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A novel framework for quantitative resilience assessment in complex engineering systems during early and late design stages

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ABSTRACT

Recently, resilience assessment has evolved and grown in prominence, yet most studies are carried out on operational stage when sufficient knowledge on the processes is available, overlooking the design stage, a time frame that is more suitable for making a resilient system. To this end, this work aims at developing a novel quantitative resilience assessment framework for engineering systems with two different approaches that practically analyse resilience at the early and late design stages when detailed information on the system's safety and resilience capabilities may be deficient. In the early design stage, system resilience attributes are identified, and expert judgment is used to assess their quality. In the late design stage, attributes are derived from revealed information such as detailed emergency response and safety barrier data. In both stages, dynamic Bayesian Network (DBN) is used to quantify resilience based on the acquired information. Since the green hydrogen technology is relatively novice, the application of the proposed framework is demonstrated in a resilience assessment of a green hydrogen plant undergoing hydrogen release scenarios. The proposed framework can be used as an effective tool for early design improvements as well as enhancing process safety in the late design stage of hydrogen plants or any other complex engineering system.

1. Introduction

Failures and accidents are inherent to all engineering systems and are anticipated to recur (Aven and Zio, 2014). Throughout the various phases of design and operation, encompassing simple, complicated, and complex systems, engineers endeavour to recognize potential hazards and threats through hazard identification (Zio, 2018). They assess the likelihood of failures and the potential severity of consequences through risk assessment (Hoseyni et al., 2016). Subsequently, engineers engage in risk management practices to address and mitigate associated risks, aiming to minimize the impact of potential consequences (Yousefpour et al., 2017). Despite the implementation of sophisticated and comprehensive precautionary measures, it is important to acknowledge that risk can never be entirely eliminated. The inherent complexity of engineering systems, the multitude of interacting components, and the presence of inherent uncertainties create a context where surprises and unforeseen events may still occur (Modarres, 2006; Hoseyni et al., 2014; Pourgol-Mohammad et al., 2016). Hence, beyond striving to enhance the safety of engineering systems through hazard identification and subsequent risk assessment and management, it is crucial to institute measures that effectively handle incidents when they occur by fostering a system that is "safe to fail", in other words, a resilient system (Hollnagel et al., 2008).

As a result, as much as traditional risk assessment plays a crucial role in ensuring safe design and operation of systems (i.e., by focusing on pre-failure accident scenarios), there is a need to broaden its scope to consider the post-failure phase when the ability to absorb disturbance, stresses, and shocks are duly considered by adapting to and learning from disruption occurrence (Mottahedi et al., 2021; Hoseyni et al., 2017). This is achieved by conducting a resilience assessment which involves evaluating a system's capacity to absorb and adapt to disasters and disruptive events, as well as its ability to recover functionality following a disruption (Gasser et al., 2021).

Recent decades have seen a development and rise in the importance of research on engineering systems' resilience (Abbasnejadfard et al., 2022). Although resilience assessment is now a frequently discussed notion, no unique methodology has been concurred to understand and quantify a system's resilient attributes, which severely restricts the scope of its applicability (Yarveisy et al., 2020). The existing resilience assessment research works in the engineering domain, despite their

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merit in response to a specific hazard with detailed knowledge on associated processes' and details, are ineffective in modelling disruptive events and their consequences at early and late design stages, time frames in which a system has a high chance of being made resilient. Determination of resilience at the design stage is crucial, as conventional hazard identifications combined with potential consequence estimations are insufficient. Even though traditional methodologies identify potential hazards and model accident scenarios, they often do not consider the aftermath of these accidents. Therefore, a proactive risk management mindset is required to anticipate failures and evaluate the survivability and recoverability of the system after disruptions. Identifying resilience issues early allows for the incorporation of design elements that can mitigate potential risks before they materialize, preventing costly modifications and downtime later in the operational phase. Addressing resilience during the design phase is often more cost-effective than making adjustments once the process is operational, saving significant time and resources. A process designed with resilience in mind is likely to be more robust and reliable, providing a competitive advantage by reducing the likelihood of disruptions that could impact production and customer satisfaction. Additionally, resilience assessment ensures that all components of the process are well-integrated and can work together seamlessly under stress, a holistic view often overlooked in risk assessments alone.

Resilience assessment is a complex and data-intensive process that requires a comprehensive understanding of the system's design, operation, and maintenance practices (Cheng et al., 2022). To effectively evaluate the resilience of a system, it is crucial to gather detailed information on the system's components, their interactions, and their performance under various conditions (Yodo and Wang, 2016a). Current resilience assessments often necessitate a wealth of knowledge primarily accessible during the operational stage. Assessing resilience requires a comprehensive understanding of the day-to-day functioning, response mechanisms, and adaptive strategies employed during normal operations (Chen et al., 2022). This operational knowledge becomes paramount in evaluating how well a system can endure and recover from disruptions (Yang et al., 2023). Consequently, an effective resilience assessment relies heavily on insights gained from real-world experiences and the practical application of strategies, making the operational stage a critical source of information for a thorough evaluation of resilience capabilities (Amer et al., 2023). For instance, to assess the resilience of processes industries, it is essential to collect data on their performance under normal operating conditions and in the face of disruptions (e.g., natural disaster). Analysing this data, which illustrates the system's behaviour under normal conditions, its robustness in withstanding accidents, and the efficacy of maintenance activities in facilitating swift recovery, becomes crucial in pinpointing vulnerabilities within the processes (Pawar et al., 2021; Shirali et al., 2012).

In the early design phase, resilience assessment faces additional challenges, notably the limited availability of realistic data regarding the operational conditions of plants. This is crucial, especially when considering the impact of aging on plant safety through the analysis of condition monitoring data (Hoseyni et al., 2019; Yang et al., 2015), a perspective primarily accessible during the operational stage (Chau et al., 2022). While techniques exist to update static risk measures over time based on plant aging and monitoring data, operational/dynamic risk measures, essential for a comprehensive resilience assessment, depend on real-time operational data (Jun et al., 2021; Bai et al., 2022). Obtaining such realistic data proves challenging during the early design stage when sufficient plant data may not be readily accessible.

Applying existing resilience assessment methods to the early and late design stages faces challenges beyond data scarcity. The dynamic and uncertain nature of design changes, limited operational feedback, intricate interconnectedness of components, and evolving requirements differentiate the design stages from the operation phase (Buede and Miller, 2016). The absence of historical operational data in the design stage, coupled with resource constraints and a focus on preventive measures, further complicates resilience assessment at this stage. Furthermore, specific design objectives for each stage should also encompass considerations for the resilience of the system, where early design emphasizes overall concept and functionality, and late design refines details and addresses specific performance requirements. The varying levels of detail and uncertainty in design representations pose challenges (Lough et al., 2009), with early design involving conceptual models and late design incorporating detailed engineering drawings (Tan et al., 2017). Limited predictive power in early design decisions, influenced by trade-offs between cost, performance, and safety, underscores the need for resilience assessment methods that aid designers in understanding these implications without extensive operational data. Considering the dynamic evolution of systems and the importance of feedback mechanisms and iterative design process, resilience assessment methods should adapt to the design process seamlessly.

To address these challenges, this work presents a novel framework that quantifies the dynamic resilience of complex engineering systems. It incorporates two distinct approaches tailored to address the unique challenges encountered in two different time frames of the design process: I) first approach introduces a practical way to assess the quantitative resilience of a system in the early design stage and shows how to define the key characteristics of a system for the resilience without having much knowledge on systems feature in this conceptual design phase and then use expert judgment to identify the attributes of resilient design and calculate the system resilience quantitatively. II) second approach, provides a model to quantify the dynamic resilience in the late design stage when more study on hazard identification, process safety and potential accident scenarios are available. In both proposed approaches, Dynamic Bayesian Network (DBN) is chosen to be used for the temporal quantification of the system's resilience in a dynamic and probabilistic manner.

In light of the complexities of designing new energy systems to reach the net-zero goals, the application of the proposed methodology is demonstrated in a green hydrogen production plant, with a specific emphasis on analysing scenarios related to hydrogen release.

This research is novel as it proposes a practical innovative methodology to fill the research gap in considering the resilience assessment at the design stages. Moreover, to the best of the authors' knowledge, there is no research work dedicated to the quantitative resilience assessment of green hydrogen plants or, generally, any engineering system in the early and late design stages. Existing methodologies predominantly focus on assessing resilience at the operational stage benefitting from the abundance of detailed information on system's specifications, and approved to be excessively complex, requiring a high level understanding on the system as well as computationally intensive modelling to execute the interconnectivities of an entire system impacted by disruptions. However, during the design stage, which is the focal point of the paper, detailed information on system specifications is typically lacking, making it difficult to apply existing methodologies effectively. The proposed framework aims to address this gap by providing a novel approach for quantitative resilience assessment during the early design stage, where information is scares and traditional methodologies may not be suitable. This work provides a practical tool for integrating resilience into the design stage, a critical phase when system resilience is usually overlooked in favour of cost and performance while the cost of implementing resilience measures is typically lower, highlighting proactive resilience-building as a cost-effective strategy.

The remainder of this paper is organized as follows. In Section 2, the proposed framework for quantitative resilience assessment is discussed in detail. In Section 3, the real case study is presented and discussions and results of applying the framework to the case study are provided. In Section 4, concluding remarks are provided.

2. Quantitative resilience assessment framework

In this section, firstly, a brief introduction to the concept of resilience in engineering is provided. Then, the dynamic Bayesian network and its application in quantifying resilience is introduced. Finally, the proposed framework for quantitative resilience assessment at the early design and late design stages is provided.

2.1. Resilience assessment

Resilience, with diverse definitions across different fields, is a key area of research, especially within the field of engineering. Various definitions are available based on the studied systems and their characteristics while all highlighting common features like absorptive capacity, adaptability, and recoverability (Abbasnejadfard et al., 2022). Resilience, as per the US National Academies of Sciences, Engineering, and Medicine, is "the ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to and recover rapidly from disruptions" (National Academies of Sciences, 2012). In our view, resilience extends beyond the traditional risk and reliability assessments to not only consider the pre-accident phase of the disruption as in conventional risk assessment, but also to deal with the post-accident phase of the systems to evaluate how a system survives an accident and recovers from subsequent consequences. Traditional idea of risk analysis focuses on achieving safety by ensuring complete protection against disruptions and the control of system change (i.e., fail-safe design). Resilience is a novel approach more focusing on the capacity of systems to restructure and recover from disruptions (i.e., safe to fail design). Although resilience is a capability of a system rather than a probability, as seen in traditional risk measures and reliability indicators, it's crucial to recognize that the risk and resilience are interconnected and should not be managed independently, despite the current distinctions in their essence and focus (Yang et al., 2023; Logan et al., 2022). It is imperative to utilize methods resembling extensive reliability or risk assessment methodologies to model accident scenarios and predict consequences accurately. Understanding the accident, its probability of occurrence, and its adverse impacts on the system, along with possible scenarios and their probabilities, is essential. Subsequently, the system's survival to the accident and its recovery to normal functionality are evaluated using this acquired information. It's important to note that resilience models are not identical to risk assessment models; instead, they offer a more comprehensive approach to addressing system resilience and recovery from disruptions encompassing both pre and post-accident phases.

