level) even without external maintenance activities after being affected by disruptions. Therefore, improving the two capacities during the design phase can reduce the system's dependence on external maintenance activities (i.e., restoration capacity).

After determining the $f_1(t)$ and $f_2(t)$, the corresponding resilience behaviors can be ascertained by combining with the Eq. (9). The resilience behaviors are illustrated in Fig. 9(b). It can be seen that the resilience decreases from 1 at time 0–0.352 at the 10th hour. If the absorption capacity is reinforced, the minimal value 0.352 can be enhanced and the corresponding time span can be reduced (i.e., less than 10 h). The adaptation capacity of the system determines the slope of the curve from R_1 to R_2. The stronger the adaptation capacity, the greater the R_2 and the slope.

From the view of intrinsic safety, it is worth noting that in the system design phase, the absorption and adaptation capacity should be intensified to help systems address uncertain disruptions and decrease the system's dependence on restoration capacity. However, for an already established system, increasing the absorption and adaptation capacity is difficult, especially the absorption capacity, unless change and optimize the structure of systems.

In real-world conditions, the restoration capacity is dependent on the available maintenance asset M_a and operational cost O_c. In the current study, maintenance asset stands for non-consumable materials, e.g., human resources, tools, and necessary equipment. Therefore, maintenance assets determine the repair rate μ_2 of the system. The more maintenance asset, the higher the repair rate of components. In the process of maintenance activities, the system performance gradually increases. Operational cost is determined by the amount of time required for maintenance activities t and the number of maintenance teams n, which can be seen in Eq. (11). Therefore, for a given operational cost O_c, when the number of maintenance teams (n) increases, the duration t of maintenance activities decreases. In practical circumstances, nevertheless, the maintenance asset M_a and operational cost O_c are limited. To determine the influence of M_a and O_c on restoration capacity, various scenarios are developed to quantify the system resilience.

The system resilience depends on both the maintenance asset M_a and operational cost O_c. There is an optimal solution between M_a and O_c. Various scenarios are set to determine the optimal solution, and the corresponding system resilience is measured. Combining with Fig. 9(b), the entire resilience behavior is illustrated in Fig. 10. The yellow line is determined by the process of absorption and adaptation (i.e., Fig. 9(b)). The green dotted lines are quantified by the different scenarios shown in Table 2. It can be seen from Fig. 10, as maintenance asset M_a and operational cost O_c increase, the restoration capacity of the system enhances. The more M_a, the faster the system resilience increases and the shorter the time to reach R_A. The required time for each scenario can be determined by the developed DBN model, and the results are demonstrated in the third column of Table 2.

However, both the increase of maintenance asset M_a and the increase of operational cost O_c will lead to the rise of total maintenance cost C. Hence, the optimal solution can be employed to help the system to restore to the MARL within the optimal cost C. Assuming it costs $10,000 to form a maintenance team and each team spends $1000 per hour on maintenance activities. The maintenance asset M_a, operational cost O_c, and the total maintenance cost

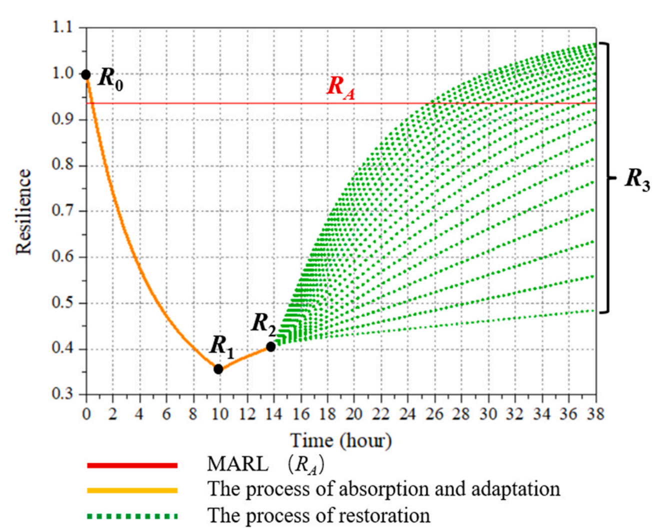

Fig. 10. The system resilience behavior changes with restoration capacity.

Table 2
The specific data of the optimization process.

