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Quantitative resilience assessment of chemical process systems using functional resonance analysis method and Dynamic Bayesian network



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ABSTRACT

The emergent hazards of chemical process systems cannot be wholly identified and are highly uncertain due to the complicated technical-human-organizational interactions. Under uncertain and unpredictable circumstances, resilience becomes an essential property of a chemical process system that helps it better adapt to disruptions and restore from surprising damages. The resilience assessment needs to be enhanced to identify the accident's root causes on the level of technical-human-organizational interactions, and development of the specific resilience attributes to withstand or recover from the disruptions. The outcomes of resilience assessment are valuable to identify potential design or operational improvements to ensure complex process system functionality and safety. The current study integrates the Functional Resonance Analysis Method and dynamic Bayesian Network for quantitative resilience assessment. The method is demonstrated through a two-phase separator of an acid gas sweetening unit. Aspen Hysys simulator is applied to estimate the failure probabilities needed in the resilience assessment model. The study provides a useful tool for rigorous quantitative resilience analysis of complex process systems on the level of technical-human-organizational interactions.

1. Introduction

1.1. Resilience

The technology is moving forward, and the process safety measures are increasingly becoming automated to facilitate the safe environment in the chemical process plants. However, automation has also led to complexities and accident occurrence due to technical-human-organizational interactions. Nowadays, the safety goal of industrial plants is not only preventing accidents but also dealing with the daily

disturbances and variabilities to sustain the system in the normal operational state. To achieve this goal, the industrial system management should be more flexible and resilient [[18],[43]]. Resilience engineering application in the process plants is particularly important because of the high level of complexity that arises from the non-linear interconnections and high level of variability and uncertainty which arises from this complexity [9].

In scientific literature, the term resilience first appeared in materials engineering to describe the ability of the material to return to the initial shape after deformation (Trautwine,1907). Then this term was used in

List of Abbreviations & Symbols: BT, Bow-Tie; CO₂, Carbon dioxide; CPT, Conditional Probability Table; CV_{ij}, Cumulative variability; DBN, Dynamic Bayesian Network; DEA, Diethanolamine; E, New observation; FRAM, Functional Resonance Analysis Method; FWKO TK, Free Water Knockout Tank; H₂S, Hydrogen disulfide; MCS, Monte Carlo Simulation; MTBF, Mean time between failure; MTTR, Meantime to repair; OV, Overall variability; $pa(X_i^0)$, $pa(X_i^{t-2})$, $pa(X_i^{t-1})$, $pa(X_i^t)$, parent nodes at time step 0, ..., t-2, t-1, t; P(X_i^t), Joint Probability of a series of variables; P(X^t), Joint Probability of conditional nodes; P(X|E), Posterior probability; PLC, Programmable Logic Computers; POF, Probabilities of failure; QRA, Quantitative Resilience Assessment; R(t), Reliability value after a certain time; S1, The normal state at time t₁ when the disruption occurs; S2, The state with the lowest functionality due to disruption occurrence at time t₂; S3, The state of the system after the adaptation stage at time t₃; S4, The recovered state of the system after restoration is finished at time t₄; SADT, Structured Analysis and Design Technique; SIS, Safety Instrumented Systems; SME, Subject Matter Expert; t, time; TK, Tank; V_{ij}^t, Variabilities of upstream functions based on timing; V_{ij}^p, Variabilities of upstream functions based on precision; VLV, Valve; X_i^{t-1}, Represents previous state of the node at time step t-1; α_{ij}^t and α_{ij}^p, Amplification factors based on the timing and precision; β, Shape parameter; λ, Constant failure rate, the inverse of the mean time between failure; μ, Repair rate, the inverse of the meantime to repair; η, Scale parameter

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the ecological domain as the ability of the ecosystem to sustain the original species by absorption of the changes and disturbances [15]. Later, this term started to be used in organizational [[6],[26]], psychological [32]; Bananno, 2004), economical [14],[38],[40]], social [1], and social-ecological domains (Gumming et al., 2005; [28]).

In the engineering domain, resilience has been used in various fields such as water management [[30],[45]], transportation management [[3],[3],[13],[20]], infrastructure engineering [[5],[34],[46]] and process industries [[2],[8],[11],[22],[42]]. In all of those, the resilience was defined as the intrinsic property of the system to respond and adjust the functioning before or after a mishap or disturbance so as to sustain the normal operational performance of the system [43]. According to Hollangel et al. (2007), a resilient system should:

- (1) Provide a secure or flexible response to instant or continuous disturbances;
- (2) Conduct self-monitoring of its performance;
- (3) Predict risks and risk development opportunities; and
- (4) Learn from past events.

1.2. Dynamic Bayesian network (DBN) for resilience assessment

Yodo et al. [24] developed a DBN model for resilience assessment. They viewed resilience as a constant value though a probabilistic resilience metric was used. Cai et al. [7] considered the performance and time-related properties in resilience assessment, in which high availability and a short time to recovery characterized the system's high resilience. They applied DBN to predict the future values of availability and their temporal variation by employing the data available at the current state. However, they evaluated resilience as a parameter dependent on the failure and repair rates of the system components (i.e., the technical factors). Tong et al. [44] proposed to measure resilience using system functionality. A DBN model was developed to quantify the probabilities of system functionality states based on the four attributes of resilience, namely absorption, adaptation, restoration, and learn. Zinetullina et al. [48] used a bow-tie (BT) diagram to support the development of the DBN model and applied it to analyze the resilience of a two-phase separator operating in a harsh environment. In both approaches, resilience is defined as the ability of the system to sustain high functionality under disruptive effects or restore the low functionality state to a high functionality state. Kammouh et al. [25] also used DBN for resilience assessment, where resilience was defined in terms of fast recoverability, reduced vulnerability, reduced failure likelihood, robustness, or reduced failure consequences. Kammouh et al. [25] measured resilience at pre-, intra-, and post-disruption stages.

The majority of the previous studies considered resilience as a static property of the system. It is an oversimplified assumption for complicated process systems when interacting with human operators, organizational factors, and various disruptions.

1.3. Functional resonance analysis method (FRAM) for resilience assessment

FRAM, firstly introduced by Hollnagel [17], can qualitatively model how a complex system functions considering socio-technological interactions [35]. Sawaragi et al. [41] conducted a FRAM analysis for the aircraft accident in Columbia in 1995 and investigated the main reasons and conditions behind that accident. De Carvalho [10] used FRAM to analyze the reasons behind the mid-air collision between two aircraft in Amazonian Sky in 2006. Later, FRAM was employed in other domains. Shirali [42] exploited FRAM for the identification of the emergent risk in a process plant. Rosa et al. [39] used FRAM for identifying the hazards associated with the performance variability of the couplings in the construction industry. The couplings are the interconnections between the main functions (or activities) of the system that contribute to

the accomplishment of the main goal of the system. Patriarca et al. [35] presented a semi-quantitative approach for FRAM analysis with the employment of Monte Carlo Simulation (MCS) for air traffic management systems. Having a quantitative FRAM model facilitates the identification of the most critical coupling that needs prominent attention.

Furthermore, it helps to maintain the safe state of complex systems effectively and cost-efficiently. Before Patriarca et al. [35], Rosa et al. [39] proposed to quantify FRAM and identify critical couplings with the employment of AHP and Subject Matter Expert's (SME) judgment. However, the limitation still exists in the subjectivity of the judgements for the variability of the function parameters. This limitation could be mitigated to some extent by the application of MCS to the variables.

The existing resilience assessment methods are ineffective in modeling emergent disruptions and complicated technical-human-organizational interactions. The nonlinear interactions among the system components, human and organizational factors, and their interdependencies with function variabilities are not well treated in the resilience assessment models (Andersson et al., 2002; Levenson, 2004; [43]). Conducting FRAM analysis at the initial stage of the quantitative resilience assessment of a complex system could facilitate a more rigorous analysis of the system's operational state and identify concrete solutions to enhance system safety [39].

FRAM could be considered as a viable method for resilience assessment due to two main reasons:

- (1) FRAM identifies the root causes on the level of non-linear technical-human-organizational interactions [43].
- (2) A FRAM model consists of activities performed both on and by the system. The resilience parameters can better be characterized by actions of the objects rather than by their presence ([35]b).

1.4. Objective of the study

The present study aims to develop a quantitative resilience assessment method for chemical process systems, in which technical-human-organizational interactions are considered. To the authors' knowledge, this paper will, for the first time, integrate FRAM and DBN to facilitate the assessment of the ability of a chemical process system, its operators, and associated organization to respond to unprecedented disruption, recover from unexpected damages, and learn from those events.

In this paper, the FRAM is mainly applied to describe system functions and identify potential variabilities and their critical coupling. This study helps to advance the knowledge of the approaches where the FRAM has been applied with other methods for the resilience engineering of chemical process systems. The DBN is used to quantify the dynamic resilience of process systems. The DBN includes nodes to represent the absorption, restoration, adaptation, and learning parameters. Nodes are structured according to the outcomes of the FRAM analysis. The main steps of the methodology will be described, and its application will be demonstrated on a two-phase separator."

2. Methodology

Fig. 1 describes the methodology employed in this study. First, the FRAM analysis on the process system will be accomplished in conjunction with the MCS. Resultantly, the critical coupling will be identified. For the critical coupling, the attributes of the resilience will be developed, and the DBN model will be built. The conditional probability tables of the nodes in the DBN will be filled with probabilities of failures (PoF) collected from the literature and Subject Matter Experts (SMEs), and calculated with the Aspen Hysys simulation. DBN model will be updated with additional safety measures, and the generated resilience curve will be compared with the previous resilience profile. After that, the first developed DBN model will undergo sensitivity analysis to identify the most influential safety measures. The following sections describe the main steps of the proposed method.