Various metrics have been proposed to capture different aspects of resilience in engineering systems, each suitable for specific challenges and properties (Aruväli et al., 2023). Choosing appropriate measurement metric for systems in applications with different levels of detail poses numerous challenges as there are numerous field-specific metrics for different domains to assess resilience for example in power systems (Bhusal et al., 2020; Umunnakwe et al., 2021; Daeli and Mohagheghi, 2022), transportation (Sun et al., 2020; Mohebbi et al., 2020), critical infrastructures (Francis and Bekera, 2014a; He et al., 2022), process industry (Jain et al., 2018a, 2018b), societal communities (Johansen et al., 2017; Zhang et al., 2022), etc. Many of these metrics face difficulties in practical implementation and often fall short of fully encompassing resilience concepts and dimensions. Technical resilience metrics can be broadly classified into three groups: attributes-based metrics focusing on specific properties like probability of failure and robustness; topological metrics examining the structure of systems with an emphasis on network topology; and performance-based metrics designed to measure resilience through operational or service performance metrics across the entire disruptive event, covering both the disruption and recovery phases (Trucco and Petrenj, 2023; Szatmári et al., 2024). These categories provide diverse perspectives and approaches to assessing technical resilience, catering to the specific focus and requirements of the analysis. Each category has its own set of limitations. Attributes-based metrics may oversimplify the complexity of real-world systems and fail to capture interdependencies among system components and may not catch the temporal performance of infrastructure systems. Topological metrics may overlook important functional aspects of resilience and may not fully account for dynamic system behaviour. These metrics while being easier to measure as they require less data, provide limited information on systemic resilience. Performance-based metrics may face challenges in accurately measuring resilience due to the diverse range of metrics used and the subjective nature of performance assessments.

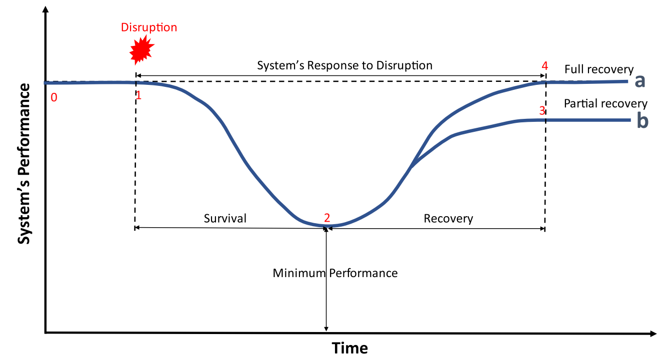

Fig. 1. Resilience curves showing the performance of the system after disruption with: *(a)* full and *(b)* partial recovery.

The resilience of a system can be shown with different metrics as discussed earlier but it can be intuitively shown with a performance-based curve known as resilience curves, first introduced by Bruneau, et al., that represent the quantitative and qualitative characteristics of system performance (Bruneau et al., 2003). Typically, these curves show how system performance changes prior to, during, and following a disruption. Fig. 1 shows two typical resilience curves where the first curve gains full recovery from the disruption while the second curve depicts partial recovery.

There are various elements (called resilience attributes, hereafter) that constitute a system's dynamic response to disruption. As can be seen in Fig. 1, there are two distinct parts in the resilience curve, the first being the survival with the drop in the performance after disruption until the minimum performance level (points 1–2 in Fig. 1) and second, being the recovery from the minimum performance level to partial (point 2–3 in Fig. 1) or full recovery states (point 2–4 in Fig. 1). These two parts represent the main dimensions of resilience and have been offered different names, or split into more dimensions in the literature (Hosseini and Barker, 2016).

Resilience is a unique characteristic of an engineering system that represents the reliability and maintainability of the system against disruptive events. Therefore, it is required to assess the system's resilience in light of a probabilistic perspective to better represent the system's dynamics of resiliency. Therefore, Dynamic Bayesian Network, a probabilistic model based on Bayesian statistics, is selected to quantitatively assess the resilience.

2.2. Proposed framework for resilience assessment at design stages

In this Section, a novel framework of resilience assessment at the design stage is proposed. To conduct a resilience assessment, firstly, it is required to gain knowledge on the hazards, potential disruptions and imposed risks, as well as the capability of the system to absorb and survive the disruption and recover from its consequences. This means that a comprehensive knowledge on the processes, system characteristics, maintenance capabilities and threatening hazards are required to make a resilience model. This knowledge is not well obtained at the design stage when hazard identification studies are in progress. Therefore, based on the available information on identified hazards and accident scenarios and consequences, the design stage is divided into two general time frames, namely the early design stage and the late design stage. Since the knowledge on system's characteristics are different in

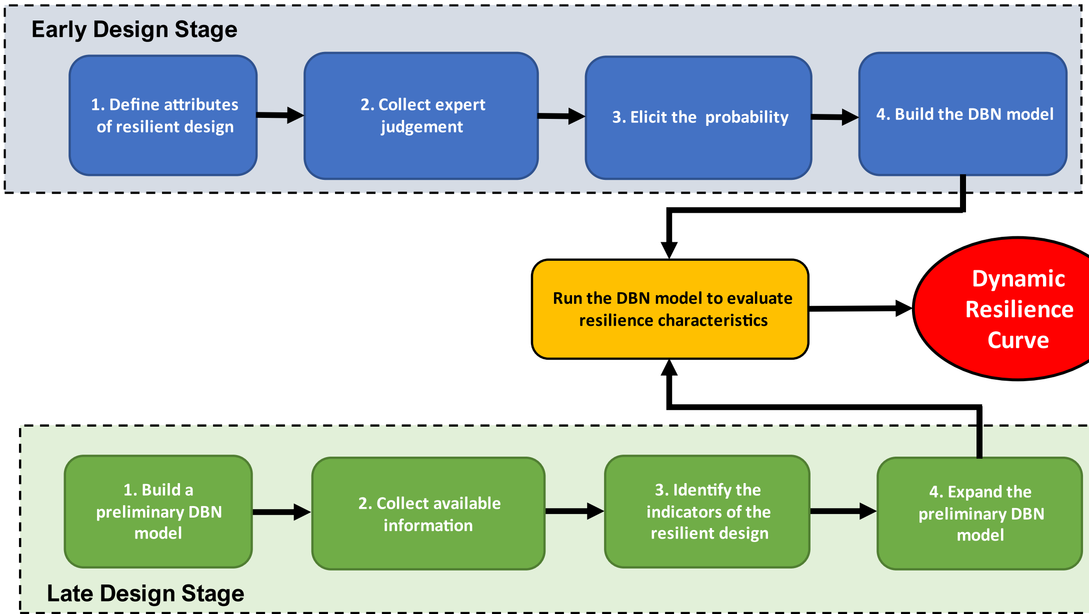

Fig. 2. The schematic presentation of the resilience assessment farmwork at both the early and late design stages.

these two stages, two different approaches are proposed in order to perform a quantitative resilience assessment. Fig. 2 shows, in brief, the proposed framework for the resilience assessment at the early and late design stages. The main difference between these two stages lies in the depth of the information available regarding the system's characteristics on dealing with an accident prior, during and after the disruption (i.e., attributes of resilient design). During the early design stage, these attributes may not be readily apparent, and it is required to firstly define them and then use the expert judgment to evaluate their quality in the studied system. On the contrary, at the late design stage, as more information becomes available and system response to accidents is assessed and safety barriers are clearly defined, some useful data like the event trees, fault trees, bow-tie diagrams, accidents scenario, failure and maintenance rates and much more are revealed which are mostly based on past operational experience of similar systems, expert judgment or design goals. This available data provides a great tool to redefine a more realistic resilience assessment model and to recalculate the resilience. For this reason, we intentionally do not link step 4 of the early design stage to the first step of the late design stage due to the differing levels of available information and knowledge maturity between these stages. In the early design stage, focus is on conceptualization and identifying resilient design attributes, whereas in the late design stage, more comprehensive data becomes available, allowing for a refined DBN model tailored to the system's specific characteristics. At each design stage, the quantified resilience will serve as an effective and practical tool, based on the available information, to inform the decision-making process and improve resilience.

As can be seen in Fig. 2, Dynamic Bayesian Network (DBN) is used to make a mathematical model of the system from the acquired information and to quantify resilience. DBN, an advanced Bayesian Network (BN), is a reliable probabilistic approach for analysing and forecasting under uncertainty that also, dynamically, takes into account the concept of time (Dagum et al., 1992). This method is capable of analysing failures based on multiple interdependencies of causes and effects and updating the prior estimated failure probabilities when new posterior data become available (Murphy, 2002). DBNs provide a framework for capturing dynamic system behaviour by modelling influences over discrete time steps. It is essential to clarify that the structure and parameters of a DBN remain stationary, ensuring consistency in modelling the underlying stochastic process and that does not imply that the network structure or parameters change dynamically. Rather, DBNs provide a framework for modelling dynamic systems, where the system's behaviour evolves over time. A DBN is represented as a directed acyclic graph, with each time-slice containing its own set of variables. This approach enables the modelling of temporal dependencies and the evolution of the system's state over discrete time steps providing a great tool to enhance the model's predictive capabilities and to provide a more comprehensive understanding of system resilience dynamics.

