# Integrating FRAM with Dynamic Graph Approach for Risk Analysis during Maintenance Operation

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Maintenance operation in an oil and gas facility is a socio-technical endeavor under varying demands and situations. While some recent papers have focused on modeling the risk of such operations by updating QRA, there is still a growing need for understanding how different actions during maintenance operation may affect safety and increase the risk of hydrocarbon release. To assess the risks arising from dynamic interactions in a complex socio-technical system, this paper follows a Safety-II perspective and utilizes the Functional Resonance Analysis Method (FRAM). The FRAM intends to describe how performance variability of system functions may affect the risk. To investigate the functional performance variability as well as its propagation through the model, Risk Influencing Factors (RIFs) are defined, and their effectiveness is evaluated. To facilitate the modeling and better understanding of the evolution of the system, the study has adopted the directed graph interpretation of FRAM modeling and has improved it, by considering the role of RIFs in functional performance variability. This approach captures the effect of changes within the system and provides a systematic prioritization of critical stages and interactions during maintenance work through graph topological analysis.

*Keywords*: Maintenance operation, FRAM, Risk Influencing Factors (RIFs), Dynamic graph, Socio-technical systems, Safety-II.

## 1. Introduction

Although the maintenance is carried out as a risk reduction measure, almost one third of hydrocarbon leakage incidents in oil and gas industry happened during preventive maintenance, testing and/or cleaning (Vinnem and Røed, 2015). Maintenance work is a complex socio-technical process with a number of key aspects that can contribute to hydrocarbon leaks due to the manual intervention, not complying with the requirements and instructions, and not verification of errors (Vinnem et al., 2014). To ensure safe operation and reduce the risk of hydrocarbon leaks, risk-informed decisions are necessary. Many publications such as Bucelli et al. (2018), Bubbico et al. (2020), and Lee et al. (2019) attempted to reflect the risk fluctuations via updating of the QRA. Traditionally, QRA is highly focused on technical systems, and non-technical factors cannot easily be considered (Skogdalen and Vinnem, 2011). Methodologies such as Barrier and Operational Risk Analysis (BORA) method (Aven et al., 2006), Operational Conditional Safety (OTS) method (Vinnem et al., 2009), Risk modelling-Integration of Organizational, Human and Technical factors (Risk-OMT) model (Vinnem et al., 2012), and quantitative risk modeling of maintenance work by Zhen et al. (2018) have been developed to reflect human and organizational factors in QRA.

Maintenance operations are often associated with short-term effects on normal daily operation in an oil and gas installment. Yang and Haugen (2015) express the risk associated with these effects as activity performance risk (APR). In APR, the focus is more on avoiding accident

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occurrence rather than expected loss as a measure of risk. QRA only provides information regarding the probability of an accident as an indicator of acceptable risk based on measuring average unavailability of barriers. This clearly means that QRAs will not necessarily provide decision-makers with useful information on how risk is presented and how particular changes to RIFs during operation may affect the system status. Maintenance operation is a complex socio-technical process; therefore, an appropriate safety approach must be adopted. There are two ways to ensure the safety of systems: one is to eliminate potential hazards or why things go wrong. In this perspective, which is termed Safety-I, the risk assessment leave us unaware of how everyday actions affect the safety. On the contrary, Safety-II focuses on the system's ability to succeed under varying conditions (Hollnagel et al., 2015) and combining the two ways of thinking. For this purpose, adopting a systemic perspective for risk analysis, the Functional Resonance Analysis Method (FRAM), initially developed by Hollnagel and Goteman (2004), helps in identifying nonlinear combinations of events and interrelationships of complex socio-technical systems.

The FRAM describes how a system should function to meet its objectives (i.e., "everyday" performance), and helps understand the variability of functions which alone or in combination may prevent accidents from happening. The advantages of adopting FRAM for risk assessment have been discussed in a variety of case studies (Patriarca et al., 2020). In case of maintenance operation, Hosseinnia et al. (2019) employed the FRAM to facilitate the modeling of dynamic interactions and to evaluat the most critical RIFs. Although FRAM approach may indeed reduce the surprises by increasing the system and risk understanding, it should be combined with other methods to adequately support the decision-making on risk issues (Bjerga et al., 2016). Several recent papers have focused on utilizing and combining established methodologies with FRAM to improve the risk assessment (Patriarca et al., 2020).

