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From Expert Judgment at the Early Design Stage to Quantitative Resilience Curves Using Fuzzy AHP and Dynamic Bayesian Networks

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The early design stage is the most effective time to introduce cost-effective measures to increase the resilience of the engineering systems against accidents and disruptive events, yet, since the current resilience assessment methodologies require sufficient knowledge on system characteristics and accidents scenarios, the resilient design is usually overlooked at this stage. This paper proposes a practical methodology for resilience assessment at the early design stage and links the qualitative assessment of system characteristics and expert judgment to a dynamic quantitative resilience assessment. In particular, the resilient characteristics of a system is identified and evaluated by the experts. Then, Fuzzy Analytic Hierarchy Process (AHP) is used to evaluate the contributing factors of the resilient design. Finally, Dynamic Bayesian Network (DBN) is used to make a dynamic mathematical model that represents the system response to disruptive events and integrates the identified system characteristics and expert judgment into a model that quantifies the dynamic resilience curve. The application of the methodology is demonstrated in a carbon capture and storage (CCS) system against the loss of containment accident. This paper presents a feasible methodology for the industries to introduce the system resilience at the early design stage and helps them to design safer, more reliable and available systems.

Keywords: Resilience, Design Stage, Dynamic Bayesian Network (DBN), Fuzzy AHP, Expert Judgment, Carbon Capture and Storage.

1. Introduction

The goal of resilient assessment, a rapidly developing field in engineering, is to design and manage complex systems that can resist and adjust to unforeseen interruptions or failures. It highlights the significance of designing systems that are flexible and adaptable to changing circumstances in addition to being reliable (Ahmadi, Saboohi and Vakili 2021, Mottahedi, et al. 2021). The existing methods for analysing resilience are complicated, demand a deep grasp of safety, and require advanced knowledge on accident scenario modelling, rendering them unavailable and inaccessible for many industries, specially at the early design stage when these knowledge are not sufficient (Dinh, et al. 2012, Arcuri, et al. 2022).

This paper provides an accessible methodology to evaluate the resilience of the systems at the early design stage amid deficient knowledge on system characteristics. Firstly, the attributes of a resilient design in an engineering system is defined. Expert judgment can then be used to evaluate these attributes contribution on the resilience of the system in a qualitative manner. These qualitative evaluations can also be used to provide pairwise comparison of resilient attributes by the Fuzzy Analytic Hierarchy Process (AHP) method to dedicate a weighting for each attribute of the resilient design. The outcome of this analysis can then be integrated into a dynamic Bayesian network (DBN) to probabilistically calculate the resilience and provide a transient resilience curve.

The application of the proposed methodology is applied to the resilience assessment of a Carbon Capture and Storage (CCS) system of a process plant at the early design stage that may undergo Loss of Containment (LOC) accident and resilience curves are calculated to show the dynamic transient response of the plant to this disruption.

The remainder of the paper is organized as follows: in Section 2, the attributes of the resilient design are defined and the methodology to evaluate the system resilience at the early design stage by DBN is introduced ; in Section 3, the calculation of weightings of resilient attributes by fuzzy AHP is discussed; in Section 4, the methodology is applied on the case study; finally, Section 5 provides some concluding remarks.

2. Resilience Assessment at The Early Design Stage

At the early design stage, the knowledge on system's capabilities in responding to failure and disruptive events is very limited. Therefore, we define some general characteristics of resilience to enable modelling the system. Firstly, we define resilience as the capability of any engineering system to survive the failures and recover to normal condition. Two main attributes are, therefore, defined as survivability and recoverability (Hollnagel 2013). Each attribute also relies on other detailed characteristics that is called metrics, and each metric is dependent to some characters of the system called as indicators. These characteristics are carefully gathered from literature and defined in detail in Table 1 for the survivability of the system.

Table 1. Subcategories of the system survivability

Metric	Indicator
Early Warning	Diversity of Monitoring
	Duplication of Monitoring
	Operator Knowledge
Robustness	Safety Margin
	Reliability - Equipment Design
	Reliability - Predictive Maintenance
	Reactive Maintenance
	Management of Change
Absorptive Capacity	Operator Knowledge
	Administrative Knowledge
	Segregation of Equipment
	Layers of Safety Systems
	Design of Safety Systems
	Emergency Procedures
	Tests of Emergency Response Systems
	Diversity of Emergency Services
	Fail-Safe Design
Flexibility	Redundancy of Safety-Critical Utilities
	Modularity of Unit Operation
	Modularity of Facilities

Table 2 defines the detailed characteristics of the system that contribute to system recoverability.