In resilience assessment, DBN is adopted to make a mathematical model that reflects the probabilistic dependencies between causes and effects of disruptive events as well as the system recovery (Tong et al., 2020). Yodo et al. first used DBN as a tool to quantify the resilience of engineering systems (Yodo et al., 2017). Other research works have also applied a DBN-based approach to resilience assessment for a refinery unit (Tong et al., 2020), power supply and control systems (Cai et al., 2021), oil and gas processes (Zinetullina et al., 2021), housing infrastructure (Sen et al., 2022), and subsea infrastructure (Yazdi et al., 2022). Some recent applications of the DBN-based resilience quantification are as follows: Sun et al. used a DBN-based resilience approach considering the optimization of the maintenance cost (Sun et al., 2022). Tong and Gernay employed DBN to model the interconnections among process facilities with focus on analysing the domino effects (Tong and Gernay, 2023). Zeng et al. used DBN for quantitative resilience assessment of chemical plants against Natech-related cascading multi-hazards (Zeng et al., 2023). The most recent studies includes using DBN to assess resilience-oriented maintenance optimization (Alipour et al., 2024), seismic resilience (Tasmen et al., 2023), multidimensional urban resilience (Chen et al., 2023), and resilience of complex systems coupled with evidence propagation (Caetano et al., 2024). Interested readers can refer to the mentioned references for detailed mathematical background. A brief introduction to DBN is provided below:

DBN, a Bayesian network, that has been supplemented with additional mechanisms to simulate influences over time represents the cause and effects in a probabilistic and graphical model that consists of arcs and nodes. In Bayesian Network (BN), based on an inference algorithm that uses Bayes' theorem, marginal and conditional probabilities are used to determine the joint probability of the nodes $X=(X_1, X_2, \ldots, X_n)$. A DBN comprises of a sequence of BNs and relates variables along a discretized timesteps in contrast to typical BNs. A node at time t in a DBN model is reliant on its parent nodes at time t as well as their states and parent nodes at previous time steps (Tong et al., 2020; Jensen and Nielsen, 2007). The joint probability (at time t) of a series of variables

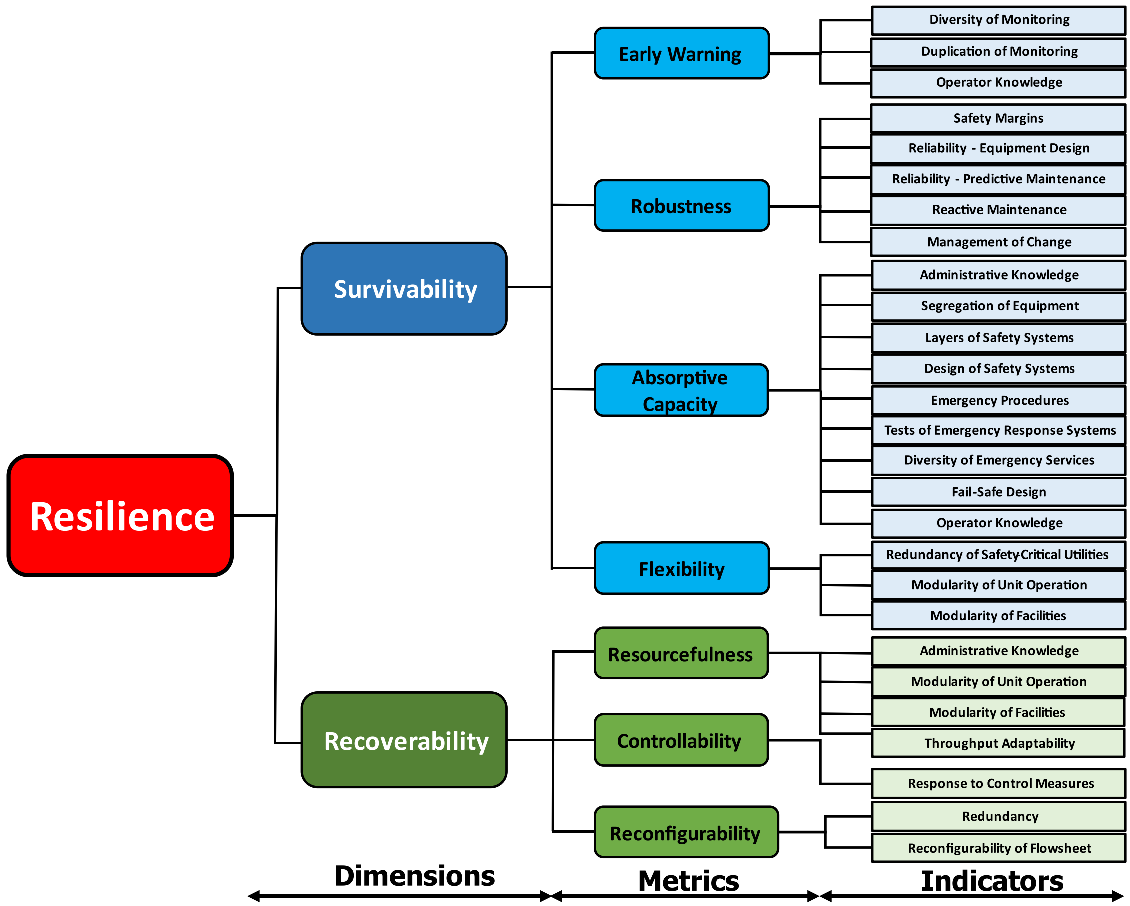

Fig. 3. Proposed scheme for identifying attributes of resilience.

$X^t = (X_1^t, X_2^t, X_3^t, \ldots, X_n^t)$ is quantified using Eq. 1 as:

$$P(X^t) = \prod_{i=1}^{n} P\left(X_i^t | X_i^{t-1}, pa(X_i^t), pa(X_i^{t-1}), pa(X_i^{t-2}), \ldots, pa(X_i^0)\right) \quad (1)$$

where $pa(X_i^t)$ represents the parent node X_i at time t, and X_i^{t-1} is the previous state of node X_i at time step *t-1*. All of the elements that affect the system's resilience are combined to make a DBN model and are represented with random variables in nodes while their dependencies are linked with arcs. The proposed methodology and detailed discussions for each stage is provided in Section 2.2.1. and 2.2.2.

2.2.1. Early design stage

At the early design stage, the knowledge on the system is at its minimum, therefore, it is needed to, first, identify the resilience attributes of the system, and then use the expert judgment to evaluate the quality of these attributes that are defined to clearly evaluate the imposed risk, safety barriers and restoration capabilities of the system and to make a mathematical model that represents the system resilience. The framework for the resilience assessment at the early design stage, shown in Fig. 2, entails 4 major steps that are discussed in detail as follows.

Step 1: Define attributes of resilient design

First step is to identify the attributes of the system resilience that should represent the system's dynamic response in surviving the disruption and then in recovering from the consequences and should be identified with multiple clearly segregated system properties. In this work, the attributes of system resilience are divided into three categories namely dimensions, metrics and indicators of the resilient design. Dimensions are the most general attributes of resilience being expanded to more detailed properties of the system named metrics and those are, also, expanded to the indicators of resilient design.

Different resilience dimensions can be distinguished from a system's dynamic reaction to a disruption. Various dimensions have been outlined in existing literature, such as the model proposed by Hollnagel et al (Hollnagel et al., 2008)., which describes resilience in terms of anticipation, monitoring, response, and learning. Hosseini and Barker identified absorption, adaptation and restoration (Hosseini and Barker, 2016) as key dimensions, while Baroud et al. outlined resilience in terms of reliability, vulnerability, survivability and recoverability (Baroud et al., 2014), Similarly, Yodo and Wang defined survival and recovery as fundamental dimensions of resilience (Yodo and Wang, 2016b).

A broad dimension definition is required in this stage which at the same time captures all system dynamics to respond to a disruption. As resilience represents the ability of a system to both survive a severe disruption with little negative impact and subsequently recover from that, the resilience dimensions are defined as survivability and recoverability with the following definitions:

- *Survivability*: An engineering system's capacity to decrease the severity of an impact due to disruption is referred to as survivability. A system's ability to sustain a certain amount of disruption, without completely failing, can be conceived as the difference between normal performance and its minimum interrupted performance (points 1–2 in Fig. 1) (Taleb-Berrouane and Khan, 2019).
- *Recoverability*: The ability of an engineering system to take corrective actions and return to normal operating circumstances after being interrupted is captured by recoverability. A system's ability to recover and bounce back to normal performance can be conceived as the difference between minimum performance (point 2 in Fig. 1) and

its full or partial recovered performance level (points 3 or 4 in Fig. 1) (Yodo and Wang, 2016b).

Survivability and recoverability are influenced by other system characteristics called as resilience metrics. Although this approach aligns with several methodologies in the literature, varying labels have been employed for these dimensions. For instance, survivability and recoverability have been likened to restoration and reliability, absorptive and adaptive capacity, as well as static and dynamic resilience (Yodo and Wang, 2016a; Tong et al., 2020). The terminology used here is deliberately selected to minimize confusion between dimensions and other attributes linked to a resilient system. This provides a comprehensive framework while minimizing confusion with other terms used in the literature. As a result, the associated metrics (as a subset of these two dimensions) are also accurately reflecting the characteristics of the system within these main dimensions. Based on the literature survey, we have decided to dedicate four metrics that contribute most to survivability and three metrics to recoverability. The defined metrics are:

Survivability Metrics

- *Early Warning*: the ability of a system to monitor anomalies and quickly identify disruptions (Dinh et al., 2012; Hoseyni et al., 2021, 2023).
- *Robustness*: a certain degree of stress that a system can handle without experiencing performance issues (Bruneau and Reinhorn, 2007).
- *Absorptive Capacity*: the capacity of disruption's consequences that the system can block or absorb (Francis and Bekera, 2014b).
- *Flexibility:* a system's capacity to function reliably under a variety of process settings as a result of error-tolerant design (Ishfaq, 2012).

Recoverability Metrics

- *Resourcefulness*: the amount of resources a system has access to and how rapidly it can deploy those resources (Yodo and Wang, 2016b).
- *Controllability*: the capacity to guide and lead a system from a disruption to a regained equilibrium state (El-Halwagi et al., 2020).
- *Reconfigurability*: the ability of a system to fluidly switch between and use several configurations (Oboudi et al., 2019).

Metrics ought to be measured and described in terms of quantifiable system characteristics, which we characterise as indicators of resilient design. In this work, 27 indicators of resilient design are defined that consider not only the engineering design, but also take into account management and human factors (Vesey et al., 2023). Fig. 3 shows, in detail, the proposed attributes of the resilient design that is defined to evaluate the system resilience at the early design stage.

The indicators summarized in Fig. 3 were developed with a keen emphasis on simplicity and versatility, ensuring they are easily applicable across a range of engineering systems, particularly in the early design phase where comprehensive data is scarce. Based on extensive literature reviews, these indicators capture essential aspects of resilience, providing various opportunities for enhancing system robustness. Notably, these indicators have undergone validation in a qualitative resilience assessment of early design process plants, as detailed in the authors' previous work (Vesey et al., 2023). Building upon this foundation, the current research seeks to further validate and refine these indicators through a quantitative approach, with the aim of enhancing their effectiveness in assessing and improving system resilience. It's noteworthy that there are considerably more indicators related to survivability, which is unsurprising given its deeper understanding and extensive research within process safety. It's important to recognize that this set of indicators serves as a foundation, implying that additional system properties contributing to resilience could be incorporated in future iterations of the model. This adaptability is especially crucial as the comprehension of resilient recovery evolves over time.

Table 1
Qualitative terms for rating the quality of indicators of the resilient design (Liu et al., 2014).