Graph theory has been widely used to describe many complex systems and has proven to be well suited to investigate new non-linear characteristics that are otherwise difficult to express. Several authors have attempted to combine graph theory and FRAM for different analysis purposes. Lee and Chung (2018) defined a Human–System Interaction (HSI) network, equipped with node functions and node agents for a complementary classification of variability. The most explicit attempt in the context of the resilience based on the human-oriented readability of traditional FRAM has been proposed by Bellini et al. (2016) that points out the FRAM network translation to support quantitative analysis of urban transport systems. Recently Falegnami et al. (2019) showed that any FRAM instantiation can be interpreted as a multilayer network, allowing bridging the gap between network analysis and FRAM-based analysis of complex systems. Although these studies provided some insight regarding combining graph theory with FRAM, there is still not a precise pass regarding risk analysis in a dynamic sense and considering the human, technical, and organizational Risk Influencing Factors (RIFs) for evaluating the functional variabilities. For this purpose, this paper defines a simplified approach for evaluating the functional variability based on RIFs for operational risk assessment.

The present study has adopted a multilayer graph interpretation of FRAM model (Falegnami et al., 2019). The model has been improved by evaluating the functional variability based on RIFs in a dynamic situation for the purpose of evaluating APR in maintenance operation. In Section 2, the developed methodology is explained by considering FRAM's fundamental building steps and integrating it with graph theory. A walk through the application of the method is discussed on a maintenance process in section 3, and section 4 discusses the results and how the change of the functional variability in different operational conditions affects operational decision-making. Finally, section 5 concludes the study.

## 2. Method

This section describes the methodology for integrating FRAM with the graph theory and how to evaluate the functional variabilities based on RIFs. The approach includes some of FRAM's original building stages and additional ones for developing dynamic FRAM graph model.

### 2.1. *Identifying and describing the system functions*

Based on system knowledge and through the analysis of processes and tasks, available procedures, historical data, and experts judgment, it is possible to characterize the system by its functional structure. In FRAM, a function is made up of six aspects: Input (I), Output (O), Precondition (P), Resource (R), Control (C), and Time (T).

### 2.2. *Function's performance variability and identifying related RIFs*

It is crucial to understand how each function of the system varies since its performance variability has an essential role in the everyday work process. In this step, the potential variabilities of the functions are defined in terms of timing and precision (Hollnagel, 2012). These variabilities can be characterized by asking questions such as: Which conditions can lead to an increase/decrease of performance variability? Which functions are affected? How can the variability express itself, and how may this affect or be affected by other functions?

To provide an answer to these questions, the original FRAM method (Woltjer and Hollnagel, 2008) suggested identifying the common performance conditions, which address the human, technological, and organizational aspects of each function. However, this categorization is very general and cannot incorporate the effect of plant-specific conditions on the performance variability of each function in maintenance operations. Therefore, it is necessary to identify RIFs related to each function's aspect (Hosseinnia et al., 2019). For this purpose, the BORA-Release (Aven et al., 2006) framework for the identification of RIFs is used. The main groups of RIFs and their detailed taxonomy of generic RIFs are listed as bellow:

- Group 1: Charact. of the personnel performing the tasks (R1-Competence, R2-Working load /stress, R3-Fatigue, R4-Work environment)
- Group 2: Charact. of the task being performed (R1-Methodology, R2-Task supervision, R3-Task complexity, R4-Time pressure,R5-Tools, R6-Spares)
- Group 3: Charact. of the technical system (R1-Equipment design, R2-Material properties, R3-Process complexity,R4-Human Machine interface, R5-accessibility, R6-System feedback, R7-Technical condition
- Group 4: Admin. control (R1-Procedure, R2-Work permit, R3-Disposable work description)
- Group 5: Org. factors (R1-Programs, R2-Work practice, R3-Supervision, R4-Communication, R5-Acceptance criteria, R6-Simultaneous activities, R7-Management of changes)

### 2.3. *Integrating FRAM model with dynamic graph*

It has been demonstrated by Falegnami et al. (2019) that a calculated instantiation in the FRAM model can be represented with a network by associating a node to each function and a directed edge to each coupling (upstream output to downstream function's aspect). A classic FRAM model graph consists of a set of vertices (nodes), a set of edges (arcs), and the function's variability score as the weight of edges with the assumption that the structure of the graph is static. However, the systems characteristics change over time, and the functions' variability is dynamic. Dynamic graph models were systematically proposed in the 1990s to solve dynamic applications (Harary and Gupta, 1997).