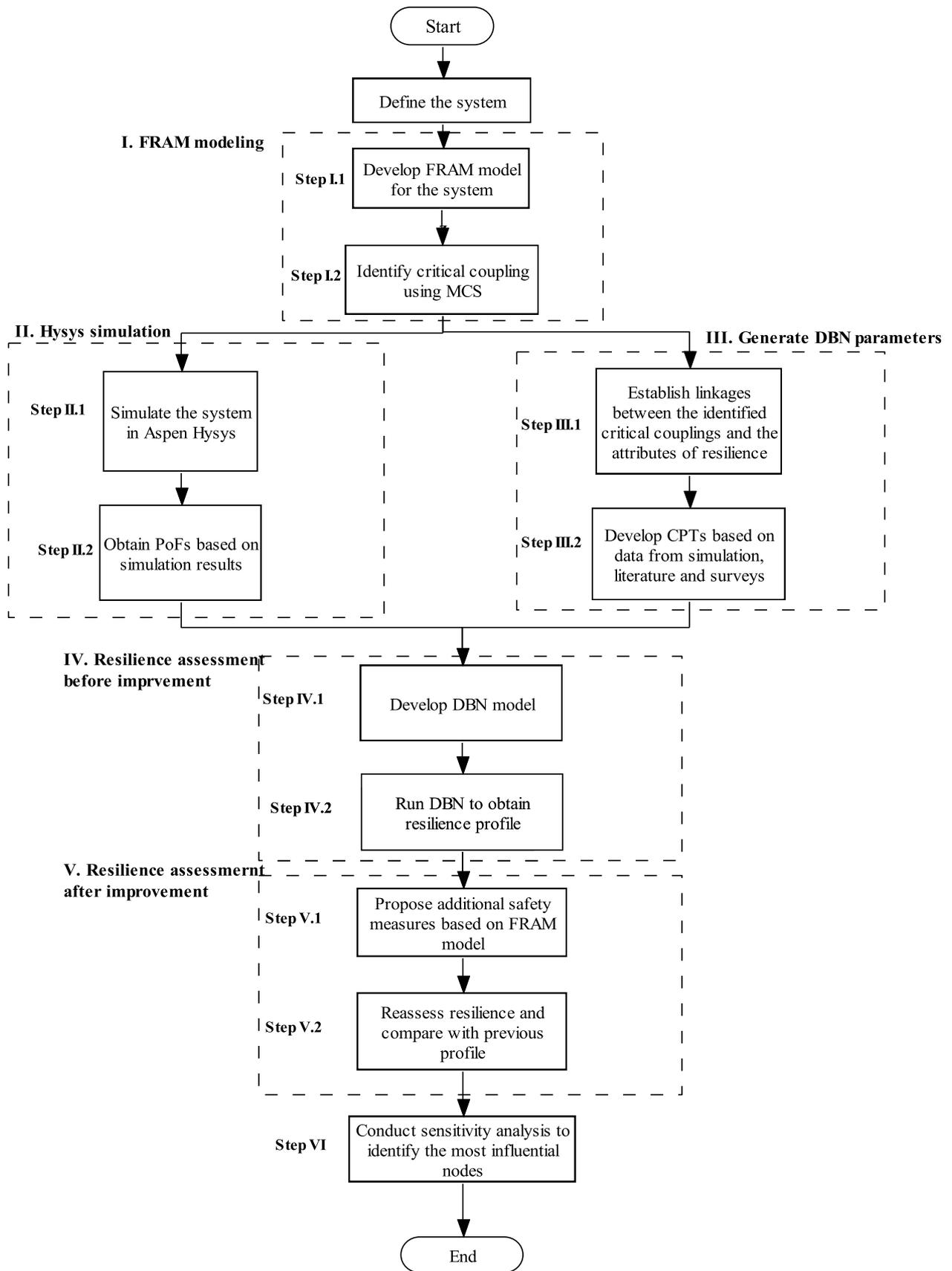


Fig. 1. The proposed methodology for dynamic resilience assessment.

2.1. Step I. FRAM modeling

At the beginning of the FRAM analysis, it is necessary to identify the goal of the FRAM analysis, specifically whether it is accident investigation analysis or the risk assessment [35].

2.1.1. Step I.1: develop FRAM model for the system

Firstly, the main activities or functions performed by or on the system to reach a particular outcome are defined. Functions are interconnected via the aspects placed in the corners of the hexagon, according to the Structured Analysis and Design Technique (SADT) [35]. Each function consists of six aspects: input, output, precondition, resources, time, and control. The output of one function (upstream function) serves as one of the five aspects of the other function (downstream function) in a coupling. The other function is the downstream function. The six aspects of a function are as follows [35]:

- Input (I)- the aspect that initiates the function
- Output (O)- the outcome of the function, which serves as the input for the downstream function
- Precondition (P)- the condition that should be performed before the initiation of the downstream function
- Resource (R)- that the function needs to produce the output
- Time (T)- temporal requirements or constraints obliged to the function, such as start time or finish time.
- Control (C)- what performs the control and monitoring of the function to achieve the set outcome.

2.1.2. Step I.2: identify critical coupling using MCS

(1) Step I.2.1 Identify the variability

Each function has its variability. Variability could be classified as positive if it reduces the risk of possible accident development or negative, otherwise. According to Hollangel [19], variability could be classified based on multiple phenotypes, such as time, precision, flow rate, speed, duration, direction, object, and force. In this study, variability manifestation based on time and precision will be used. The reasons are user-friendliness and readability of the analysis and the universal application of those phenotypes for any function.

The variabilities of “time” are classified as on time, too late, too early, and not at all. Not at all is used for the cases when the function is performed that late that its outcomes are no longer attractive. For “precision”, the variabilities are classified as precise, acceptable, imprecise, and wrong. Based on the SME’s judgment, those classifications are ranked with numbers and further used in MCS [35].

(2) Step I.2.2 Aggregate the variability

This step deals with the variability of the couplings. Variability of the couplings may arise as a result of each function’s internal variabilities or the impact of the upstream function. When the coupling produces large negative variability, this results in the resonance of the connected functions and identifies the critical path. These couplings are called critical. The critical coupling defines the leading cause of the accident in the accident investigation scenario, or the main factors contributing to the hazard development in risk assessment.

If the upstream function generates positive variability, this results in the dampening of the variability of the downstream function [35]. In step I.2.4, the MCS is integrated to identify the exact critical coupling, which results in the malfunction of the two-phase separator of the acid sweetening unit.

(3) Step I.2.3 Manage the variability

This step aims to suggest measures to increase positive variabilities

and decrease negative variabilities. Improvement recommendations need to be made for the identified critical coupling to avoid the accident from happening, or in case of an accident, to restore the system to the high functional state. Based on the critical coupling identified in the next step, we will develop the DBN model consisted of the absorption, adaptation, and restoration parameters for resilience assessment.

(4) Step I.2.4 MCS analysis

MCS is the tool for the mathematical modeling of multiple systems using random sampling to obtain outcomes as close as possible to reality (Zio, 2013; [31]). MCS method is mostly employed for solving complicated and multidimensional problems and equations. For instance, it is used for estimating differential and integral equations, for addressing the deterministic and stochastic problems, for simulating the random case development scenarios. One of the frequent applications of the MCS is in reliability and risk analysis of the engineering systems. The outcome of the MCS analysis facilitates the estimation of the probability of failures (PoFs) [[12],[29],[33],[47]].

In this research work, the MCS is used to estimate cumulative variabilities in the FRAM model. The idea of MCS for estimating the cumulative variability in the FRAM Model was taken from the work of Patriarca et al. [35]. In their work, they identified the critical couplings as ones with a high tendency to cause an accident. They also provided the resonant path that emerges as a result of the variability accumulation for the neighboring functions to the critical couplings. The critical couplings were determined by setting the critical cumulative variability value and the confidence level of 95%. The couplings for which 5% of the cumulative variabilities were greater than the setpoint value, equal to 24, was classified as critical. Hence, the corresponding recommendations were provided by Patriarca et al. [35] to avoid accident occurrence.

In this paper, a similar approach of MCS for cumulative variability estimation is employed to identify the critical couplings in FRAM. However, in this paper, MCS also serves as a bridge between the FRAM model and the DBN model for the quantitative resilience assessment of the process unit.

From the SMEs’ judgment in the work of Patriarca et al. [35], the discrete probability for each of the four variability states based on the timing and precision were defined (Tables 1–3).

In this study, the variability of timing was assumed to be too late, and variability of precision was assumed to be of acceptable precision. For illustrative purposes, the random samples from normal distribution were assigned to the values of the variabilities based on timing and precision.

The amplification factors are distributed based on the timing (α_{ij}^T) and precision (α_{ij}^P) relations of the upstream and downstream couplings. The output of a function may vary with respect to timing (e.g., being too early, on time, too late, or omitted). It may also vary for precision (e.g., being precise, imprecise, or acceptable). Based on the effect of the variability of the upstream function conveyed to the downstream functions, the amplification for both timing and precision are assumed in the ranges in Table 4. Amplification factors describe the impact that

Table 1
Variability scoring based on Timing and Precision [35].

	Variability	Score
Timing	On-Time	1
	Too Early	2
	Too Late	3
	Not at all	4
Precision	Precise	1
	Acceptable	2
	Imprecise	3
	Wrong	4

Table 2
Discrete probabilities for Timing variabilities [35].

	1	2	3	4
Probability of being too early	0.15	0.7	0.1	0.05
Probability of being On-time	0.7	0.15	0.1	0.05
Probability of being too late	0.15	0.05	0.7	0.1
Probability of not at all	0.1	0.05	0.15	0.7

Table 3
Discrete probabilities for Precision variabilities [36].