Emergency teams (n)	MARL (R_A)	MART (Hours)	Required time t (Hours)	Maintenance asset M_a ($)	Operational cost O_c ($)	Total cost C ($)
1	0.935	30	305	10,000	304,000	314,000
2	0.935	30	110	20,000	220,000	240,000
3	0.935	30	69.5	30,000	208,500	238,500
4	0.935	30	55.6	40,000	222,400	262,400
5	0.935	30	39.8	50,000	199,000	249,000
6	0.935	30	32.9	60,000	197,400	257,400
7	0.935	30	28.2	70,000	197,400	267,400
8	0.935	30	24.3	80,000	194,400	274,400
9	0.935	30	21.1	90,000	189,900	279,900
10	0.935	30	19.2	100,000	192,000	292,000
11	0.935	30	17.5	110,000	192,500	302,500
12	0.935	30	16.2	120,000	194,400	314,400
13	0.935	30	14.9	130,000	193,700	323,700
14	0.935	30	13.5	140,000	189,000	329,000
15	0.935	30	12.6	150,000	189,000	339,000
16	0.935	30	12.1	160,000	193,600	353,600
17	0.935	30	11.2	170,000	190,400	360,400
18	0.935	30	10.6	180,000	190,800	370,800
19	0.935	30	10.2	190,000	193,800	383,800
20	0.935	30	9.5	200,000	190,000	390,000

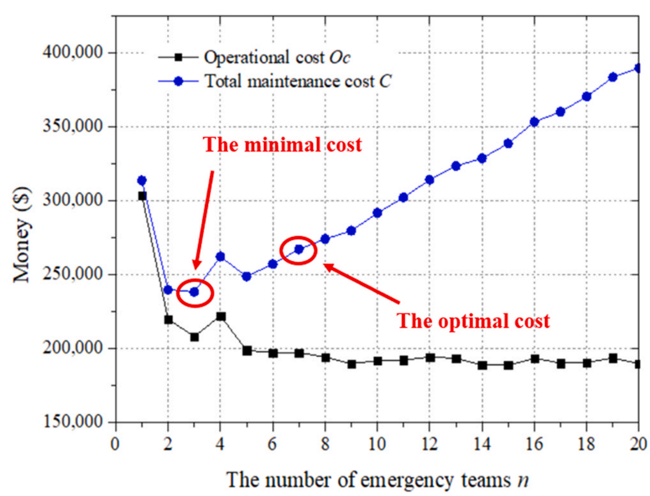

Fig. 11. The relationship between the total cost C and maintenance resource and budget.

C can be determined based on Eq. (11). The relationship between the total cost C and the number of emergency teams n and operational cost is illustrated in Fig. 11. From Fig. 11 it can be seen that as the number of emergency teams increases, the O_c decreases in general. This is because O_c is not only dependent on the number of emergency teams n but also on t, which can be seen in Eq. (11). When n increases, the t is decreased at the same time. It is worth noting that when the n is greater than 5, the operational cost fluctuates around $190,000. After this point, increasing the number of maintenance teams has little effect on the O_c. Instead, it increases the investment of maintenance assets, thus leading to an overall increase in the total cost C.

As shown in the fourth column in Table 2, as the number of maintenance teams increases, the time required for system resilience to reach R_A decreases rapidly. However, as the number of maintenance teams continues to increase, the rate of required time reduction gradually decreases, especially when the number of emergency teams n increases from 12 to 20, the time required is reduced by only 6.7 h. The input-output efficiency is low in this situation. Once the maintenance asset M_a and operational cost O_c are determined, the total cost C can be ascertained by Eq. (11). The results can be seen in the last column of Table 2. The total cost C decreases first and then increases with the increase of the number of maintenance teams. Note that when the number of maintenance teams n is 4, the total maintenance cost C is larger than when n equals to 3. This is because when n is 3, the total operation time is $3 \times 69.5 = 208.5$ h, while when n is 4, the total operation time is $4 \times 55.6 = 222.4$ h, leading O_c increases from $208,500 to $222,400. The minimal C is $238,500, and the corresponding maintenance asset M_a and operational cost O_c are $30,000 and $208,500. Therefore, when maintenance team n is equal to three, the corresponding operational cost and the total maintenance cost C is minimal. However, when the number of maintenance teams is three, the required time for system resilience to restore to the 90% of the lost resilience is 69.5 h, which is much longer than the maximal acceptable restoration time (MART) i.e., 30 h. Therefore, the minimal cost is not the optimal one. Based on the MART, which is defined as 30 h in this study, the optimal cost is $267,400, the corresponding M_a is $70,000, and O_c is $197,400. Therefore, when the number of maintenance teams is 7, the total cost C is optimal.

The resilience of process systems can be strengthened by improving the absorption, adaptation, and restoration capacity. From the inherent safety perspective, the best choice is to increase the absorption and adaptation capacity. Absorption capacity can reduce the influence of uncertain disruptions on the system. Put another way, the stronger the absorption capacity, the greater the performance P_1 and the resilience R_1 after disruptions. In ideal cases, the system may not need to adapt from disruptions and restore to a new equilibrium state, while the P_1 of the system after absorbing the impacts of the disruptions is within a safe range (e.g., above 90% of the initial resilience). For the same reason, the adaptation capacity of the system can also be utilized to improve the system resilience. For example, improving system flexibility and installing protective measures can increase the adaptation capacity of the system. The absorption and adaptation capacity of a system are dependent on the system structure. When the system possesses strong absorption and adaptation capacities, the system is less dependent on restoration capacity. From the perspective of inherent safety, improving the absorption and adaptation capacity of the system is better than increasing the restoration capacity of the system.