Qualitative terms	IFNs
Extremely low (EL)	(0.10,0.90)
Very low (VL)	(0.25,0.70)
Low (L)	(0.30,0.60)
Fairly low (FL)	(0.40,0.50)
Medium (M)	(0.50,0.50)
Fairly high (FH)	(0.60,0.30)
High (H)	(0.70,0.20)
Very high (VH)	(0.75,0.20)
Extremely high (EH)	(0.90,0.10)

The detailed model shown in Fig. 3 provides a holistic and broad approach to assess the main attributes of resilience in any engineering system at the early design stage and helps to overcome the lack of sufficient information to analyse the resilience. The indicators of the resilient design can be considered as the root cause that directly affect the resilience metrics which contribute to the dynamics of the two main pillars of a system's resilience (i.e., resilience dimensions of survivability and recoverability). For example, as can be seen in Fig. 3, diversity of monitoring, duplication of monitoring, and operator knowledge are the three indicators that influence the "early warning" metric which itself is one of the four metrics of the survivability dimension. These indicators can be evaluated by the experts and their judgment provide the required information to make the DBN-based resilience model.

Step 2: Expert judgment

As the second step of the framework after defining the attributes of resilient design, expert judgment should be collected on the defined attributes to evaluate system resilience capabilities. Linguistic phrases are proposed to the experts to judge the indicators, and Intuitionistic Fuzzy Numbers (IFNs), an extension of fuzzy sets, are designated to the collected judgment (Atanassov, 1986). The key advantage of IFNs is that experts can convey their judgments with a wide range of ambiguities and uncertainties by using qualitative terminologies.

A questionnaire can be built and sent to the experts to evaluate an engineering system's characteristics on 27 indicators of the resilient design. The experts are asked to evaluate each indicator of the resilient design and provide their judgment on the quality of that indicator in the studied engineering system. The expert judgment is provided based on 9 qualitative ratings shown in Table 1 ranging from extremely low (i.e., the quality of the indicator of resilient design in the system is extremely low) to extremely high. The IFNs associated with each qualitative term is also extracted from literature and provided in Table 1 (Liu et al., 2014). Each qualitative term represents a subjective assessment of the quality of indicators related to resilient design. The IFNs (a,b) associated with each term represent the degree of membership (a) and non-membership (b) assigned to the indicator's quality. For example, the term "Extremely low (EL)" is associated with the IFN (0.10,0.90), indicating a high degree of non-membership (b=0.90) and a low degree of membership (a=0.10). Similarly, the term "Medium (M)" is associated with the IFN (0.50,0.50), indicating equal degrees of membership and non-membership, suggesting uncertainty in the assessment. Together, the membership and non-membership degrees provide a comprehensive representation of the degree of inclusion and exclusion of an element in a particular category or set. They allow for a nuanced assessment of the level of confidence or uncertainty associated with the evaluation of qualitative terms in the context of IFNs. These qualitative terms and their corresponding IFNs serve as a basis for experts to evaluate the quality of indicators in the studied engineering system.

Step 3: Probability elicitation

As the 3rd step of the framework, after the evaluation of the indicators of resilient design are collected from experts, D number theory, a generalisation of Dempster-Shafer evidence theory for effective modelling of uncertainties (Zarei et al., 2021), is used to elicit the

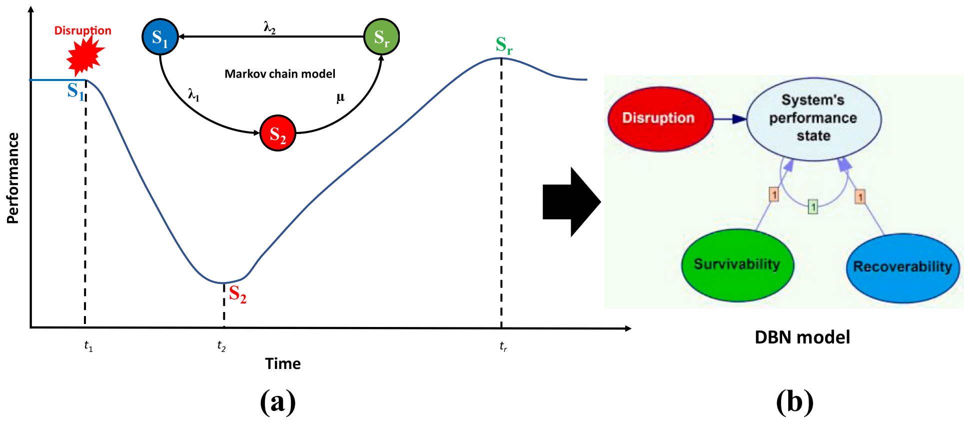

Fig. 4. (a):The resilience curve, states after disruption, and proposed Markov chain model at the early design stage; (b) DBN model for resilience assessment.

probabilities using the IFNs of Table 1. In other words, IFNs are converted to D numbers and aggregation of D numbers is used to obtain the experts opinions. Let's assume that $D=\{(a_1,b_1), (a_2,b_2), \ldots, (a_m,b_m)\}$ is a D number obtained from m experts opinions where their evaluated IFNs are converted to D numbers' first and second components, a_j and b_j respectively. The opinions of all experts can be aggregated into the crisp possibility (CP) as shown in Eq. 2 (Yazdi, 2019):

$$CP = \sum_{j=1}^{m} (w_j.a_j.b_j) \tag{2}$$

where w_j is the j^{th} expert's importance weight.

Following the computation of the crisp value representing the possibility of an indicator, the probability of the indicator (P_r) is then elicited using the Onisawa equation (Onisawa, 1990) as shown below:

$$P_r = \begin{cases} \frac{1}{10^k}, CP \neq 0 \\ 0, CP = 0 \end{cases} \quad , \quad k = 2.301 \times [\frac{1}{CP} - 1]^{1/3} \tag{3}$$

The Onisawa equation is widely used to elicit the failure probability from expert opinion in numerous reliability engineering references (Sahin et al., 2022, 2021; Masalegooyan et al., 2022; Kabir et al., 2018) and we used this equation for the illustration purpose. However, it is important to acknowledge that the utilization of the Onisawa equation is not without its critiques. Some scholars may argue that there are more reliable ways for probability elicitation. Some other practical solutions are given in the literature (Dubois and Prade, 2015; Chanas and Nowakowski, 1988) to replace this equation. There is also an established methodology for eliciting experts' probabilities given by O'Hagan et al. in 2006 which can be used instead (O'Hagan et al., 2006).

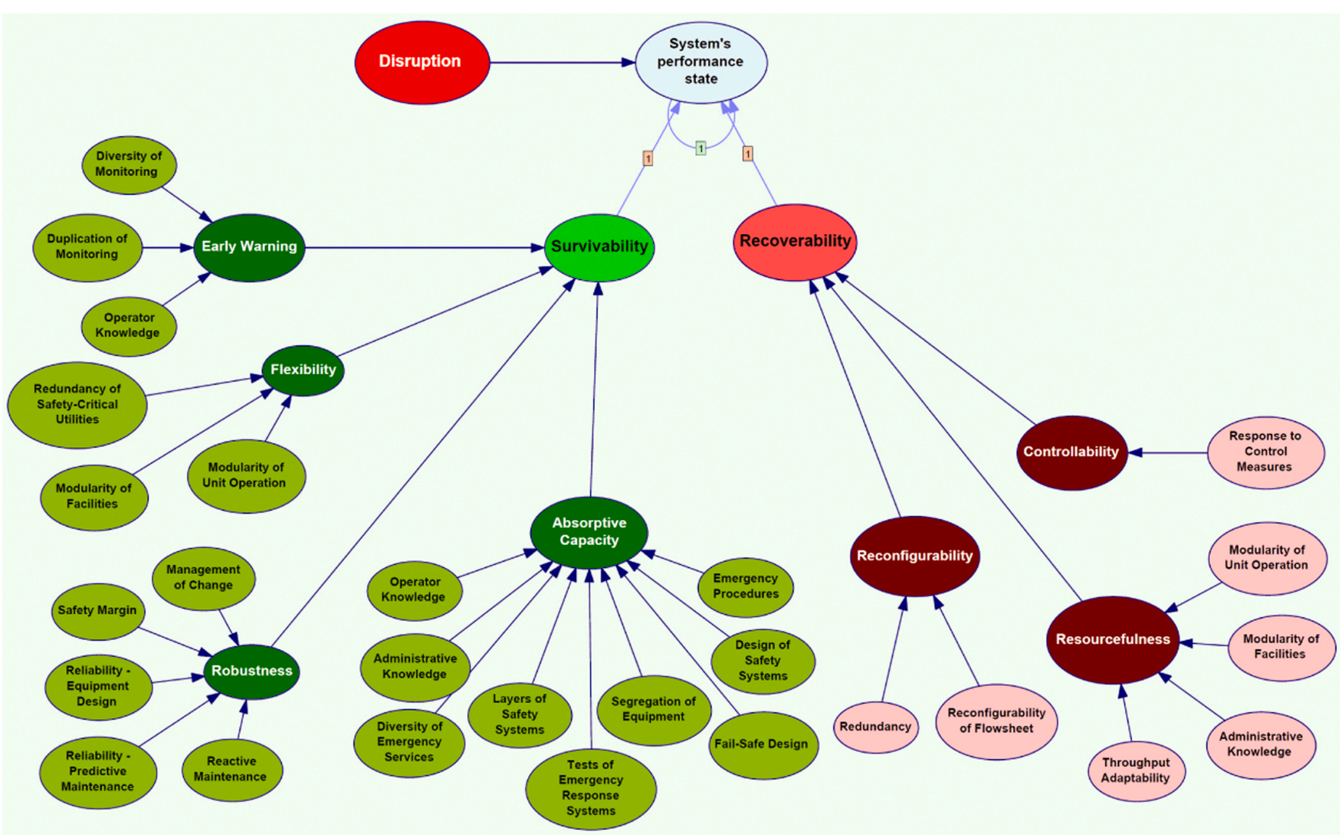

Fig. 5. DBN model for resilience assessment connecting the resilient attributes at the early design stage.