	1	2	3	4
Probability of being Precise	0.7	0.2	0.05	0.05
Probability of being Acceptable	0.05	0.7	0.2	0.05
Probability of being Imprecise	0.05	0.2	0.7	0.05
Probability of being Wrong	0.1	0.1	0.1	0.7

the upstream function has on the downstream function connected to it. For example, if the amplification factor on “timing” is equal to 0.5 (i.e., the dampening effect applies), the time aspect of the upstream function being “too late” may result in the downstream function to be on time. If the amplification factor is equal to 10, then the upstream function that is too late will result in the downstream function being too late either. If the amplification factor is equal to 1, the upstream function will not affect the variability of the downstream function.

For illustrative purposes, the normal distributions were assigned to the values of amplification factors.

The overall variability is defined as a product of the variabilities of upstream functions based on timing (V_j^T) and precision (V_j^P) (Eq (1))

$$OV_j = V_j^T * V_j^P \tag{Eq 1}$$

To calculate the overall variability, each value of too late timing (Table 2) and acceptable precision (Table 3) were multiplied correspondingly.

The cumulative variability (CV_{ij}) is the joint variability of the coupling. It is estimated by multiplication of the overall variability and amplification factors for timing and precision assigned for the corresponding coupling.

$$CV_{ij} = OV_j * \alpha_{ij}^T * \alpha_{ij}^P \tag{Eq. 2}$$

In this study, we conducted the MCS in Excel to estimate the OV and CV. For the variables, including timing, precision, and associated amplification factors, we assumed they follow normal distributions. We derived the mean and standard deviation values for the scores of “too late timing” and “acceptable precision” based on Tables 2 and 3. First, using Eq. (1), the OVs were calculated based on randomly generated samples of variability values of timing and precision. Then, using Eq. (2), the CVs were obtained based on a random sampling of the amplification factors. 1000 iterations were applied. It is worth noting that the number of iterations may affect the results. This aspect should be investigated in future work.

At the next stage, the set-point and the confidence level are assigned in Excel for 1000 generated random numbers with normal distribution using Eq. (2). The confidence level in this work is set to be equal to 95%. After the generation of 1000 random numbers, five percentiles value of those random numbers is compared with the predefined set-

point (in the case study, a set-point of CV = 24 was assigned). If the five-percentile number is higher than the set-point, the corresponding coupling is set as the critical. The critical value of 24 can be customized by the model user, and the confidence level of 95%. It depends on the user's requirement for the criticality level. It is also worth investigating how the choice of CV and confidence level may affect the results of the entire resilience assessment model.

The further recommendations and work on risk prevention or accident recovery are prioritized, starting from the coupling with the highest five percentile number.

2.2. Step II Hysys simulation

The PoFs are obtained from Aspen Hysys Dynamics simulation for the process unit using the strip charts for the parameters characterizing the performance of the process system of interest [21]. From the strip chart, the time range of the system malfunction or being in the out of normal operating range is divided by the total time range of operations.

$$PoF = \frac{\text{Malfunction time range}}{\text{Total operational time}} \tag{Eq. 3}$$

The PoF characterizing the functioning of the process system could also be extracted from Aspen Hysys Sensitivity analysis. In this case, simulation is run at the specified range of the several input parameters. The output is monitored for the number of scenarios out of the normal range scope. Then, the PoF is estimated as the ratio of the amount of the abnormal outcomes to the total number of outcomes.

$$PoF = \frac{\text{No. of abnormal outcomes}}{\text{Total no. of outcomes}} \tag{Eq. 4}$$

The estimated PoFs are then inputted into the corresponding nodes of the DBN model developed in the next step.

2.3. Step III generate DBN parameters

DBN is a probabilistic graphical model. It has the same structure and principles as the Bayesian network, with an exception that it allows estimating the joint probabilities of the variables with time. Thus, using DBN allows estimating the joint probabilities at time $t, t + 1, t + 2$, and so on ([23]; Neapolitan, 2004). It consists of the nodes (variables) and arcs that link the nodes and allow deriving the interdependencies of the nodes based on the conditional probabilities. The nodes are classified as the parent nodes, child nodes, and the root nodes. The root nodes are assigned for marginal probabilities. The rest are assigned for the conditional probabilities. The joint probability of conditional nodes is calculated at the child node dynamically (Eq. (1)) [23].

$$P(X^t) = P(X_1^t, X_2^t, X_3^t, \dots, X_n^t) = \prod_{i=1}^n P(X_i^t | X_i^{t-1}, pa(X_i^t), pa(X_i^{t-1})pa(X_i^{t-2}) \dots pa(X_i^0)) \tag{Eq. 5}$$

In DBN and BN, the joint probability could be updated with the addition of new nodes.

$$P(X|E) = \frac{P(X, E)}{P(E)} = P(X, E) / \sum_x P(X, E) \tag{Eq. 6}$$

Having these characteristics, DBN enables predicting the spatial and temporal evolutions of systems probabilistically [27]. In resilience

Table 4
The ranges for amplification factors [37].

Value of α_{ij}^T (or α_{ij}^P)	Description
> 1	The variability of the downstream function is amplified by the output of the upstream function
= 1	The variability of the downstream function is not affected by the output of the upstream function
< 1	The variability of the downstream function is dampened by the output of the upstream function

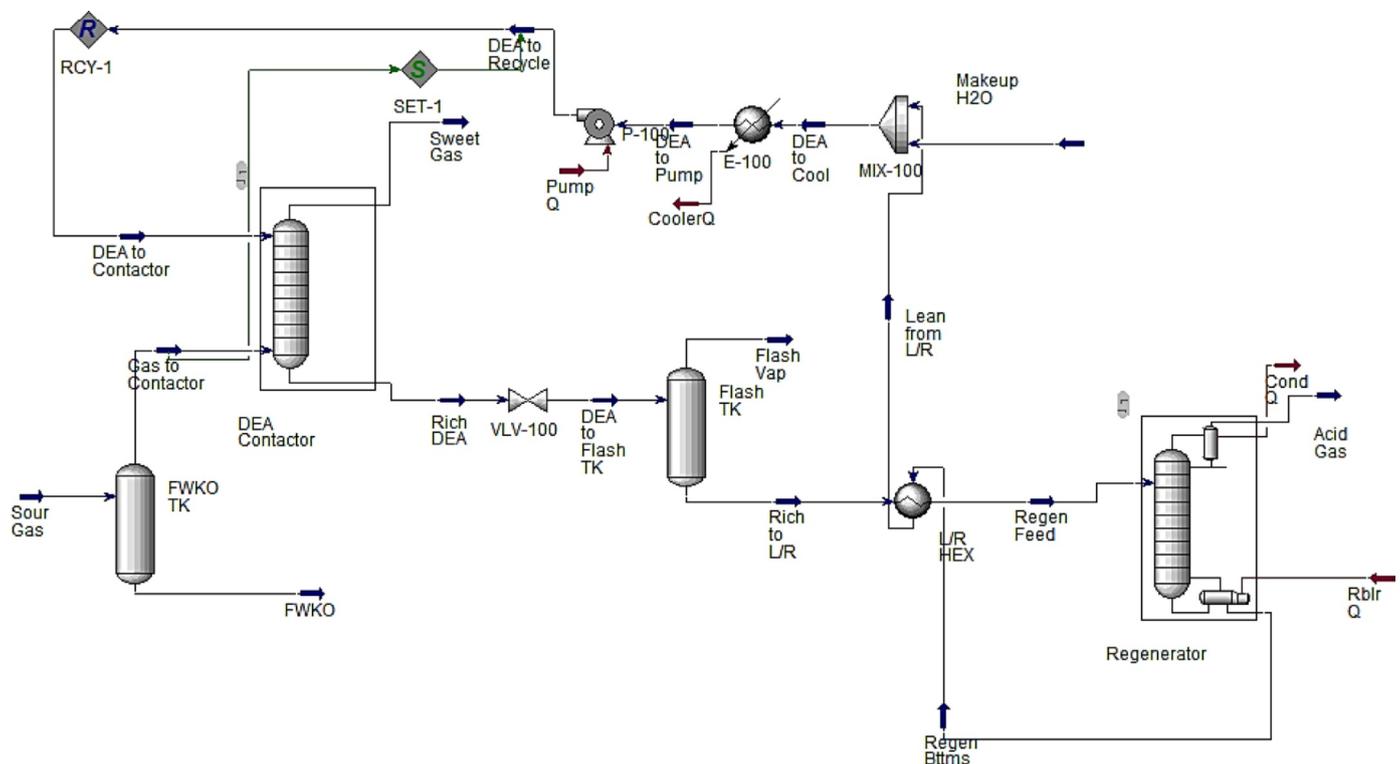


Fig. 2. Acid gas sweetening unit modeled in Aspen Hysys [21].

engineering, it was first applied by Yodo et al. (2016) for the assessment of the reliability and restorative properties of the system. However, their study was limited to an estimation of restoration only; however, resilience consists of four parameters, which are absorption, adaptation, restoration, and learning. Furthermore, in their research, the resilience was considered as a constant term. In contrast, the resilience is a characteristic that changes following the changes of variabilities of components and either internal or external disturbances [44].

2.3.1. Step III.1 establish linkages between the identified critical couplings and the attributes of resilience

The Absorption, Adaptation, and Restoration nodes are complemented with the nodes corresponding to the most critical coupling obtained as a result of the FRAM and MCS. For example, if the identified most critical coupling are the inaccurate performance of the level controllers and interlock system and late or incorrect response of the operator in the control room, the nodes for Absorption, Adaptation and Restoration can be selected corresponding to only the performance of the level controllers and interlock system and the performance of the operator in the control room.

2.3.2. Step III.2 develop conditional probability tables (CPTs)

The CPTs of the nodes can be filled based on the outcomes of the simulations, historical data, and data from the surveys.

For the nodes in DBN, two states were assigned in the CPTs, “High Functionality” and “Low Functionality”. As for assigning the marginal probabilities, the “Low Functionality” section in CPT was filled with the PoF values, estimated from Aspen Hysys simulation, historical data, and data from the surveys. “High Functionality” section was filled by subtracting the estimated probabilities (in the corresponding “Low Functionality” section of the CPT) from 1.