Table 2. Subcategories of the system recoverability

Metric	Indicator
Resourcefulness	Modularity of Unit Operation
	Modularity of Facilities
	Administrative Knowledge
	Throughput Adaptability
Controllability	Response to Control Measures
Reconfigurability	Redundancy
	Reconfigurability of Flowsheet

Interested readers can refer to the author's previous work for details on defining these attributes of the resilient design (Hoseyni, Vesey and Cordiner 2023).

These attributes of the resilient design can be sent to the experts to judge their quality and presence in the studied system to evaluate the capabilities of the system to respond to disruptions. A DBN model can also be used to translate these characteristics into a mathematical model that quantifies the resilience.

2.1. DBN Model for Resilience Assessment

Dynamic Bayesian Network (DBN) is a probabilistic graphical model that depicts the temporal dependencies of a system and offers a framework for modelling and reasoning on complicated systems throughout time (Ghahramani 1998). DBN has been recently used to model the resilience of engineering systems (Tong, Yang and Zinetullina 2020). In a DBN, the system is modelled as a directed acyclic graph (DAG), where each node in the network stands in for a random variable and the arcs between nodes signify their probabilistic interdependencies. Arcs are connected from parent nodes to child nodes in

DBN. The nodes that are not connected to any parent nodes are referred to as root nodes and are assigned marginal probabilities. Conditional Probability Table (CPT) is used in DBN to specify the conditional dependencies of nodes given their parents. Using the CPTs and the Markov assumption, the probability of the variables in a DBN can be represented as follows:

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

where $pa(X_i^{t-1})$ is the parents of node X_i in the DAG at time step t-1 and X_i^t represent the state of node X_i at time t (Murphy 2002).

The attributes of the resilient design can be mapped into a DBN model to mathematically link the attributes presented in nodes to each other. Fig. 1 shows the proposed DBN model that is introduced by the attribute presented in Tables 1 &2. 27 indicators are assigned to the root nodes which will be associated with marginal probabilities and are connected with arcs to their corresponding metrics. CPTs will be built to specify the probability of a node given the state of its parent nodes and will be calculated by the fuzzy AHP methodology.

Fig. 1. The proposed DBN model for resilience assessment

As can be seen in Fig. 1 the attributes are finally linked to the "survivability" and "recoverability" nodes where these 2 nodes are also connected to the "system's performance state" node which is also connected by the "disruptive event" node (Hoseyni and Cordiner 2023).

To run the DBN model, we need to assign marginal probabilities to the 27 root nodes of Fig. 1 (i.e., 27 indicators shown in Tables 1&2). For doing that expert opinion can be collected and transformed to numbers by probability elicitation techniques such as Delphi, D number theory or SHELF tool (O'Hagan, et al. 2006). This part is beyond the scope of this paper and for that we will assume that all the indicators are present in our system with 0.99 probabilities. In other words, we assume that the failure or malfunction of the system that results each attribute not to be present is 1%. If the probability elicitation from expert judgment or historic data become available, then the obtained probabilities can be updated in the marginal nodes.

After assigning marginal probabilities for the root nodes, we need to build CPTs that shows the contributing weights and interdependencies of the child nodes and parent nodes. Fuzzy AHP, a multi-criteria decision-making tool, is used for that purpose which is discussed in next section in detail.

3. Fuzzy AHP

Fuzzy AHP (Analytic Hierarchy Process) is a development of the AHP technique that helps decision-makers deal with the uncertainty and ambiguities that frequently appear in decision-making. In fuzzy AHP, instead of employing exact numerical values, pairwise comparisons between criteria are conducted using linguistic terminologies like "slightly more important" or "much more important". The degree of each term's membership on a scale from 0 to 1 is then represented by fuzzy numbers that are mapped onto these linguistic phrases (Saaty 2001).

Fuzzy AHP can be used to make the pair-wise comparison of the nodes of the DBN model and build the CPTs. In the context of DBNs, Fuzzy AHP can be used to obtain conditional probabilities by incorporating multiple criteria or dimensions that may affect the probability distribution of a given variable (Wang, et al. 2017). Expert judgment is, firstly, used to make a pairwise comparison of the contributing factors of each node where experts are asked to make a qualitative comparison on pairs of contributors based on qualitative terminologies presented in Table 3.