The representative FRAM graph model is a pair $G = (N, E, w)$, where $N = N_1, N_2, N_3, \ldots, N_n$ is a set of nodes (functions), and $E$ is a set of edges. Each edge is an ordered pair $(n_i, n_j)$, $i \neq j$. If there is an edge from node $i$ (upstream function) to node $j$ (downstream), node $i$ is called tail while node $j$ is called head $i \neq j$. The edge-weight, $w$, is defined as $w : E \rightarrow WE$ , where $WE$ is the function's variability score. A dynamic graph G is updated when one or more than one of the following three entities change: $N$ (a set of nodes), $E$ (a set of edges), and $w$ (weights of edges).

An update on a graph is an operation that adds or removes nodes or edges (topological change), or changes weights of edges or attributes of nodes (parametric change). In this study, only the function's variability (i.e., edge-weight) is considered as a graph update. Between each update, the graph can be regarded as a static graph. Therefore, a dynamic graph can be viewed as a discrete sequence of static graphs, and each graph can be studied by using the static graph theory.

### 2.4. *Evaluating the edge weights*

In order to evaluate the prior edge weight, it is necessary to first characterize the performance variability of all the background functions according to the identified RIFs in Section 2.2 To formalize the relationship between the RIFs and the functional variability, it is assumed $I$ background functions have been identified while $J_i$ RIF groups realize the variability in background function $(i)$. Let $RIF_{ijk}$ be the $k^{th}$ RIF of the $j^{th}$ group for the $i^{th}$ background function.

The status of $RIF_{ijk}$ can be assessed similarly to the BORA release method, based on assigning a score to each identified RIF for function $(i)$. Each $k^{th}$ is given a score from A to F, where score A corresponds to the best standard in the industry, score C corresponds to the industry average, and score F corresponds to worst practice in the industry (Aven et al., 2006). Here for analysis purposes, the scores can be identified on a six-point scale. The lower the score the better the performance (i.e., A score is equal to 1 and F would be 6).

Besides evaluating the RIF score, it is necessary to consider that not all the RIFs have equal importance regarding the performance variability of a function. Therefore, for each $RIF_{ijk}$ the relative importance is compared to the other RIFs in group $j$ by using weights. The assigned weight is calculated based on the principles discussed in the BORA release method. Experiences from the field can help to define the linguistic and the numerical scores according to the specific process performance for the RIFs. Further, it is assumed that the combined impact of $RIF_{ijk}$ could be described by Eq. (1), where $x_{ijk}$ is the value of the $k^{th}$ RIF at a specific time t, and $S_{ijk}$ is the relative weight of the RIF. If there is more than one RIF, the RIF values are assumed to be additive.

$$RIF_{ij}(t) = \sum_{k=1}^{k_{ij}} S_{ijk}\left(x_{ijk}\left(t\right)\right) \qquad (1)$$

Then, the variability of the upstream output of Background Function (*i*) can be calculated using Eq. (2),where the $OV_i$ is equivalent to the background function edge weight $w_i$ in graph G, and

$M_{ij}$ shows the relative importance of the specific RIF group (*j*) in percentage for evaluating the function variability.

$$OV_i(t) = \sum_{j=1}^{J_j} M_{ij} \left( RIF_{ij}(t) \right) \quad (2)$$

The output of the downstream function ( $i$') is dependent on the outputs from the upstream functions. It should be noted that in this method, the dampening or amplifying effect of upstream function on downstream function has not been considered. Based on this assumption, the variability score in downstream function ( $i$') can be defined as Eq. (3). n is the number of $ii$' couplings of function $i$'; in terms of a graph it can be described as incoming edges of node $i$':

$$OV_{i'}(t) = \frac{\sum_i^n OV_i(t)}{n} \quad (3)$$

The functional variability can be stated in terms of precision and timing. Regarding the function precision, an output can be precise, acceptable, imprecise, or wrong (Patriarca et al., 2017a). A rating scale, as shown in Table 1, can express the effects on the performance of function variability: the higher the score, the more variable the output.