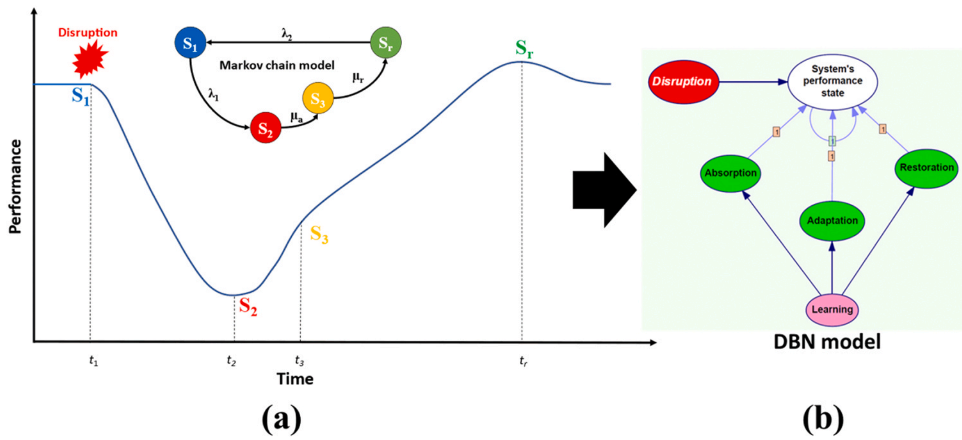

Fig. 6. *(a)* The resilience curve, states after disruption, and proposed Markov chain model at the late design stage; *(b)* DBN model for resilience assessment.

Step 4: Build DBN model

The 4th step is to build a DBN model from the available data. The DBN model is built based on the performance level of the system. After the occurrence of disruption, the performance of the system changes (see Fig. 4(a)). Three states are defined to show the effects of disruption in system's performance:

- S_1: the normal operating state when disruption occurs at t_1.
- S_2: the disrupted state that system encounters due to the disruption's damaging effects and drops the performance to the minimum level at t_2.
- S_r: Final recovered state when system returns to a desirable performance at t_r.

A Markov chain model can be used to model the transition among these three states. The transition among these three states are modelled using transitional probabilities λ_1, μ, and λ_2 as shown in Fig. 4(a). The transition, after the disruption, from the normal state S_1 to the disrupted state S_2 is identified with transitional probability $\lambda_1 = \frac{1}{MTBF_1}$ where $MTBF_1$ is the mean time between failure after the occurrence of disruption. The disrupted state S_2 is transited to the recovered sate of S_r with transitional probability of $\mu = \frac{1}{MTTR}$ where $MTTR$ is the mean time to repair with internal auto-repair as well as external maintenance activities. λ_2 can be obtained using $MTBF_0$ as the mean time between failure at normal operating condition as $\lambda_2 = \frac{1}{MTBF_0}$. It is worth mentioning that when the system enters the new recovered stable state of S_r, a new cycle begins where the system starts over its normal operating condition decaying with the constant rate of λ_2. A mathematical model for the quantitative assessment is built by transforming the Markov chain model into a DBN model that entails parent node of disruption and two other parent nodes that represent the dimensions of resilient design (i.e., the survivability and recoverability nodes) (See Fig. 4(b)) (Tong et al., 2020).

The preliminary DBN model of Fig. 4(b) can be extended to include the metrics and dimension of resilient design at the early design stage as shown in Fig. 5. The indicators of the resilient design can be defined as the root parent nodes of the extended DBN model where the elicited probabilities are included in these nodes as marginal probabilities. Parent nodes causal impacts are assumed to be independent and the effects of parent nodes on child nodes are represented with conditional probabilities. The disruption node identifies external and internal elements that could contribute to system failure and reduced system reliability and comes with two states of 'True' or 'False' meaning that the disruption may be either true or false. Similarly, all nodes related to the attributes of resilient design are dedicated two states of 'High' or 'Low'. The child node 'system's performance state' includes the 3 performance states namely S_1, S_2, and S_r with the transitional probabilities λ_1, μ_r, and λ_2 that are transformed to the conditional probability of the node given the dimensions of the resilience.

The DBN model of Fig. 5 serves as a good tool for conducting resilience assessment of any engineering system at the early design stage where the system response to disruption are quantified with the elicited and conditional probabilities and that enables quantifying the probability of system performance states at the child node by using Eq. (1).

The last steps of the framework, as shown in Fig. 2, would be to run the DBN model and obtain the resilience curve. The probability that a system will maintain operating in a normal state (remaining in S_1) or return to a recovered state from a disrupted state (reaching S_r) at each time step during and after a disruption can be used to determine a system's resilience (Zinetullina et al., 2020). Therefore, at each time step, the resilience of the system equals to the sum of the probabilities of states S_1 and S_r obtained from the system's performance state node after running the model. The aggregation of these probabilities at different time steps is used to build the quantitative resilience curve.

2.2.2. Late design stage

At the late design stage, as the design process has evolved, some hazard identification studies have been completely performed and some knowledge on system absorption and restoration capabilities are identified. This knowledge is presented at the last levels of design when hazard identification studies are completed and event trees and faults tress and bow-tie diagrams are released on different accident scenarios and their relevant safety barriers. These knowledge can be used to identify the resilience attributes and assess the system resilience. The four steps shown in Fig. 2 are discussed with further details as follows.

Step 1: Build a preliminary DBN model

As shown in Fig. 2, the first step, is to build a preliminary DBN model. Before building the model, it is required to define dimensions of resilient design. In this stage, we propose much more comprehensive dimensions for the resilient design. Resilience dimensions are defined as absorption, adaptation, restoration and learning (Zinetullina et al., 2020). A system's innate capacity to withstand and survive disruption is known as absorption. Adaptation is the system's ability to adjust to a disturbed state, and to recover without the help of external restoration efforts. The ability of a system to embrace external efforts to fix the harm brought on by the disruptions and return it to a new normal operating condition is referred to as restoration. The new normal state is when the system bounces back to equilibrium and can be different than the normal pre-disruption state. Finally, learning is the capability of a system to provide useful feedback from evidence collected from prior incidents and aids in the generation of new information for disruption countermeasures (Zinetullina et al., 2021).

A Markov chain model is used to represent the resilience dimensions and performance changes after disruption that are shown with four

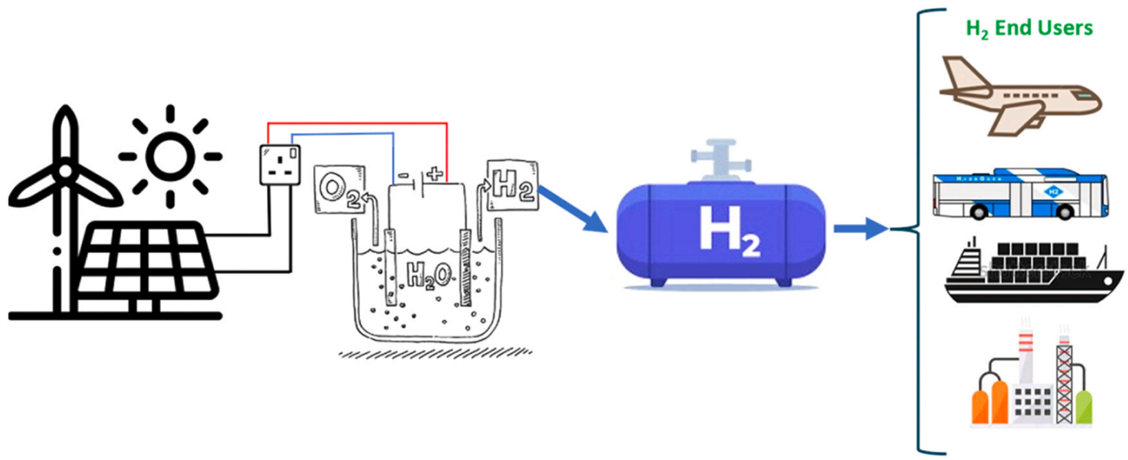

Fig. 7. Green Hydrogen production scheme.

states being:

- S_1: the normal operating state when disruption occurs at t_1.
- S_2: the disrupted state that system encounters the minimum performance level at t_2.
- S_3: the performance slight improvement state reached after adaptation by the temporary self-activated response at t_3.
- S_r: Final stable recovery state that system reaches a desirable performance at t_r thanks to the restoration.

Fig. 6(a) shows the mentioned states in the resilience curve and schematically represent the Markov chain model that is defined for transition among states.

The transition among these four states are modelled with the Markov chain model using transitional probabilities being λ_1, μ_a, μ_r, and λ_2 as shown in Fig. 6. λ_1 and λ_2 are defined similar to the early design stage based on MTBF (See Section 2.3.1). The system may begin to repair itself after a disruption before any external maintenance is carried out (i.e., adaption with self-repair activities like sprinkler system activation to extinguish the fire). The length of this adaptation process is identified by the response time (T_{res}) and is used to quantify the adaptation rate as $\mu_a = \frac{1}{T_{res}}$. After adaptation, external maintenance activities take place to restore the system to its normal operating condition with the rate $\mu_r = \frac{1}{MTTR_r}$ where $MTTR_r$ is the mean time to repair the system with external maintenance measures. The preliminary DBN model, shown in Fig. 6(b), is built form the Markov chain model similar to that of the early design stage except the fact that the child node of "system's performance state" includes four performance states namely S_1, S_2, S_3, and S_r. Furthermore, the dimensions of the resilient design represented by absorption, adaptation, restoration nodes are further influenced by learning, disruption, and the system's performance.

Step 2: Collect available information

As step 2 of the framework, any available knowledge on system characteristics that has been evaluated in hazard identification studies, including event trees, fault trees, bow-tie diagrams, failure and maintenance rates should be extracted. A comprehensive study should be conducted to extract this information from the hazard identification studies that are performed during the design stage of the system. As wells as the knowledge extracted from process safety, hazard identification and risk assessments studies performed, the recovery characteristics of the system including the auto-repair, external maintenance activities and failure and repair rates should be clearly identified.

Step 3: Identify the indicators of the resilient design

The collected information provided at the late design stage are thoroughly studied, in this step, and indictors of the resilience design are identified from this data. The data provided by the fault trees are usually related to the root events of the disruption and can be identified as indicators of resilient design used to expand nodes that will be the parent nodes of the disruption node while safety barriers provided in the event tree can be used to expand the resilience indicators used as nodes of absorption, adaptation and restoration. Other available information depending on attributes of resilient design can be identified to be mapped into the DBN model that represents all characteristics of disruption, safety barriers and system's restoration capabilities.

Step 4: Expand the preliminary DBN model

When the indicators of the resilient design are identified from the available information, the indicators can be presented with the DBN nodes and mapped into the preliminary DBN model of Fig. 6(b). The available probabilities in the bow-tie diagrams (BTs), event trees (ETs), and fault trees (FTs) are used as the marginal probabilities or conditional probabilities of the nodes in the DBN model (Zinetullina et al., 2020). DBNs offer a solution to the limitations of traditional risk assessment models such as FTs, ETs, and BTs, which struggle to effectively assess the interconnectedness of risk factors and adapt to changing conditions or uncertainty by providing a temporal connection among parameters (Wu et al., 2016; Zhang et al., 2024). While there are limited references using the hierarchical Bayesian networks (HBNs) to quantify resilience (Vairo et al., 2020; Sen et al., 2020), and they can handle temporal data to some extent, DBNs are well-suited for modelling temporal dynamics and simulating scenarios to assess system resilience over time.