As for the parent nodes of “Absorption”, “Adaptation” and “Restoration”, consisting of the different combinations of the functionality states of the corresponding nodes, the conditional probabilities were assigned based on the expert judgment for each separate scenario. They are starting from the highest conditional probability when all

constituting nodes have a high functionality and finishing with the lowest conditional probability for the case when each constituting node has a low functionality state.

2.4. Steps IV and V resilience assessment before and after improvement

The DBN model will be developed based on the Absorption, Adaptation, Restoration, and Learning parameters for the most hazardous case identified by the FRAM model.

For Absorption, Adaptation, and Restoration nodes, additional safety nodes are added. Then the resilience profile is compared with the previous one. The updated resilience model should present the enhanced resilience properties for a longer time until the functionality drops. A higher value of the functionality should be attained after the restoration stage.

2.5. Step VI sensitivity analysis for identification of the most influential nodes in DBN model

Sensitivity analysis facilitates identifying the nodes that have a high impact on the state of the system's functionality. This will assist in the application of the specific safety measures for the system. First, the sensitivity analysis was conducted in GeNie (<https://www.bayesfusion.com/genie>). As a result, the most influential nodes for the “State of Functionality” target node are identified. Next, for each influential node, the evidence was changed to the low functionality state for the ten-time steps sequentially. Based on the obtained results, the parameters having the highest impact on the system's resilience reduction of the system are identified.

3. Case description

This case study will focus on the quantitative resilience assessment of a two-phase vertical separator of the acid gas sweetening unit. Sour gas treating unit is a part of the oil and gas preliminary treating plants. It accomplishes the absorption of the sour gasses (mainly carbon

dioxide (CO₂) and hydrogen disulfide (H₂S)) with diethanolamine (DEA) from the gas coming after the crude oil stabilization. Crude oil stabilization is the process during which oil coming from the well is separated into three phases (mainly gas, oil, and water). The pressure is reduced in the stabilizer from the high upstream pressure to the normal operating pressures not to harm gas, oil, and water treating process units.

Fig. 2 presents the process flow diagram of the acid gas sweetening. Aspen Hysys, a chemical process simulator, was used to simulate this process. First, sour gas is depleted from process hydrocarbons in the two-phase separator FWKO TK. Then, dehydrated sour gas goes to the absorption column, where it is scrubbed using the DEA solution and leaves the column as a sweet gas for further production of the sales gas. The rich DEA stream, with CO₂ and H₂S, then is separated from the hydrocarbons in the separator Flash TK and passes to the regenerator column, where the products, lean amine and acid gas are produced. Lean amine stream is refluxed to the absorption column and acid gas serves as the feed for the Sulfur Recovery Unit [21]. In this study, the simulations were conducted with a focus on the analysis of the valve failure scenarios. Based on the simulation results, the PoFs of valve actuator failure (as a node contributing to the internal disruption of the system) were estimated.

4. FRAM-DBN model development

The resilience assessment was conducted on a two-phase oil and gas separator located before the coalescing filter and acid gas contactor column. The two-phase separator has the level controllers and interlock system for the liquid outlet stream, pressure controller and interlock system for the gas outlet, pressure safety valves activating in case of the overpressure, alarms interconnected with 2-out-of-3 alarm counting mechanism. Methanol is injected at the inlet of the feed stream to avoid the hydrates forming in the pipes. The performance indicators are monitored and controlled distantly by an operator in the control room and by an operator at the unit area.

4.1. FRAM analysis

The FRAM analysis was developed according to the steps described in the methodology part (Section 2). First, the functions connected with the operational functions of the two-phase separator was listed. Then, the functions listed in Table 5 were interconnected with each other with the assistance of the six aspects. The values of the amplification factors in Table 5 were assigned based on expert judgment. For example, coupling “Pressure indicators” being an input parameter to the “Pressure Safety Valves” has an amplification factor based on the timing of 60 ± 10 , where 60 is the mean value and 10 is the standard deviation. The values of mean and standard deviation were applied in MCS to define the normal distribution formula in the Excel file. The value of the amplification factor based on timing, in this example, means that the function of “pressure indicators” acts “too late”. This results in the output of the “pressure safety valve” being “too late”.

Then the MCS method was employed following the process described in the work of Patriarca et al. [35] with the application of myFRAM (<https://functionalresonance.com>). The scenario of having too late response of the acceptable precision was assumed. Next, the variabilities for each of the function couplings and amplification factors were assigned for each coupling. The cumulative variabilities have been estimated for each coupling according to the Eq. (2).

For each of the variables in Eqs. (1) and (2), including V_j^T , V_j^P , α_{ij}^T , and α_{ij}^P , 1000 random positive numbers were generated by sampling from the normal distributions with the parameters defined in Table 5 to compute the cumulative variability. Setting the 95% confidence level and set-point value of 24 for the overall variability, the outcome of each of 31 couplings was compared with the set-point value. If the 5-percentile value of the given coupling was greater than 24, it was

considered as critical (Fig. 3 developed using the FMV, <https://functionalresonance.com>). In the following case, the coupling of the highest criticality was considered, which is the coupling of the operator of the control room controlling the level and interlock system, resulting in the cumulative variability value at 5 percentiles of 38. Thus, imprecise and/or too late a response of the operator at the control room to the level alarms and indicators has the highest potential to cause an accident. Furthermore, the imprecise performance or too late response of the level alarm and interlock systems has the highest potential to result in the accident or two-phase separator failure.

4.2. DBN model

Based on the outcome of the FRAM analysis, the DBN model is developed for the coupling with the highest criticality. The node “Disruption” lists the potential malfunctions that may cause accident development. The nodes “Absorption” and “Adaptation” contain the current safety absorption and adaptation measures applied for the two-phase separator. “Restoration node” includes the recommendations for the enhancement of the 2-phase separator performance.

4.3. Application of simulation for extraction of PoFs

The PoF for the “2-phase separator performance” node was estimated using the sensitivity analysis module in the Aspen Hysys simulator. The sensitivity analysis is a one-at-a-time (OAT) method. The input parameters were the ranges of the pressure, temperature, and flow rate of the feed. The “Nested” state-input type was specified for the input parameters. Thus the sensitivity analysis was automatically run throughout the specified ranged first for pressure, then for temperature and finally for flow rate. The monitored parameter for each simulation run was the dihydrogen sulfide concentration in the “Sweet Gas” stream, leaving the amine contactor. As a failure, the case of having the H₂S concentration higher than 4 ppm was assumed. Consequently, the PoF equivalent to 0.122 was estimated using Eq. (4). A total of 700 simulation runs were carried out, which was the maximum number of runs that the program allowed to perform for the specified ranges. It was a pragmatic decision to stop at 700 iterations due to the software limitation and may affect the accuracy of the results. It is worth noting that the users may consider conducting a sensitivity analysis of the number of simulation runs to identify an appropriate number. The PoFs of the other nodes were identified using Aspen Hysys Dynamic simulation scenarios.

Scenario 1. Valve actuator Failed Open.

The Aspen Hysys Dynamic simulation for estimation of PoF was completed for the two-phase separator located before the absorption column (Fig. 5). The separator products were the sour gas routing to the absorption column and processed hydrocarbons routing to the stabilization unit. The PoF evaluation was accomplished with the strip charts generated as a result of the dynamic simulation (Fig. 6). For filling the disruption node “Valve actuator Failed Open”, the valve VLV-102 fail-open scenario was simulated in Aspen Hysys Dynamic (Fig. 5). The normal liquid percent level was set to the value of 20–50%. However, the level of liquid in the tank dropped to 4.13% when the valve VLV-102 failed open (Fig. 6). Employing Eq. (3) the PoF for the node “Valve actuator failed Open” was estimated:

$$PoF_1 = \frac{\text{Malfunction time range}}{\text{Total operational time}} = \frac{56540 \text{ min} - 56301 \text{ min}}{56540 \text{ min} - 55340 \text{ min}} = \frac{239 \text{ min}}{1200 \text{ min}} = 0.199$$

Scenario 2. Valve actuator Failed Close.

For the node “Valve Actuator Failed Shut” the Aspen Hysys

Table 5
The FRAM couplings with indicated amplification factors.

Downstream function		Upstream function				
Name of function	Aspect	Name of function	α_{Tij}	α_{Pij}	Couplings	5%
2-phase separator	Input	Feed(Sour gas + PHC)	10±3	40±20	C1	1.21
	Input	Methanol Injection	30±20	30±20	C2	0.00
	Control	Operator at the Control Room	50±20	40±20	C3	3.62
	Control	Operator at the unit area	50±20	50±20	C4	7.40
	Control	Level controllers and Interlock systems	60±20	50±10	C5	18.70
	Control	Hand/manual Valves	10±5	10±5	C6	0.06
Feed(Sour gas + PHC)	Control	Level controllers and Interlock systems	60±30	40±20	C7	2.42
Pressure Indicators	Precondition	Feed(Sour gas + PHC)	10±5	10±5	C8	0.12
	Precondition	2-phase separator	10±6	10±6	C9	0.01
Pressure Safety Valves	Input	Pressure Indicators	60±10	40±10	C10	17.84
	Control	Operator at the Control Room	70±10	50±10	C11	26.90
	Control	Operator at the unit area	60±20	50±20	C12	12.88
Level Alarm Systems	Precondition	Feed(Sour gas + PHC)	10±7	10±7	C13	0.00
Level controllers and Interlock systems	Input	Level Alarm Systems	80±10	50±20	C14	23.67
	Control	Operator at the Control Room	70±20	80±10	C15	37.88
Toxic Flammable Gas Detection Systems	Precondition	2-phase separator	10±3	10±3	C16	0.52
Operator at the Control Room	Precondition	Regular Equipment Commissioning	40±30	50±30	C17	0.01
	Resource	Toxic Flammable Gas Detection Systems	50±20	60±20	C18	11.89
	Resource	Pressure Indicators	50±20	60±30	C19	4.93
	Resource	2-phase separator	10±2	10±2	C20	0.73
	Control	Toxic Flammable Gas Detection Systems	40±20	50±20	C21	3.57
Operator at the unit area	Resource	Pressure Indicators	10±3	60±20	C22	3.19
	Control	Toxic Flammable Gas Detection Systems	70±10	60±20	C23	26.03
	Precondition	2-phase separator	10±1	70±10	C24	5.96
Regular Equipment Commissioning	Resource	Toxic Flammable Gas Detection Systems	10±6	50±30	C25	0.01
	Resource	Pressure Indicators	10±7	60±30	C26	0.02
	Time	Operator at the unit area	50±30	60±20	C27	0.88
Coalescing Filter	Input	2-phase separator	10±1	20±10	C28	0.74
Amine Contactor	Input	2-phase separator	10±3	30±20	C29	0.01
Reflux Drum	Input	2-phase separator	30±10	40±10	C30	7.02
Hand/manual Valves	Control	Operator at the unit area	50±30	60±20	C31	0.06