Table 3. Triangular fuzzy AHP conversion scale (Bozbura, Beskese and Kahraman 2007)

Qualitative Terminology	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Just equal	(1, 1, 1)	(1, 1, 1)
Equally important	(1/2, 1, 3/2)	(2/3, 1, 2)
Weakly more important	(1, 3/2, 2)	(1/2, 2/3, 1)
Strongly more important	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Very strongly more important	(2, 5/2, 3)	(1/3, 2/5, 1/2)
Absolutely more important	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)

Triangular fuzzy AHP conversion scales shown in Table 3 are then used to change the qualitative terminology into Fuzzy numbers. Then, Chang's extent analysis method (Chang 1996) is used to calculate the weights of each contributor. In this method, the fuzzy synthetic extent is defined for the i^{th} criteria using Eq. (2):

$$S_i = (\sum_{i=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} \quad (2)$$

Then, the degree of possibility of $M_2=(a_2,b_2,c_2) \geq M_1=(a_1,b_1,c_1)$ is calculated using Eq. (3):

$$V(M_2 \geq M_1) = hgt(M_2 \cap M_1) = \begin{cases} 1 & if b_2 \geq b_1 \\ 0 & if a_2 \geq c_2 \\ \frac{a_1 - c_2}{b_2 - c_2 - b_1 + a_1} & otherwise \end{cases} \quad (3)$$

The possibility that a convex fuzzy number M_i is greater than k other convex fuzzy numbers $i=(1,2,\ldots,k)$ is:

$$V(M \geq M_1, M_2, \ldots, M_k) = \min V(M \geq M_i) \quad (4)$$

Assuming that $d'(A_i)=\min V(S_i \geq S_k)$ for $k=1,2,..,n$ and $k \neq i$, the weight of the contributors is defined as:

$$W' = (d'(A_1), d'(A_2), \ldots, d'(A_i))^T \quad (5)$$

Final weight of the contributers is calculated by normalizing the weight vector of Eq. (5).

4. Case Study

A post-combustion CCS system is considered to apply the methodology. As schematically shown in Fig. 2, the CO_2 that is produced from fuel combustion or other process activities is captured, compressed and sent to the storage section to be injected into a reservoir. This system is prone to the LOC and release of captured carbon to the environment which we consider it as the disruptive event and model the system for its resilience.

The DBN model proposed in Fig. 1 is used to model the resilience of the CCS system in case of the LOC accident which has environmental impacts. The survivability of the system to absorb the disruption as well as the recoverability to restore from the disrupted state to a normal operating state is quantified.

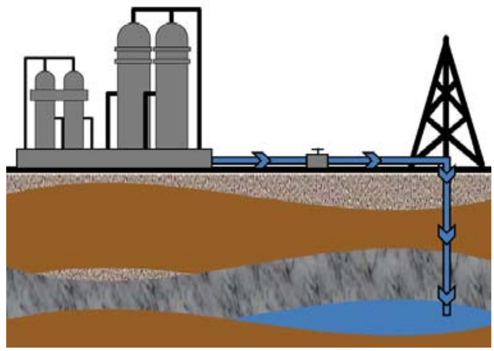

Fig. 2. A schematic view of the CCS system (Paltrinieri, et al. 2014)

To make the DBN model of Fig.1 successfully analyse the disruption, we need to define the marginal probabilities of the 27 indicators of resilient shown in Tables 1&2 (parent nodes of the DBN model in Fig. 1) with marginal probabilities. These probabilities can be estimated by expert judgment and probability elicitation techniques. In this work we assume that the indicators are present in the system with 99% probability.

For building the CPTs that is used to relate the probabilistic interdependencies of other nodes, fuzzy AHP is used to find the weights of the contributors that will be used as conditional probabilities. Questionnaire are provided to expert to judge the pairwise comparison of the indicators using the linguistic terminology of Table 3. For example, the node "Early warning" in Fig. 1 is the child node of 3 other nodes, namely "Diversity of Monitoring", "Duplication of Monitoring" and "Operator Knowledge". Experts are asked to compare each pair of nodes and rate their importance based on the qualitative terminology of

Table 3. The pairwise comparison of the contributors of the "Early Warning" node is collected from the experts and their judged terminology is converted to triangular fuzzy scales as shown in Table 4.