Finally, the expanded DBN model is run to quantify the probability of four states of the system's performance state (i.e., S_1, S_2, S_3, and S_r) at each time step. The resilience curve is then quantified as the sum of the probabilities of states S_1 and S_r similar to the method provide at the early design stage.

3. Case study

Green hydrogen, as its name implies, is an environment-friendly process where hydrogen is produced by splitting water molecules using electrolysis which is empowered by the electricity generated from renewable sources like wind and solar (Domínguez et al., 2022). This process produces hydrogen as a product and oxygen as a by-product from the feedstock water. Fig. 7 shows schematic presentation of green hydrogen production process.

The framework is applied to an alkaline water electrolysis hydrogen production facility. The main equipment of the case study includes rectifiers, electrolysis cells, cooling system, compressors, gas holders, demisters, water cells, pall filtration system, H_2 gas dryer and storage tanks (Zarei et al., 2021).

Table 2
Expert judgment on the indicators of resilient design.

Indicator of Resilient Design	Expert #1	Expert #2	Expert #3	*CP*	P_r
Diversity of Monitoring	VH	H	FH	0.15	7.90E-05
Duplication of Monitoring	H	VH	M	0.154	8.71E-05
Operator Knowledge	VH	FH	L	0.162	1.05E-04
Safety Margin	H	FH	VH	0.153	8.50E-05
Reliability - Equipment Design	VH	VH	EH	0.144	6.79E-05
Reliability - Predictive Maintenance	FH	M	VH	0.198	2.15E-04
Reactive Maintenance	VL	M	VH	0.195	2.04E-04
Management of Change	VH	H	FH	0.15	7.90E-05
Operator Knowledge	H	H	FH	0.144	6.79E-05
Administrative Knowledge	M	FL	L	0.228	3.51E-04
Segregation of Equipment	H	H	FH	0.144	6.79E-05
Layers of Safety Systems	VH	VH	FH	0.153	8.50E-05
Design of Safety Systems	VH	VH	H	0.149	7.71E-05
Emergency Procedures	VH	H	FH	0.15	7.90E-05
Tests of Emergency Response Systems	VH	EH	VL	0.1615	1.04E-04
Diversity of Emergency Services	M	FH	VL	0.2215	3.17E-04
Fail-Safe Design	VH	VH	M	0.16	1.00E-04
Redundancy of Safety-Critical Utilities	VH	FH	FL	0.164	1.10E-04
Modularity of Unit Operation	M	FL	EL	0.219	3.05E-04
Modularity of Facilities	M	FL	EL	0.219	3.05E-04
Modularity of Unit Operation	H	FH	L	0.156	9.13E-05
Modularity of Facilities	H	FH	L	0.156	9.13E-05
Administrative Knowledge	M	L	VL	0.2215	3.17E-04
Throughput Adaptability	H	FH	VL	0.1555	9.02E-05
Response to Control Measures	M	FL	FL	0.23	3.61E-04
Redundancy	H	H	M	0.151	8.10E-05
Reconfigurability of Flowsheet	H	M	FL	0.179	1.50E-04

3.1. Resilience assessment at the early design stage

Using the framework proposed in Section 2.2.1, at the early design stage, attributes of resilient design depicted in Fig. 3 are used to identify the risk and resilience characteristics of the case study. A questionnaire is prepared and sent to three experts to evaluate 27 indicators of the resilient design. Table 2 shows the collected experts opinions that have evaluated each indicator with the linguistic terms provided in Table 1. The IFNs of Table 1 is then transformed to D numbers. Using Eq. (2), the crisp possibility (*CP*) of each indicator is calculated based on the experts opinions. It is worth mentioning that, in this work, we assumed the importance weight of 0.6, 0.3, and 0.1 for experts#1, #2, and #3 respectively. The three experts were selected based on their expertise relevant to the study. The first, with significant industrial experience in hydrogen production safety, was given a weight of 0.6. The second, an academic with process safety research experience, had a weight of 0.3. The third, specializing in resilience assessment, having limited experience on hydrogen safety, was assigned a weight of 0.1. These weights reflect their varying levels of expertise and relevance to this study and ensure a comprehensive range of insights. Using the *CP* and Eq. (3), the probability (P_r) of each indicator is elicited as shown in Table 2.

The probabilities of Table 2 are used to fill the marginal probabilities of parent nodes that represent the indicators of resilient design in the DBN model shown in Fig. 5. These probabilities will be dedicated to the marginal probabilities of the root nodes of Fig. 5 for their 'Low' state while 'High' state is assumed to be the complementary event of the 'Low' state. Parent nodes causal impacts are assumed to be independent. Thus, in order to describe the effects of parent nodes on child nodes, the noisy-or function is used assuming conditional probabilities have equal importance weights for all the contributing factors (Yazdi et al., 2022).

Assuming that the system works with high functionality (i.e., the states of the indicators of resilient design nodes are set to be in 'High' state), the resilience curve of the case study is quantified as shown in Fig. 8.

Analysing the resilience curve reveals useful information about the dynamics of the plant response to the disruption in time. It can be concluded from Fig. 8 that after the disruption occurs, it takes 6 hours to reach the minimum performance level of 0.46. Then, the recovery show its effects and plant starts to bounce back with an increasing trend in performance level. The time to reach 90 % of the lost resilience can be a good utility value to evaluate the recoverability of the system with a single value (Tong et al., 2020; Poulin and Kane, 2021). In Fig. 8, the time required to 90 % recovery of the lost resilience from the minimum performance level (i.e., time to reach 0.9×(1–0.46)+0.46 equals 35 hours) is 29 hours (i.e., 35–6=29 hours). Another useful resilience utility value is the area under the resilience curve that evaluates both survivability and recoverability. In our case, this value can range from 0 (for immediate system collapse) to 100 (for no disruption and continues maximum performance) and is equal to 89.93 for the resilience curve of Fig. 8.

A sensitivity analysis is performed on the dimensions of the resilient design to assess the survivability and recoverability characteristics of the green hydrogen plant. In this analysis, we set the state of survivability and recoverability nodes of Fig. 5 to be either High or Low. The resulted resilience curves are shown in Fig. 9.

As can be seen in Fig. 9, recoverability of the plant plays a greater role than the survivability because when recoverability of the plant is set to be low, system collapse will occur even if the survivability is high. When survivability of the plant is low but the revocability is high, the performance drops significantly to 0.1 but eventually the system bounces back and recover.

Another sensitivity analysis is performed to analyse the system's response to the scenarios where the resilience metrics are assumed to be in their low functionality state. Table 3 shows the results of this analysis where the resilience is compared with two mentioned utilities that quantify the 90 % recovery time as well as the area under the resilience curve. The percentage of the resilience reduction with comparison to the normal condition and based on the area under the curve is also provided.

As can be seen in Table 3, time to recovery in nodes that are related to recoverability dimension of the system (i.e., reconfigurability, resourcefulness, and controllability) is much longer than other nodes. Moreover, the resilience reduction is also much greater as well. Low resourcefulness, and low early warning scenarios pose the most and the least negative effect on the system resilience, respectively.

3.2. Resilience assessment at the late design stage

Knowledge on the threatening hazards, accident scenarios and safety barriers, at the late design stage, are obtained from the reference (Zarei et al., 2021) where hazard identification studies are conducted for a green hydrogen plant and the causation factors of hydrogen release

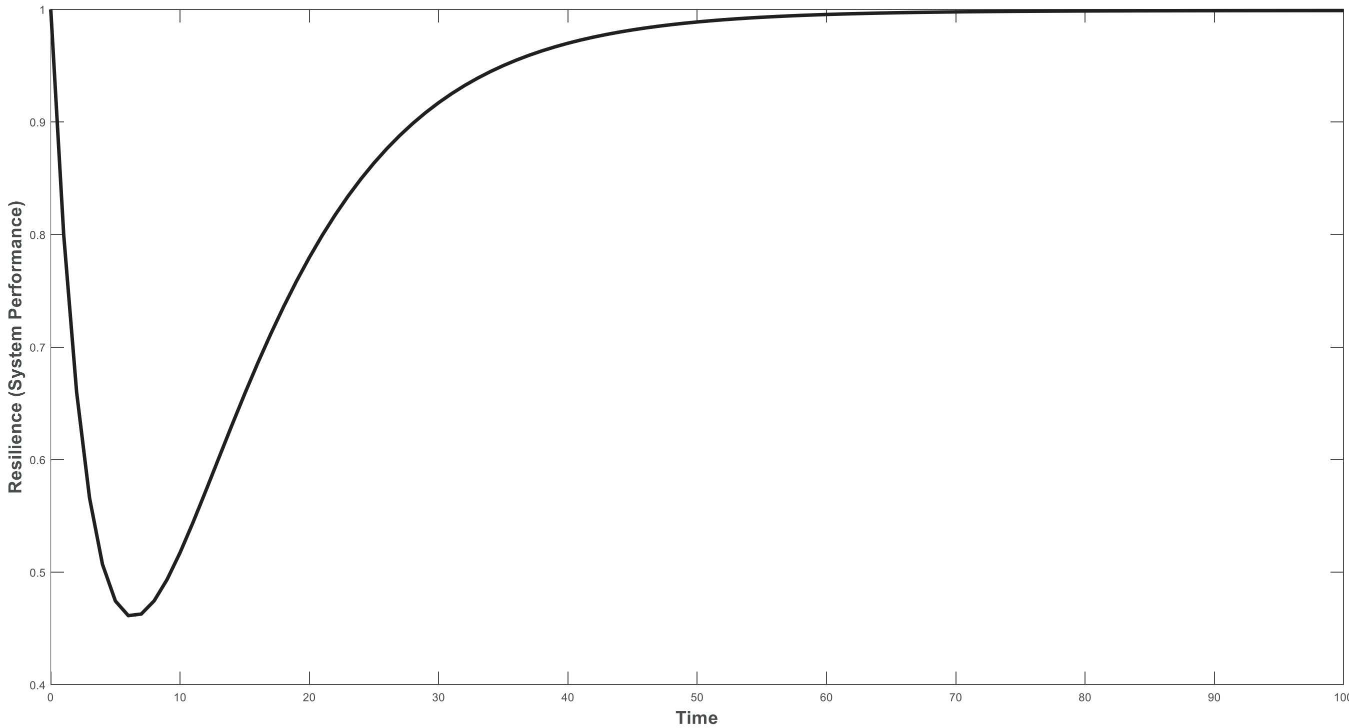

Fig. 8. Resilience curve of the case study at the early design stage.