However, the structure of process systems that have already been established is difficult to change and optimize. In other words, enhancing these systems' absorption and adaptation capacity is a challenge. Thus, more attentions have to be paid to improving the restoration capacity. The restoration capacity of systems is

Table 3
The comparative analysis of conventional methods and the proposed approach.

Methodology	References	Main parameters	Types	Goals
Reliability-based methods	(Shi et al., 2022) (Wang et al., 2022)	Reliability; Cost Reliability	Preventive	Ensuring system safety within a minimal cost
Risk-based methods	(Zhen et al., 2021) (Han et al., 2019) (Abubakirov et al., 2020)	Risk; Cost	Preventive	Ensuring system safety within a minimal cost
Availability-based methods	(Wang et al., 2022)	Availability; *MTTF*; Cost	Preventive	Ensuring system safety within a minimal cost
The proposed methodology	The present study	Resilience; Cost	Reactive	Ensuring system resilience within an optimal cost

dependent on maintenance activities. In other words, different maintenance activities cause various restoration capacity and lead to various maintenance cost C. Therefore, improving restoration capacity while reducing input costs can help systems minimize the impact of disturbances economically, which means that ensuring systems are at a safe resilience level within optimal cost C is the optimal solution.

The reliability-based and risk-based methods aim to determine the optimal maintenance interval to ensure systems safety and reduce the costs caused by unnecessary systems downtime. We have compared the characteristics of these two types of methods with the proposed method. Table 3 demonstrates the results.

There remains an issue to be addressed in the developed approach. When a system is affected by disruptions, its performance deteriorates rapidly, but it may not need to be repaired in all cases. For example, when a system is severely damaged, if the cost of repair is higher than the cost of replacement, it should be replaced by a new one. Therefore, a performance threshold should be set to determine whether the system needs to be repaired. This scenario is not taken into account in the proposed approach.

In the current study, resilience is used to optimize the maintenance cost. Since there are no external maintenance activities in the phase of absorption and adaptation, therefore, the focus of the proposed methodology is on the restoration capacity of the system resilience. In the view of inherent safety, strengthening absorption and adaptation capacity is better than improving restoration capacity. Therefore, in future work, a new model, which considers absorption, adaptation, restoration capacities, and the types of disruptions, will be developed to optimize systems structure to enhance system resilience to help the system reduce the impact and consequence caused by uncertain disruptions. In this way, all three capabilities of resilience are considered. The work in this direction is in progress.

5. Conclusions

The rapid development of technology has made process systems complex, leading to strong interaction and interdependence between components. This brings two problems: (i) it leads to systems being vulnerable to uncertain disruptions. In other words, due to the increasing complexity of process systems, the system becomes more likely to be disturbed by uncertainty; (ii) it is difficult for conventional methods to ensure system safety in the context of uncertain disruptions. Besides, there are two characteristics of disruptions in the digital age, i.e., diversity (e.g., cyber-attack, internal or external attack, intentional attack, natural disasters, etc.) and uncertainty (i.e., where, when, and how it will occur). Therefore, there is a need to take resilience thinking into account to make the system more resilient to deal with uncertain disruptions. This paper creates a resilience-based approach to optimize the maintenance cost C to help the system cope with uncertain disruptions. To measure the system resilience, the performance response function (PRF) is obtained by using the DBN model. The parameters of the DBN model are utilized to quantify three phases of PRF (i.e., $f_1(t)$, $f_2(t)$, and $f_3(t)$). After that, based on the obtained PRF, the resilience, which comprises absorption capacity, adaptation capacity, and restoration capacity, under various scenarios is measured by the proposed resilience metric. Moreover, the MRAL, MART, and obtained resilience are used to determine the optimal solution between maintenance asset M_a and operational cost O_c. On that basis, the proposed approach can provide a real-time resilience profile and provide optimal maintenance cost planning. The proposed approach aims to enhance the ability of the system to deal with uncertain disruptions through maintenance while not compromising the system's productivity.

The case study shows that there are two main ways to enhance system resilience. The first one is optimizing the system design to help a system absorb and adapt to uncertain disruptions. In this way, the dependence of the system on restoration capacity can be reduced. Secondly, the system resilience can be improved by enhancing the restoration capacity when the system design cannot be changed. In other words, optimizing the maintenance asset M_a and operational cost O_c can enhance the system resilience and reduce maintenance cost. The main contribution of the proposed approach is to help practitioners comprehensively improve the system resilience to resist the diversified and uncertain disruptions within the optimal maintenance cost. Besides, the proposed methodology can be applied to model various disruptions, not just specific, constant disruptions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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