Table 4. Pairwise comparison of the "early warning" node

Early Warning	Diversity of Monitoring	Duplication of Monitoring	Operator Knowledge
Diversity of Monitoring	(1, 1, 1)	(2/3, 1, 2)	(1/2, 2/3, 1)
Duplication of Monitoring	(1/2, 1, 3/2)	(1, 1, 1)	(2/5, 1/2, 2/3)
Operator Knowledge	(1, 3/2, 2)	(3/2, 2, 5/2)	(1, 1, 1)

As an example, the experts decided that the "Diversity of Monitoring" is equally important with "Duplication of Monitoring" or "Operator Knowledge" is weakly more important than "Diversity of Monitoring" and strongly more important than the "Duplication of Monitoring". Chang's extent analysis method (Chang 1996) is, then, used to calculate the weights of each contributor to the "early warning" node using Eqs. 2-5. The normalized weights of the early warning node is calculated as 0.240, 0.210 and 0.550 for Diversity of Monitoring, Duplication of Monitoring and Operator Knowledge respectively.

The expert judgment is conducted for all the pairwise comparison of the nodes and fuzzy AHP and Chang's extend analysis is used to find their normalized weighting. Results shown as the dependencies of parent nodes on child nodes quantified by the conditional probabilities are shown in Table 5.

Table 5. Conditional probabilities of the resilient contributors

Child Node	**Parent Nodes**	**Conditional Probability**
Survivability	Early Warning	0.273
	Robustness	0.201
	Absorptive Capacity	0.294
	Flexibility	0.232
Recoverability	Resourcefulness	0.300
	Controllability	0.374
	Reconfigurability	0.326
Early Warning	Diversity of Monitoring	0.240
	Duplication of Monitoring	0.210
	Operator Knowledge	0.550
Robustness	Safety Margin	0.280
	Reliability - Equipment Design	0.000
	Reliability - Predictive Maintenance	0.000
	Reactive Maintenance	0.280
	Management of Change	0.439
Absorptive Capacity	Operator Knowledge	0.142
	Administrative Knowledge	0.000
	Segregation of Equipment	0.073
	Layers of Safety Systems	0.142
	Design of Safety Systems	0.142
	Emergency Procedures	0.142
	Tests of Emergency Response Systems	0.142
	Diversity of Emergency Services	0.073
	Fail-Safe Design	0.142
Flexibility	Redundancy of Safety-Critical Utilities	0.620
	Modularity of Unit Operation	0.000
	Modularity of Facilities	0.380
Resourcefulness	Modularity of Unit Operation	0.000
	Modularity of Facilities	1.000
	Administrative Knowledge	0.000
	Throughput Adaptability	0.000
Controllability	Response to Control Measures	1.000
Reconfigurability	Redundancy	0.500
	Reconfigurability of Flowsheet	0.500

As can be seen in Table 5, Absorptive Capacity and Controllability has the greatest contribution to Survivability and Recoverability capabilities of the CCS system. Moreover, Redundancy of Safety-Critical Utilities as a part of the Flexibility of the system has the greatest contribution weight compared to other nodes. It can also be seen that the pairwise comparison by fuzzy AHP and expert judgment resulted in 0 contribution of 7 nodes representing their null contribution.

To model the resilience of the CCS system, the disruption node of Fig.1 is modelled to be either in "True" or "False" state where the probability of disruption (i.e., LOC accident) to be "True" is assumed to be 1%. The system's performance node is assigned with three states, namely St_0, St_1, and St_2 representing normal performance level before disruption, disrupted minimum performance and restored performance after recovery respectively.

The resilience, in each time frame, is defined as the probability of the system to be in normal performance or the restored performance (i.e., Resilience=P(St_0)+P(St_2)) (Tong, Yang and Zinetullina 2020).

The DBN model is analysed with the quantified values of Table 5 and the mentioned assumptions. The resulting resilience curve is shown in Fig. 3.

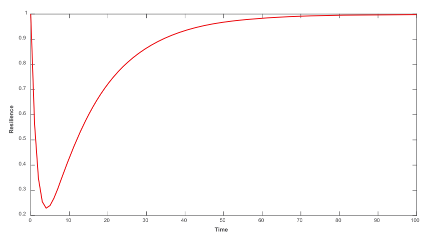

Fig. 3. Dynamic resilience curve of the CCS system against LOC accident

As can be seen in Fig. 3, after the disruption happens at t=0, the performance of the system drops immediately until it reaches its minimum value of 0.23 at t=4. Then, recovery of the system takes place and system restores the performance level. At t=100, The performance level is equal to 0.997 which shows almost full recovery of the system.

From the resilience curve of Fig. 3, the time required to recover the 90% of the lost performance is equal to 34 time steps.