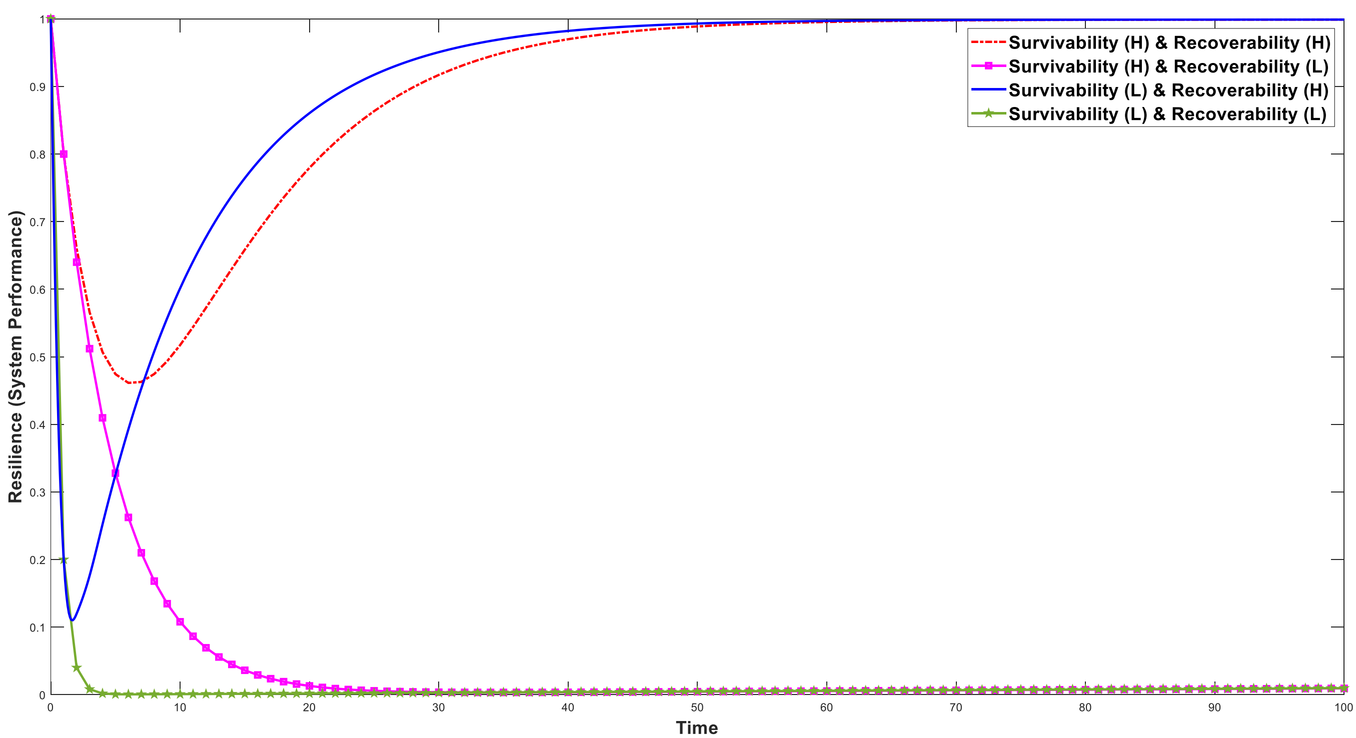

Fig. 9. Sensitivity analysis for survivability and recoverability.

scenarios are identified in the three sections of the plant (i.e., chemical, mechanical, and storage sections) leading to the disruption (i.e., H_2 release). Four safety barriers namely Release Prevention Barrier (RPB), Dispersion Prevention Barrier (DPB), Ignition Prevention Barrier (RPB), and Escalation Prevention Barrier (EPB) are dedicated to prevent the unsafe scenarios. Fig. 10 shows a schematic view of the bow-tie diagram of the studied green hydrogen plant for H_2 release scenarios. Details of 116 root events, 44 intermediate events, safety barriers and their associated probabilities can be found in Table 3-9 of the reference (Zarei et al., 2021).

Based on the preliminary DBN model of Fig. 6(b) and the bow-tie diagram of Fig. 10, the bow-tie diagram is mapped into DBN model. The expanded DBN model for resilience assessment is shown in Fig. 11.

The DBN model of Fig. 11 connects the causes of the gas release

Table 3
Sensitivity analysis for low functionality of resilience metrics.

Scenarios	Time to 90 % recovery (hours)	Resilience (area under the curve)	Resilience Reduction (%)
Low Reconfigurability	51	78.534	5.32
Low Resourcefulness	56	76.618	7.63
Low Controllability	47	80.295	3.20
Low Absorptive Capacity	41	82.05	1.09
Low Robustness	40	82.15	0.97
Low Flexibility	39	82.25	0.85
Low Early Warning	39	82.65	0.36

scenarios of the fault tree part of the bow-tie diagram to its effects at the disruption node as well as the prevention barriers and maintenance capabilities of the system. Fault tree part of the bow-tie diagram is mapped to the disruption node while BRP and RPB safety barriers of the event tree are mapped to the absorption node, IPB is mapped to the adaptation node, EPB is mapped to the restoration. Interested readers can refer to the reference (Khakzad et al., 2013) on the mathematical background of mapping a bow-tie diagram into a DBN model.

Similar to the early design stage, the DBN model can be executed for different states of the nodes and resilience curves can be quantified. A sensitivity analysis for transitional probabilities of λ_1, μ_a, μ_r, and λ_2 that represent the transition among four states of the 'System's performance state' node of the DBN model is conducted and the results are shown in Fig. 12.

Fig. 12(a-d) show the resilience curves based on the system performance for different values of the transitional probabilities and are useful for detecting the minimum performance level and when the system experience this level. The lowest minimum performance level (i.e., 0.53) occurs at the $2\lambda_1$ scenario at time step 9 (See Fig. 12 (a) blue circled line) while the highest minimum performance level (i.e. 0.81) also occurs in Fig. 12 (a) (red triangled line) at the $0.5\lambda_1$ scenario at time step 16. This shows that improvement in absorption capacity will play a key role in avoiding significant drops in system performance. Fig. 12(a-d) are also useful in realizing how the system response changes when transitional rate are changed. For example, when λ_1 decrease, $MTBF_1$ increase, and that cause improvement in system's absorption capacity and performance level. Another insight is that the change of λ_2 has the minimum effect in resilience curves.

Fig. 12(e) evaluates the resilience by the area under the curve of Fig. 12(a-d). The area under the curve aggregates the absorption, adaptation and restoration capabilities of the system presented in the resilient curves into a single value and gives a more comprehensive tool for the comparison of the resilience curves. The larger this value, the more resilient is the system in total. It can be seen that improving adaptation capability of the plant (i.e., increasing μ_a shown with blue squares in Fig. 12(e)) and improving restoration capabilities (i.e., increasing μ_r shown with green asterisks in Fig. 12(e)) will have the most positive effect on increasing the plant's resilience. Fig. 12 (f) shows that the time required to recover 90 % of the lost resilience is more sensitive to the value of λ_1 and it means that absorption capabilities should be improved if the objective is the instantaneous recovery of the plant.

4. Discussion

Analysing the results and the resilience curves reveal valuable insights into the characteristics of the plant's response to disruptions over time. The results offer crucial information regarding the post-disruption minimum performance level, the duration of recovery, and the overall recoverability capabilities of the system. Interestingly, the recoverability of the plant emerges as a critical factor, often outweighing survivability. This indicates that even if a system possesses high survivability, a lack of recoverability can lead to system collapse as shown in Fig. 9. Depending on whether recovery time, overall resilience, or minimum performance level holds greater significance, diverse strategies can be chosen to increase resilience during the design stage. This strategic flexibility allows organizations to tailor their approach to address specific vulnerabilities and optimize resilience.

In our analysis, we observed that enhancing the adaptation capability of the plant and improving restoration capabilities (see Fig. 12) have the most significant positive impact on increasing the plant's resilience. This suggests that management strategies should prioritize actions aimed at reinforcing these aspects to maximize resilience.

Moving forward, management strategies can be directed towards initiatives such as investing in technologies or processes that enhance the plant's adaptability to changing conditions. Technologies and processes such as automation systems and predictive maintenance enhance a plant's adaptability. Modular design and advanced simulation tools further optimize resilience by enabling rapid reconfiguration and informed decision-making. Additionally, efforts to improve the

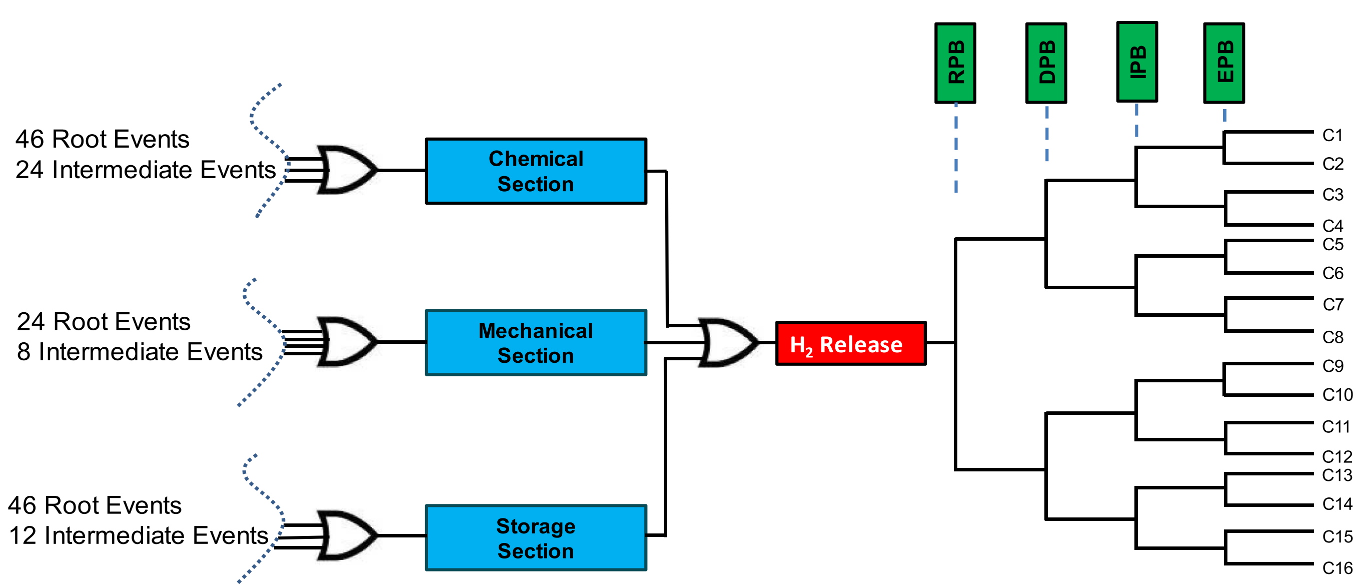

Fig. 10. The bow-tie diagram of the green hydrogen plant undergoing H_2 release scenarios.