Dynamics Simulation was run given the Actuator has Failed Shut scenario for valve VLV-102. After the valve VLV-102 failed close, the liquid level in the tank reached 95.35%. The outcome is displayed in the form of the strip chart. Based on the obtained results and Eq. (3), the PoF was estimated as:

$$PoF_2 = \frac{\text{Malfunction time range}}{\text{Total operational time}} = \frac{57480 \text{ min} - 57180 \text{ min}}{57480 \text{ min} - 57080 \text{ min}} = \frac{300 \text{ min}}{400 \text{ min}} = 0.75$$

Scenario 3. Selecting the wrong switch for the application

For the node “Selecting the wrong switch for your application”, the action of the level controller of valve VLV-102 was set to reverse instead of the direct. Resultantly the liquid level in the separator dropped from 30% to 4.18%. The PoF for this scenario was then estimated and the result was inserted into the CPT of the corresponding node in the DBN model.

$$PoF_3 = \frac{\text{Malfunction time range}}{\text{Total operational time}} = \frac{60888 \text{ min} - 60366 \text{ min}}{60888 \text{ min} - 59689 \text{ min}} = \frac{522 \text{ min}}{1199 \text{ min}} = 0.435$$

Scenario 4. Heat introduction and fire mitigation scenario

In this scenario, the PoF is estimated for node “Adding valve and interlock at the inlet stream of the separator” given fire in the two-phase separator (Fig. 7). The heat was introduced to the vessel. With the employment of the event scheduler and cause and effect matrix, the closing of all valves during the fire extinguishing was simulated with subsequent fire relief via the pressure safety valves before the pressure is returned to the normal operating pressure. After that, the closed valves were opened, and the operation continued at the recovered conditions.

The normal operating pressure range for this scenario was the pressure range of 490–520 kPa. The valves VLV-100, VLV-101, and VLV-102 were set to close at the pressure of 655 kPa. Based on the

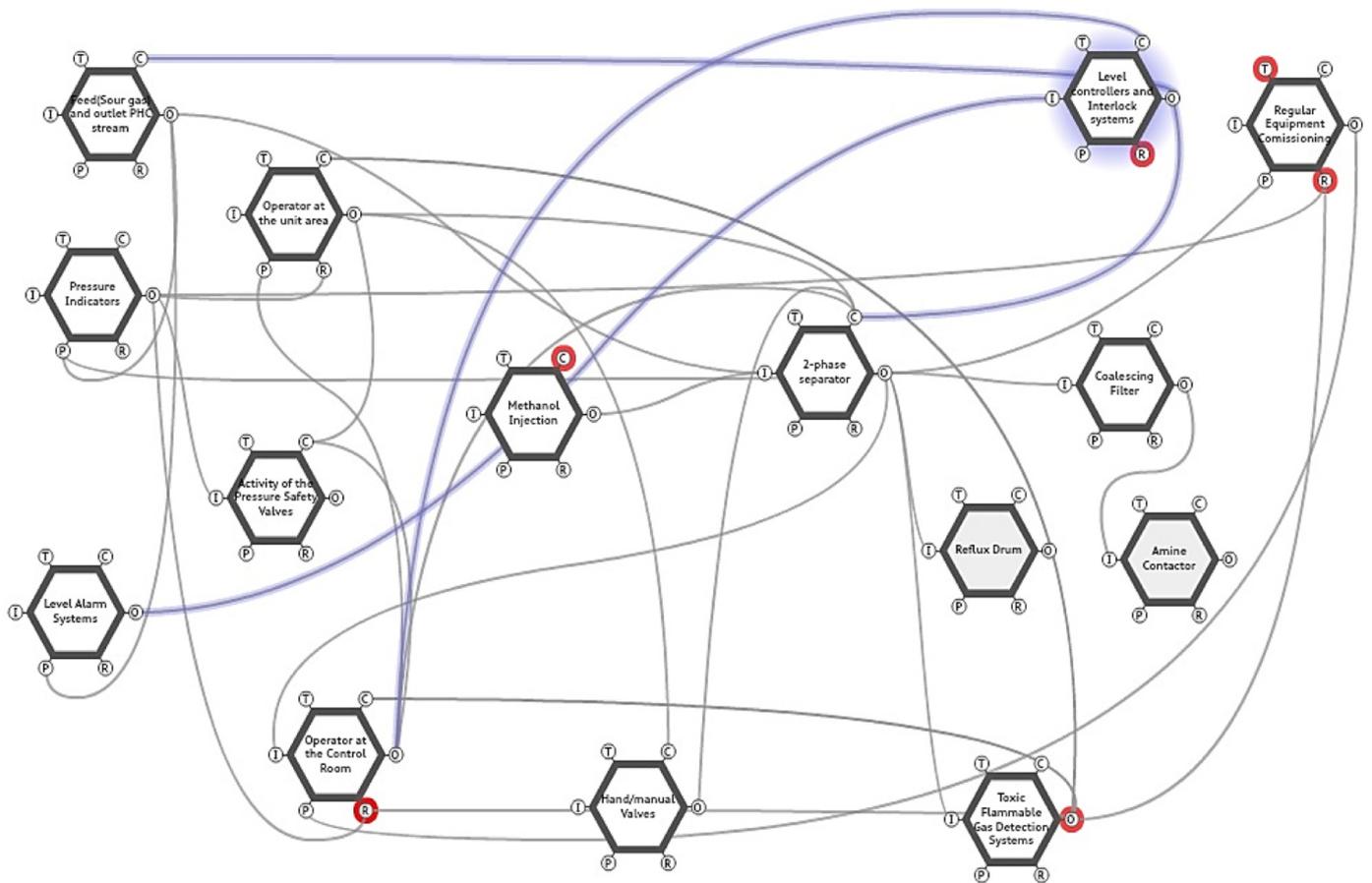


Fig. 3. FRAM Model for the activities related to the 2-phase separator [[16],[35]].

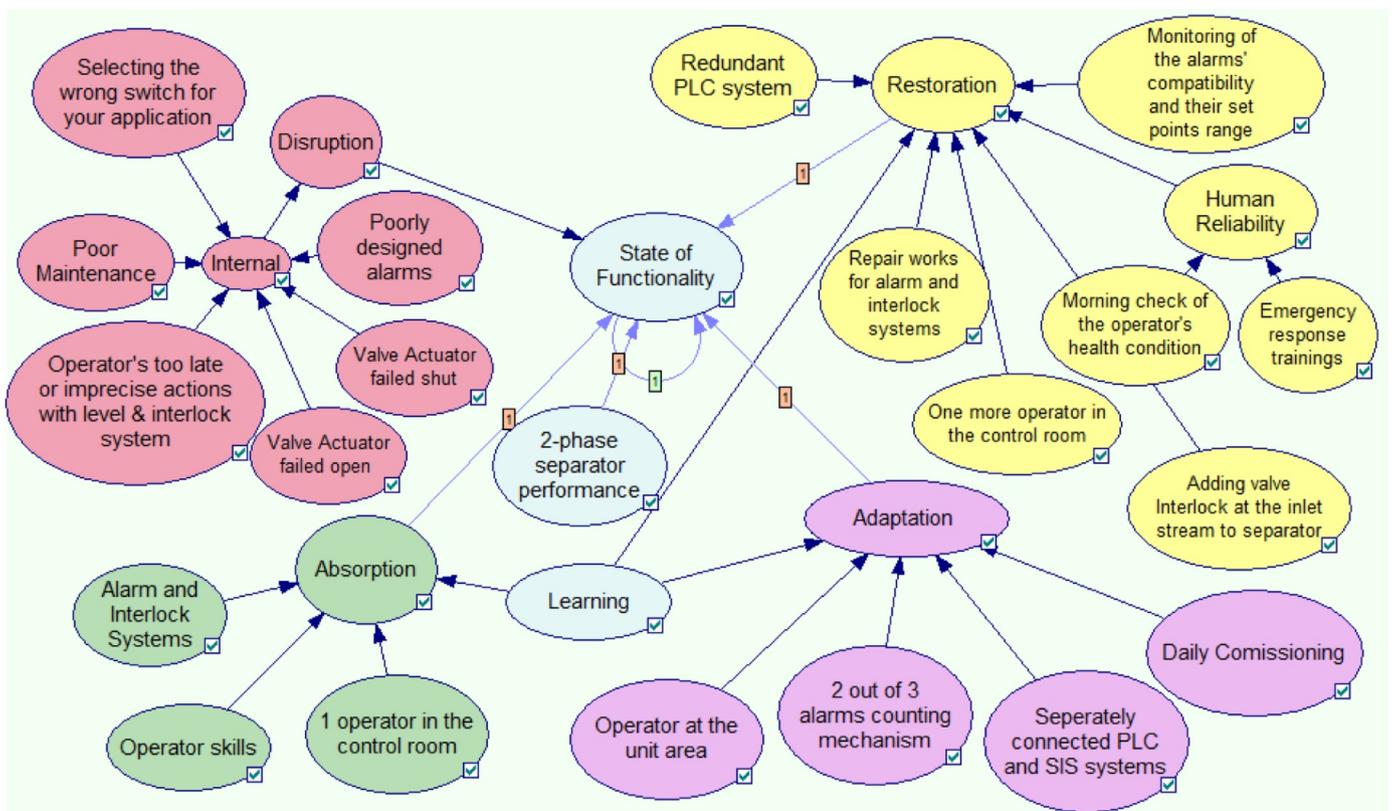


Fig. 4. Developed DBN model for the identified critical coupling.