It should be noted that the sensitivity of the resilience curves to expert judgment and its potential bias should be addressed by sensitivity analysis. This is important because the resilience curve is intended to inform decision-making, and any bias in the assessment could lead to suboptimal decisions.

5. Conclusions

In this paper, a practical methodology is proposed to quantify the resilience curve at the early design stage when sufficient information on the process and system capabilities is not available. A quantitative model, based on DBN, is introduced to perform the resilience assessment. The DBN model relates the expert judgment and its qualitative assessment of system capabilities to the dynamic resilience curve. Fuzzy AHP is used to estimate the weights of the contributors factors of the resilience by pairwise comparison and expert judgment to be used in building the DBN model and its CPTs. The application of the methodology is demonstrated in the resilience assessment of a CCS system considering LOC accident as the disruptive events. Results can be used to improve the system resilience capabilities in surviving the failures and recovering from the consequences. Design modifications to improve the resilience of the system at the early design stage can be initiated by the results of this analysis and that would be extremely cost-effective compared to the operational stage.

References

Ahmadi, Somayeh, Yadollah Saboohi, and Ali Vakili. 2021. "Frameworks, quantitative indicators, characters, and modeling approaches to analysis of energy system resilience: A review." *Renewable and Sustainable Energy Reviews* 144: 110988.

Arcuri, Rodrigo, H. C. Bellas, D. de Souza Ferreira, B. Bulhões, M. C. R. Vidal, P. V. R. de Carvalho, and E. Hollnagel. 2022. "On the brink of disruption: Applying Resilience Engineering to anticipate system performance under crisis." *Applied Ergonomics* 99: 103632.

Bozbura, F. Tunc, Ahmet Beskese, and Cengiz Kahraman. 2007. "Prioritization of human capital measurement indicators using fuzzy AHP." *Expert systems with applications* 32 (4): 1100-1112.

Chang, Da-Yong. 1996. "Applications of the extent analysis method on fuzzy AHP." *European journal of operational research* 95 (3): 649-655.

Dinh, L., H. Pasman, X. Gao, and M., Mannan. 2012. "Resilience engineering of industrial processes:

Principles and contributing factors." *Journal of Loss Prevention in the Process Industries* 25 (2): 233-241.

Ghahramani, Zoubin. 1998. "Learning dynamic Bayesian networks." *International School on Neural Networks, Initiated by IIASS and EMFCSC* 168-197.

Hollnagel, E. 2013. "Resilience engineering and the built environment." *Building Research & Information* 4 (12): 129-139.

Hoseyni, Seyed Mojtaba, and Joan Cordiner. 2023. "Quantitative Resilience Assessment At Early And Late Design Stages: An Application To Green Hydrogen Plants." *Submitted to the International Journal of Hydrogen Energy.*

Hoseyni, Seyed Mojtaba, Freya Vesey, and Joan Cordiner. 2023. "Development of an industrially applicable model for the qualitative resilience assessment of process systems at the early design stage." *Submitted to Loss Prevention in Process Industry.*

Mottahedi, A., F. Sereshki, M. Ataei, A. Nouri Qarahasanlou, and A. Barabadi. 2021. "The Resilience of Critical Infrastructure Systems: A Systematic Literature Review." *Energies* 14: 1571.

Murphy, Kevin Patrick. 2002. *Dynamic bayesian networks: representation, inference and learning.* Berkeley: University of California.

O'Hagan, Anthony, Caitlin E. Buck, Alireza Daneshkhah, J. Richard Eiser, Paul H. Garthwaite, David J. Jenkinson, Jeremy E. Oakley, and Tim Rakow. 2006. *Uncertain judgements: eliciting experts' probabilities.* Wiley.

Paltrinieri, N., J. Wilday, M. Wardman, and V. Cozzani. 2014. "Surface installations intended for Carbon Capture and Sequestration: Atypical accident scenarios and their identification." *Process Safety and Environmental Protection* 92 (1): 93-107.

Saaty, T. L. 2001. *Decision making with dependence and feedback: The analytic network process.* RWS Publications.

Tong, Qi, Ming Yang, and Altyngul Zinetullina. 2020. "A dynamic Bayesian network-based approach to resilience assessment of engineered systems." *Journal of Loss Prevention in the Process Industries* 65 : 104152.

Wang, Yan Fu, Tao Qin, Biao Li, Xiao Fei Sun, and Yu Lian Li. 2017. "Fire probability prediction of offshore platform based on Dynamic Bayesian Network." *Ocean Engineering* 145: 112-123.