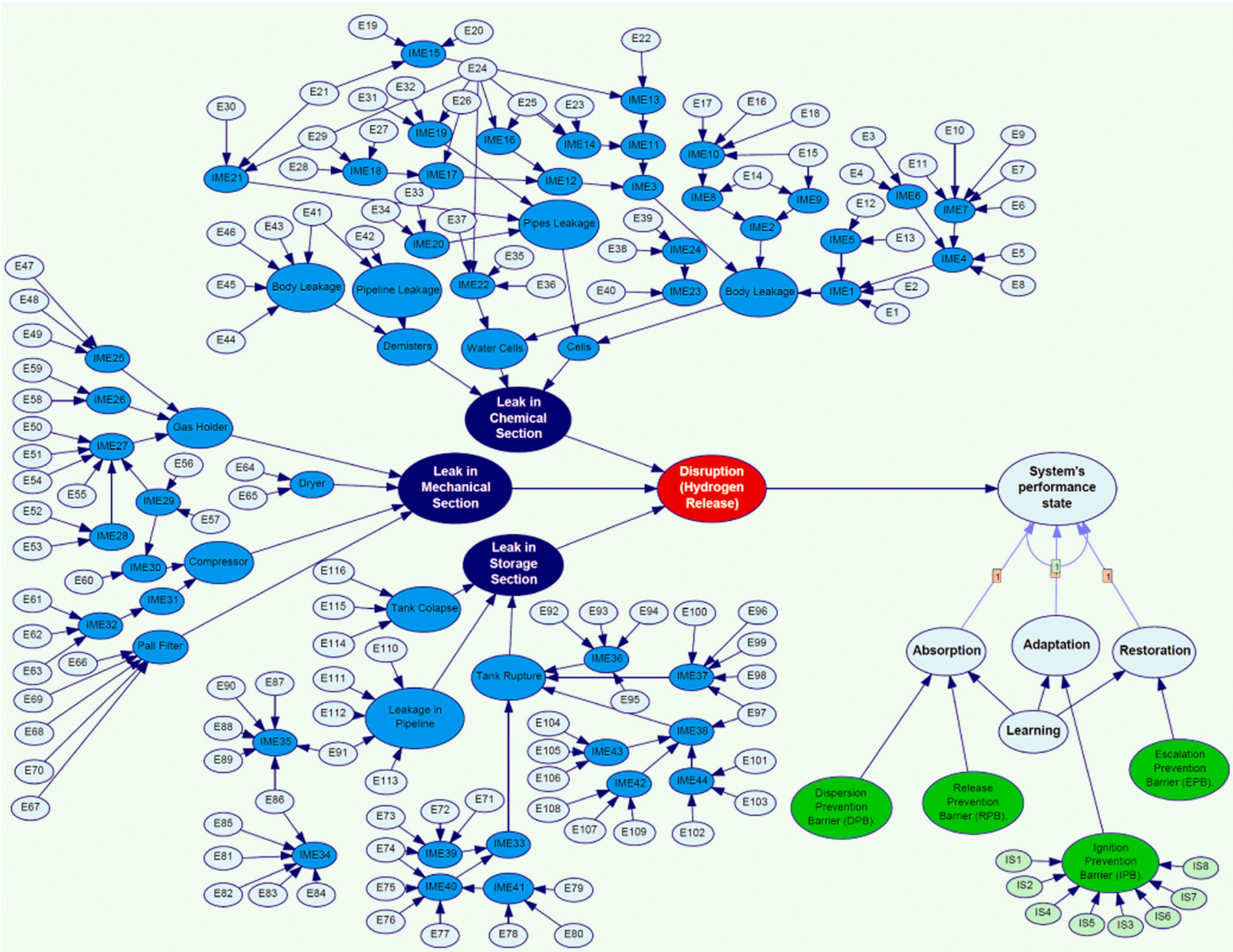

Fig. 11. DBN model for the resilience assessment of the green Hydrogen plant at the late design stage.

restoration capabilities, such as implementing efficient recovery protocols or acquiring backup systems, can significantly contribute to enhancing overall resilience. By focusing on these areas, organizations can better prepare themselves to withstand disruptions and recover swiftly, thereby ensuring continued operational effectiveness and sustainability.

The main strength of the proposed methodology lies in its adaptability, versatility and capacity for expansion to consider different system's characteristics into the resilience assessment. the multifaceted nature of resilience, is considered in the early design stage by defining indicators targeting organizational, management, and human factors, alongside early warning systems. Moreover, the model is completely flexible to be further expanded to consider more factors and establish the interdependencies of the indicators. In the late design stage when more specific information on selected accident scenarios for a number of known disruptive events becomes available, different DBN models for each disruption scenarios can be built and these factors can be extracted from the available information to be included in the DBN model through steps 3 and 4 of the late design methodology. Similarly, the DBN model of the late design stage is flexible to be expanded to include more organizational and management factors.

The primary constraint of the present methodology lies in its reliance on expert judgment for the assessment of resilient design indicators. This approach, while valuable in transforming resilience from an ambiguous concept in design stage into a simple and practical methodology, introduces subjectivity and potential biases into the evaluation process. For future model improvements, integrating data-driven and computational methods into the model can complement expert judgment, mitigate its limitations, and enhance the robustness, objectivity, and accuracy of resilience assessments.

While disruptions are typically modelled with a likelihood of component failure, it may seem that resilience assessment begins at this point, neglecting previous phases (as it may appear from the preliminary DBN models of Figs. 4–6). However, the probability of disruption occurrence is usually quantified through rigorous analysis, including hazard identification, consequence modelling, and fragility analysis. For instance, the probability of a loss of containment (LOC) due to an earthquake is determined by site-specific seismic hazard analysis and subsequent structural fragility analysis, integrating the probability of earthquake occurrence and the system's response to that earthquake, and its ensuing consequences, resulting in a disruption probability. This is evident in the late design DBN model of the case study, which demonstrates extensive nodes of hazard identifications before the hydrogen relief disruption in Fig. 11. Therefore, if disruption probability is derived from assumptions rather than detailed analysis (usually in early design phase), the resilience assessment results should be interpreted with awareness of this assumption. We urge readers to consider this limitation when applying the findings to their contexts. However, this limitation arises if the failure likelihood is based on arbitrary assumptions rather than rigorous hazard and fragility analysis.

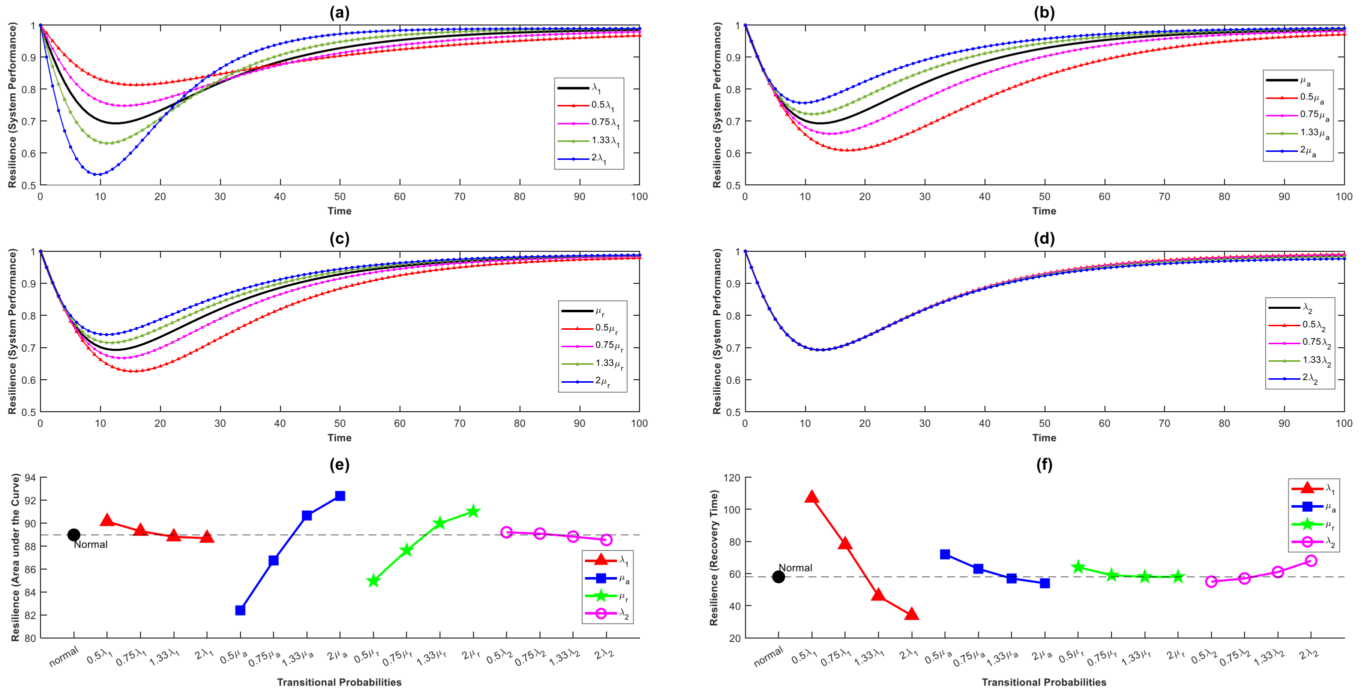

Fig. 12. Sensitivity analysis for transitional probabilities of λ_1, μ_a, μ_r, and λ_2 at the late design stage.

5. Conclusion

In this paper, a novel framework is introduced for quantitative resilience assessment of engineering systems at the early and late design stages. The application of the framework is applied in the resilience assessment of a green hydrogen production plant with a focus on gas release as a disruptive event. The introduced framework will fill the lack of applicable methodologies to quantitatively assess the resilience of engineering systems at the design stages when the knowledge on system processes are minimal. The quantitative framework provides a practical tool to quantify the resilience curves and perform sensitivity analyses on the key parameters of resilient design to identify the design defects and to suggest effective modifications that affects the resiliency of the system at most. The result of this work helps the designers to suggest efficient design changes and recommendations at the early and late design stages when system modifications are most efficient and cost-effective. Limitations inherent in our approach include the assumption of stationarity in Bayesian networks and the subjectivity and potential evaluation biases in the expert judgment process. Using continuous Bayesian networks and data-driven methods may help overcome these limitations, but this will introduce extra computational costs.

CRediT authorship contribution statement

Seyed Mojtaba Hoseyni: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Joan Cordiner:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization.

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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