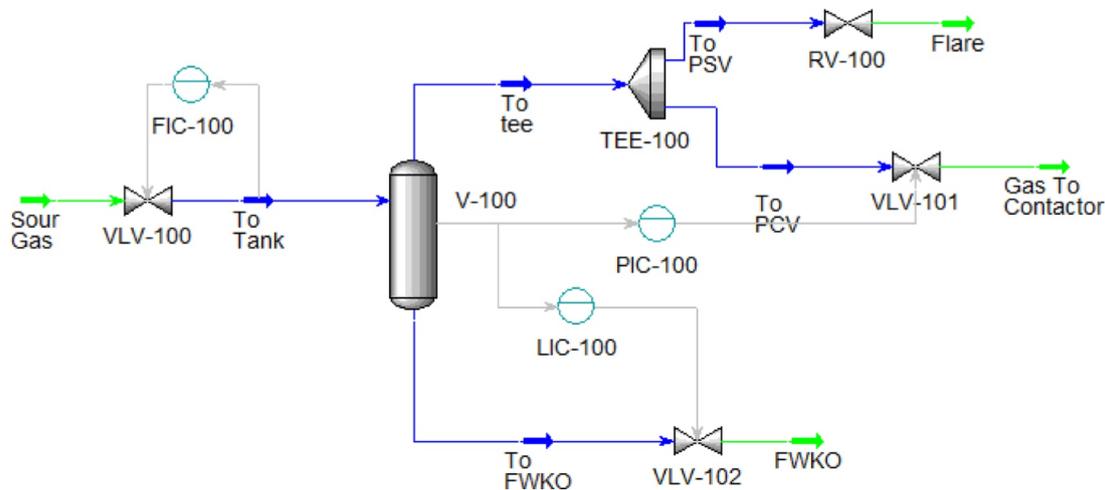


Fig. 5. Process diagram of the 2-phase separator [21].

analysis of the obtained strip charts, the disruption is seen to start at 100,499 s and finishes at 111,904 s. In contrast, the whole operation starting and ending time is 96,297 s and 117,014 s, respectively.

$$PoF_4 = \frac{\text{Malfunction time range}}{\text{Total operational time}} = \frac{111904 \text{ sec} - 100499 \text{ sec}}{117014 \text{ sec} - 96297 \text{ sec}} = \frac{11405 \text{ sec}}{20717 \text{ sec}} = 0.551$$

Given the PoFs obtained from the simulation, the resilience curve for the 2-phase separator is obtained. Fig. 8 presents the resilience of the separator given the disruption in terms of the malfunctions that may occur due to inaccurate performance or too late a response of the level alarm and interlock systems or the operator working in the control room. It takes 9 h for disruption to bring the separator to the lowest

level of resilience, i.e., 0.48. Furthermore, it takes 56 h for the system to restore to 0.94 - the highest resilience after the adaptation and restoration measures applied to the separator.

Additional nodes were considered for “Absorption,” “Adaptation” and “Restoration” (Table 6). A new DBN model (Fig. 9) for the two-phase separator was built. With the additional nodes, the resilience profile is expected to enhance. The resilience profile displays stronger “Absorption,” “Adaptation” and “Restoration” characteristics, the structure of the DBN model can be validated.

From a comparison of the results presented by Table 7, it is observed that the lowest value of resilience has increased from 48.34% to 50.00% with the addition of the new parameter for the “Absorption” node. This designated a slightly more robust absorption properties of the system.

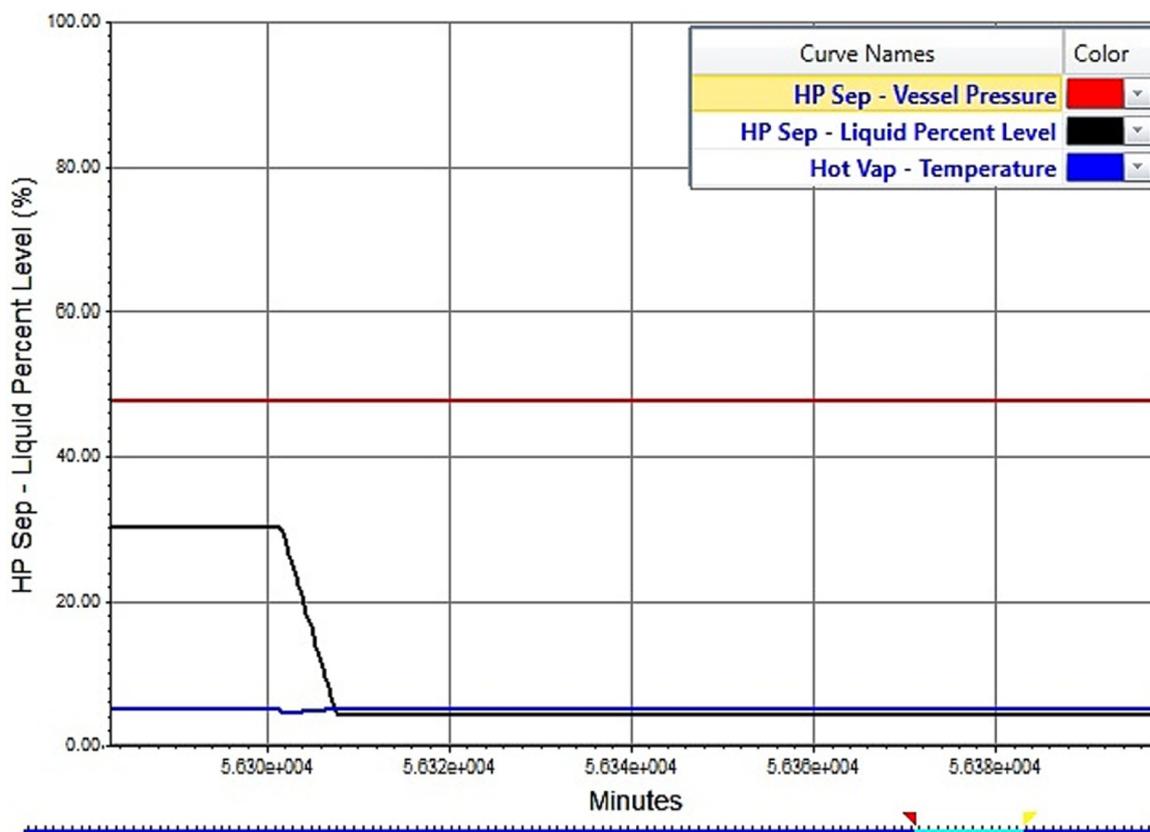


Fig. 6. Liquid percentage in the tank when Valve-102 actuator has failed open.

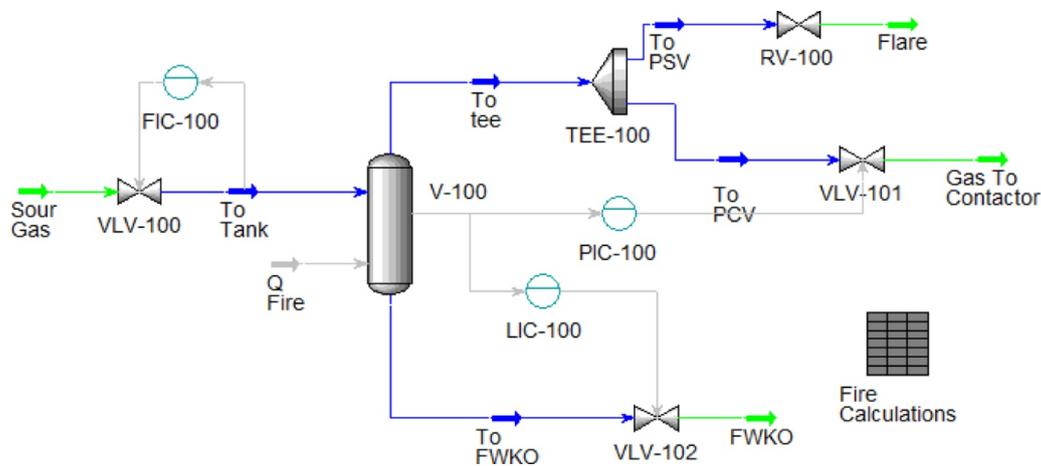


Fig. 7. Fire in the 2-phase separator simulation.

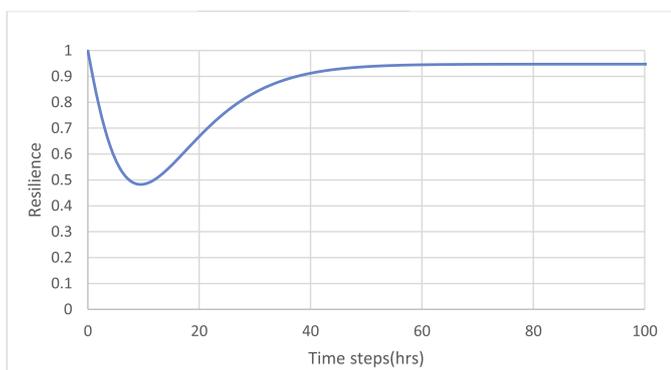


Fig. 8. The resilience curve of the system.

Table 6
Additional safety measures for DBN model.

Absorption	Additional Operator at the control room
Adaptation	Bypass Valves Relief Valves
Restoration	Replacement of the damaged valves The pay bonus system for the safe month

The final resilience state is slightly increased at the updated DBN model, and the time for 90% recovery is shorter than in the initial DBN model. Both characteristics are evidence of the strengthening of the "Adaptation" and "Restoration" parameters of the system. Thus, the DBN model is partially validated.

It is worth noting that the obtained results (regarding the safety measures recommendation) are for demonstration purposes because no independent validation was performed.

4.4. Sensitivity analysis for identification of the most influential nodes in DBN model

Sensitivity analysis was carried out to identify the nodes having the highest impact on the state of system resilience. Identification of the critical nodes assists in the allocation of specific safety measures to the system. Table 8 lists 11 scenarios that may contribute to the variation of the resilience of the system and the results of the sensitivity analysis.

Table 8 indicates that the highest impact on the resilience drop occurs at low absorption conditions. However, with the strong adaptation and restoration characteristics, the system restores to the normal operational state (90% of recovery) in the shortest time. The most significant impact on the resilience drop is caused by the effect of the

poor operator skills and not functioning alarm and interlock system. Scenarios 4–11 show the resilience reduction to the value of around 40% in approximately 9 h, representing the strong absorption properties or well-thought inherent safety design of the developed model.

4.5. Methods comparison

In this section, the previous work on the quantitative resilience assessment [48] is compared with the current study. In the previous work, the elements of BT were developed based on their association with the resilience attributes, namely, absorption, adaptation, and restoration. The developed BT was then converted into the DBN model with the nodes of absorption, adaption, and restoration as the immediate parent nodes linked to the node of "state of functionality", which was used to measure the system resilience. In the present study, instead of subjectively identifying the factors, FRAM was applied to identify the critical factors affecting the system resilience. It is a more objective approach.

Initially, it was assumed that disruption occurs due to the electricity outage and subsequent malfunction of the electric heat tracing of the three-phase separator operating under the harsh cold conditions. Comparatively, in this study, the possible reason for the separator malfunction was not assumed but found through the FRAM analysis with the MCS approach. Thus, the current research enables identifying the causes of the possible accidents, inventing and applying the particular measures for either avoiding the accident from happening or in case the accident occurred to adapt to it or recover from it in a fast manner. With this approach, the safety measure currently applied and newly proposed could be analyzed for their effectiveness for the specific failures with the employment of this method. Thus, the approach offers both a practical and cost-efficient approach to ensure safe operations in the plant.

Furthermore, some studies (e.g., Kammouh et al. [25]) did not develop DBNs for disruption and recovery attributes. They did not consider the system's learning capability as an attribute of its resilience. The present work identifies the most vulnerable technical-human-organizational interactions within the system to support DBN development, which involves the sub-networks for modeling disruptions and recovery and considers learning to be one of the attributes of resilience. Moreover, the present work enables investigating the effectiveness of the supplementary safety measures to enhance the resilience attributes.

Bellini et al. [4] have developed a Q-FRAM approach that quantifies the system's resilience at a specified time by using the System Resilience Index (SRI). SRI is estimated by applying the Choquet integral for the capacitive variabilities assigned for the function couplings, referring to the corresponding resilience "cornerstones" (anticipate, respond, monitor, learn). The value of SRI > 1 designates the risk of accident

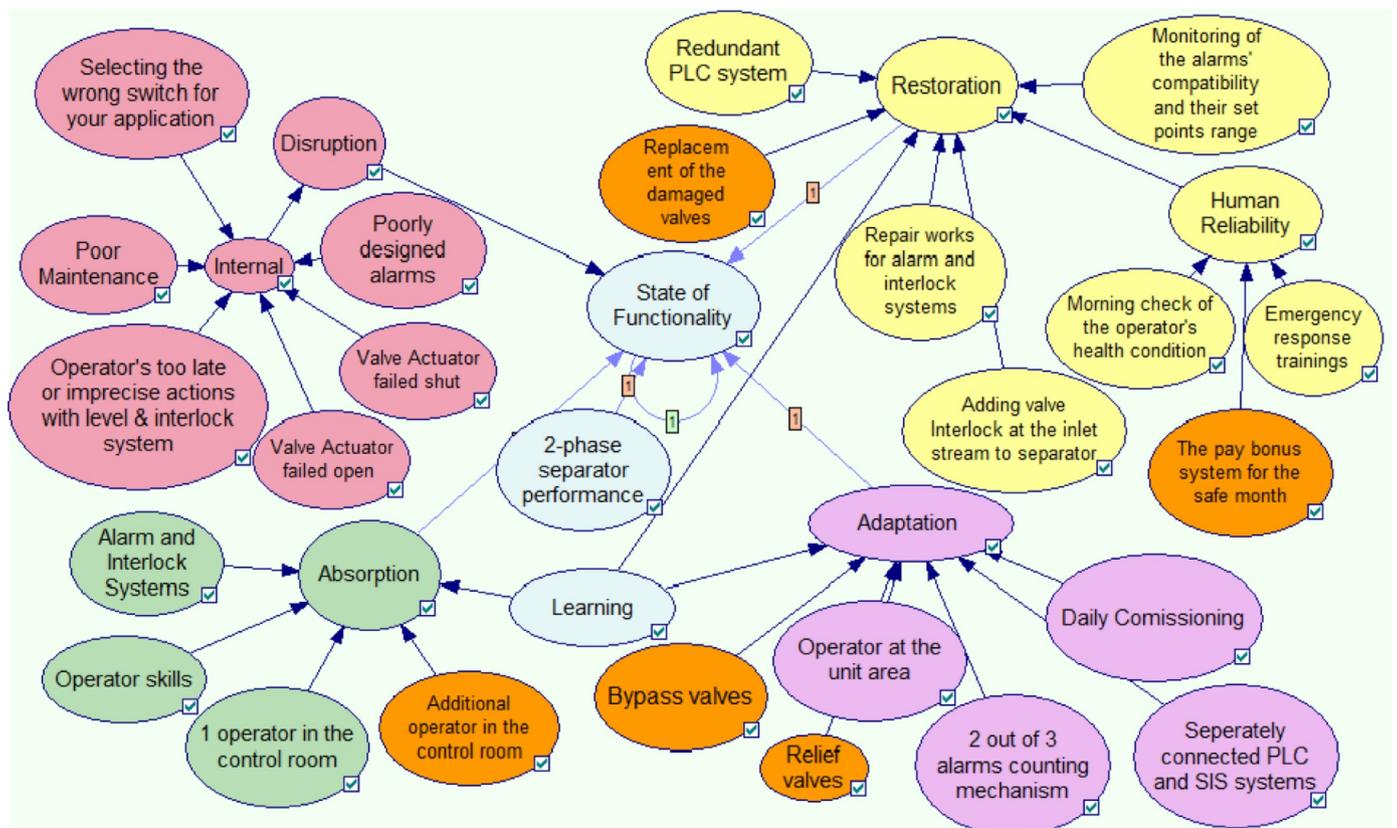


Fig. 9. Updated DBN model with additional parameters (orange nodes presented in Table 6).

development as a result of the resonance in the poor performance of the functions, and thus characterizes the system as non-resilient.

With the integration of FRAM and DBN, the present study provides the opportunity to obtain the resilience profile as a probabilistic and time-dependent evolution of a system's functionality state, affected by the critical function couplings.

5. Conclusions

Dynamic quantitative resilience assessment is a research problem of great interest in the sphere of resilience engineering for process systems. This requires the rigorous analysis of the root causes of the accidents and mishaps, and the resilience attributes of the process systems on the level of technical-human-organizational interactions. The current study demonstrated the applicability and effectiveness of the integration of the FRAM and DBN for the quantitative resilience assessment of complex process systems consisting of the technical-human-organizational aspects. The proposed approach can identify the root causes of an accident with the employment of FRAM. The essential resilience attributes strongly associated with these causes are considered in the development of the DBN to assess the temporal changes of the resilience of a complex process system. The most important safety measures can also be identified with sensitivity analysis. This study

supports that resilience should be assessed in both probabilistic and temporal terms. It investigates the usefulness of process simulators as a process data source for the estimation of failure probabilities. For future work, we are planning to investigate the opportunity of learning the structure of the Bayesian network from various data (e.g., process data, management and organizational data, operational environmental data) for dynamic resilience assessment.

CRedit authorship contribution statement

Altyngul Zinetullina: Methodology, Formal analysis, Investigation, Writing - original draft. **Ming Yang:** Conceptualization, Methodology, Formal analysis, Investigation, Writing - review & editing, Validation. **Nima Khakzad:** Formal analysis, Writing - review & editing. **Boris Golman:** Writing - review & editing, Validation. **Xinhong Li:** Writing - review & editing, Validation.

Declaration of Competing Interest

The research being reported in this paper titled "Quantitative resilience assessment of chemical process systems using Functional Resonance Analysis Method and Dynamic Bayesian Network" was supported by Nazarbayev University. The authors of this paper have the

Table 7
Comparison of resilience metrics.

Resilience metrics	Without additional safety measures	With additional safety measures
Disruption occurrence time (hrs)	9	9
Resilience decline value (%)	48.34%	50.0%
The final resilience state (%)	94.32%	94.83%
Time for resilience stabilization (hrs)	56	56
Time for 90% recovery (hrs)	38	37

Table 8
The results of sensitivity analysis.

Scenarios	Resilience Reduction(%)	Time to reach lowest reliability(hrs)	Time for 90% recovery (hrs)
Low absorption	0.27	2	21
Not functioning alarm and interlock systems	36.71	8	28
Poor operator skills	34.39	8	28
Low learning ability of the system	42.81	8	30
Low 2-phase separator performance	47.41	9	31
High disruption	48.83	10	32
No properly functioning PLC system	48.8	9	32
No repair works for alarm and interlock systems	48.32	9	32
Low human reliability	45.55	11	32
No morning check of the operators' health condition	47.75	10	32
No emergency response training	47.87	10	32

IP ownership related to the research being reported. The terms of this arrangement have been reviewed and approved by the Nazarbayev University in accordance with its policy on objectivity in research.

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References

- Adger WN. Social and ecological resilience: are they related? *Prog Hum Geogr* 2000;24(3):347–64. <https://doi.org/10.1191/030913200701540465>.
- Azadeh A, Salehi V, Arvan M, Dolatkah M. Assessment of resilience engineering factors in high-risk environments by fuzzy cognitive maps: a petrochemical plant. *Saf Sci* 2014;68:99–107.
- Baroud H, Ramirez-Marquez JE, Barker K, Rocco CM. Stochastic measures of network resilience: applications to waterway commodity flows. *Risk Anal* 2014;34(7):1317–35.
- Bellini, E., Cocone, L., & Nesi, P. (2019). A functional resonance analysis method driven resilience quantification for socio-technical systems. *IEEE Syst J*.
- Berkeley AR, Wallace M, COO C. A framework for establishing critical infrastructure resilience goals. Final report and recommendations by the council. National Infrastructure Advisory Council; 2010.
- Burnard K, Bhamra R. Organisational resilience: development of a conceptual framework for organisational responses. *Int J Prod Res* 2011;49(18):5581–99. <https://doi.org/10.1080/00207543.2011.563827>.
- Cai B, Xie M, Liu Y, Liu Y, Feng Q. Availability-based engineering resilience metric and its corresponding evaluation methodology. *Reliab Eng Syst Saf* 2018;172:216–24.
- Cincotta S, Khakzad N, Cozzani V, Reniers G. Resilience-based optimal firefighting to prevent domino effect in process plants. *J Loss Prev Process Ind* 2019;58:82–9.
- Costella MF, Saurin TA, Guimarães LBDM. A method for assessing health and safety management systems from the resilience engineering perspective. *Saf Sci* 2009;47(8):1056–67. <https://doi.org/10.1016/j.ssci.2008.11.006>.
- De Carvalho PVR. The use of Functional Resonance Analysis Method (FRAM) in a mid-air collision to understand some characteristics of the air traffic management system resilience. *Reliab Eng Syst Saf* 2011;96(11):1482–98.
- Dinh LT, Pasman H, Gao X, Mannan MS. Resilience engineering of industrial processes: principles and contributing factors. *J Loss Prev Process Ind* 2012;25(2):233–41.
- Dubi A. Monte Carlo applications in systems engineering. New York, USA: Wiley; 2000.
- Faturechi R, Miller-Hooks E. Travel time resilience of roadway networks under disaster. *Transp Res Part B* 2014;70:47–64.
- Fiksel J. Sustainability and resilience: toward a systems approach. *Sustainability* 2006;2(2):14–21. <https://doi.org/10.1080/15487733.2006.11907980>.
- Holling CS. Resilience and stability of ecological systems. *Annu Rev Ecol Syst* 1973;4(1):1–23. <https://doi.org/10.1146/annurev.es.04.110173.000245>.
- Hollnagel E., R. Hill. "Instructions for use of the FRAM Model Visualiser (FMV). Available at <http://functionalresonance.com/tools-visualisation/fram-visualisation.html> (date accessed 9th June 2018).
- Hollnagel Erik, Goteman O. The functional resonance accident model." *Proceedings of cognitive system engineering in process plant 2004*. 2004. p. 155–61.
- Hollnagel, E., Woods, D., & Leveson, N. (2006). Resilience engineering : concepts and precepts. *Resilience Engineering: Concepts and Precepts*.
- Hollnagel, E. (2012). FRAM: the functional resonance analysis method: modelling complex technical-human-organizational systems.
- Hosseini S, Barker K. Modeling infrastructure resilience using Bayesian networks: a case study of inland waterway ports. *Comput Ind Eng* 2016;93:252–66.
- Hysys A. Release 2004, simulation basis. Cambridge, MA: Aspen Technology; 2004.
- Jain P, Pasman HJ, Waldram S, Pistikopoulos EN, Mannan MS. Process Resilience Analysis Framework (PRAF): a systems approach for improved risk and safety management. *J Loss Prev Process Ind* 2018;53:61–73.
- Jensen FV, Nielsen TD. Bayesian networks and decision graphs. *Inf Sci Stat* 2007. <https://doi.org/10.1007/978-0-387-68282-2>.
- Yodo N, Wang P, Zhou Z. Predictive resilience analysis of complex systems using dynamic Bayesian networks. *IEEE Trans Reliab* 2017;66:761–70.
- Kammouh O, Gardoni P, Cimellaro GP. Probabilistic framework to evaluate the resilience of engineering systems using Bayesian and dynamic Bayesian networks. *Reliab Eng Syst Saf* 2020;198:106813.
- Kendra JM, Wachtendorf T. Elements of Resilience After the World Trade Center Disaster: reconstituting New York City's Emergency Operations Centre. *Disasters* 2003;27(1):37–53. <https://doi.org/10.1111/1467-7717.00218>.
- Khakzad N. Application of dynamic Bayesian network to risk analysis of domino effects in chemical infrastructures. *Reliab Eng Syst Saf* 2015;138:263–72. <https://doi.org/10.1016/j.res.2015.02.007>.
- Kinzig AP, Ryan P, Etienne M, Allison H, Elmqvist T, Walker BH. Resilience and regime shifts: assessing cascading effects. *Ecol Soc* 2006;11(1). <https://doi.org/10.5751/es-01678-110120>.
- Lewis EE, Böhm F. Monte Carlo simulation of Markov unreliability models. *Nucl Eng Des* 1984;77(1):49–62.
- Li Y, Lence BJ. Estimating resilience for water resources systems. *Water Resour Res* 2007;43(7).
- Li X, Chen G, Zhu H, Zhang R. Quantitative risk assessment of submarine pipeline instability. *J Loss Prev Process Ind* 2017;108–15.
- Luthar SS, Cicchetti D, Becker B. The construct of resilience: a critical evaluation and guidelines for future work. *Child Dev* 2000;71(3):543–62. <https://doi.org/10.1111/1467-8624.00164>.
- Marseguerra M, Zio E, Patelli E, Giacobbo F, Risoluti P, Ventura G, Mingrone G. Modeling the effects of the engineered barriers of a radioactive waste repository by Monte Carlo simulation. *Ann Nucl Energy* 2003;30(4):473–96.
- McCarthy, J.A. (2007). Introduction: from protection to resilience: injecting 'Moxie' into the infrastructure security continuum. Critical thinking: moving from infrastructure protection to infrastructure resilience, 2–3.
- Patriarca R, Di Gravio G, Costantino F. A Monte Carlo evolution of the Functional Resonance Analysis Method (FRAM) to assess performance variability in complex systems. *Saf Sci* 2017;91:49–60.
- Patriarca R, Bergström J, Di Gravio G. Defining the functional resonance analysis space: combining Abstraction Hierarchy and FRAM. *Reliab Eng Syst Saf* 2017;165:34–46. <https://doi.org/10.1016/j.res.2017.03.032>.
- Patriarca R, Di Gravio G, Costantino F. myFRAM: an open tool support for the functional resonance analysis method. 2017 2nd International Conference on System Reliability and Safety (ICSRS) Milan; 2017. p. 439–43. <https://doi.org/10.1109/ICSRS.2017.8272861>.
- Perrings C. Resilience and sustainable development. *Environ Dev Econ* 2006;11(4):417–27. <https://doi.org/10.1017/s1355770x06003020>.
- Rosa LV, Haddad AN, de Carvalho PVR. Assessing risk in sustainable construction using the Functional Resonance Analysis Method (FRAM). *Cogn Technol Work* 2015;17(4):559–73.
- Rose A, Liao S-Y. Modeling regional economic resilience to disasters: a computable general equilibrium analysis of water service disruptions*. *J Reg Sci* 2005;45(1):75–112. <https://doi.org/10.1111/j.0022-4146.2005.00365.x>.
- Sawaragi T, Horiguchi Y, Hina A. Safety analysis of systemic accidents triggered by performance deviation. In 2006 sice-icase international joint conference (pp. 1778–81). IEEE; 2006.
- Shirali GA, Mohammadfam I, Ebrahimipour V. A new method for quantitative assessment of resilience engineering by PCA and NT approach: a case study in a process industry. *Reliab Eng Syst Saf* 2013;119:88–94.
- Steen R, Aven T. A risk perspective suitable for resilience engineering. *Saf Sci* 2011;49(2):292–7.
- Tong Q, Yang M, Zinetullina A. A dynamic bayesian network-based approach to resilience assessment of engineered systems. *J Loss Prev Process Ind* 2020;65:104152.
- Vogel RM, Bolognese RA. Storage-reliability-resilience-yield relations for over-year water supply systems. *Water Resour Res* 1995;31(3):645–54.
- Vugrin Eric D, et al. A Framework for Assessing the Resilience of Infrastructure and Economic Systems. *Sustain Resilient Crit Infrastruct Syst* 2010:77–116. https://doi.org/10.1007/978-3-642-11405-2_3.
- Wu D, Hui K, Chandler D. Monte Carlo study of polymers in equilibrium with random obstacles. *J Chem Phys* 1992;96(1):835–41.
- Zinetullina A, Yang M, Khakzad N, Golman B. Dynamic resilience assessment for process units operating in Arctic environments. *Saf Extrem Environ* 2019:1–13.