Table 1. The functional variability score scale based on precision.

| Performance state | Variability | Variability score $(OV_i)$ rating scale |
|---|---|---|
| Precise | | $OV_i = 1$ |
| Acceptable | | $1 < OV_i \leq 2$ |
| Imprecise | | $2 < OV_i < 5$ |
| wrong | | $5 \leq OV_i \leq 6$ |

## 2.5. *Topological analysis of the FRAM graph model*

This step further expands the network analysis developed through the tensor representation. In this phase, it is possible to adopt a network metric to study the structural properties of the FRAM network model by means of some topological indicators tailored to the problem at hand. These indicators can help identify the key functions and critical couplings in the FRAM model and improve the understanding of the variability propagation in a period. The most relevant ones for the defined dynamic graph of the FRAM model are:

- *Katz centrality*,that shows the relative influence of a node within a network. In a weighted edge graph, this index considers the centrality of a node with a large number of shortest paths to other nodes. The shortest path is the path whose length (the weighted sum of its edges) is the lowest among all the possible paths. Based on this definition, the Katz centrality is a suitable metric to be used for function prioritization and fining the most influential functions within the FRAM model (Falegnami et al., 2019)
- *Edge betweenness centrality*, that finds which edges in a network are the most important. It was introduced by Girvan and Newman (2002) that generalizes Freeman's betweenness centrality to edges and define the edge betweenness of an edge as the number of shortest paths between pairs of vertices that run along with it. This information allows identifying highly critical couplings by evaluating relationships between functions of the network (i.e., edges) and hence identifying different risk influencing factor that affects this coupling.

## 2.6. *Graph update*

A Dynamic Graph can be regarded as a chain of static graphs. The initial graph (graph 1) arises when a primary state of normal operation takes place. A new static graph will occur if the operational condition is changed by time. There are two types of updates in the FRAM model graph; initially, the directed edges weight changes when any RIFs score is updated, and consequently, the functional variability changes according to Eq.(3). Besides, the topological indices defined in the previous section will be updated and will show the critical functions and coupling through different scenarios.

# 3. Method application

A case study is selected based on a description of a maintenance operation taken from the BORA studies (Halseth, 2012). For illustrative purposes, this paper only considers a part of the maintenance process, from planning until disconnecting the pump in two different situations through a period of time in the facility that may affect the maintenance process and increase the hydrocarbon leakage risk. For example, when conditions of the person who performs the maintenance is changed, and when there is a change in the task procedures.

## 3.1. *The FRAM model of the maintenance operation*

The scope of the FRAM modeling was to identify and describe the functions necessary to perform the maintenance of a pump as previously was presented by Hosseinnia et al. (2019). The model was built according to the steps described by Hollnagel (2012) and authors' intuition of how to describe the Functional Aspects based on the available information and steps of the process description. Table 2 lists the functions involved in the analysis, detailing the agent performing the background functions and the related RIFs category from Section 2.2.

Table 2. Identified functions for the case study.

| Functions | Related RIFs |
|---|---|
| Background functions: | |
| 1- Standard operating procedure (SOP) | Group 2 & 5 |
| 2- Maintenance team (MT) | Group 1 |
| 3- Coordination with control room (CCR) | Group 1 & 3 |
| 4- Operation coordination (OC) | Group 2 & 4 |
| Foreground functions: | |
| 5- Maintenance work description (MWD) | |
| 6- Prepare for maintenance (PM) | |
| 7- Shutdown process (SHP) | |
| 8- Isolate equipment with valves (IEV) | |
| 9- Depressurize lines (DL) | |
| 10- Drain (D) | |
| 11- Isolate pipeline (IP) | |
| 12- Disconnect the equipment (DE) | |

For visualization purposes, myFRAM (Patriarca et al., 2017) is used to support the building process of the FRAM model. Figure 1 depicts the overall FRAM model, which offers an overview of the inherent complexity of the process and the subsequent inherent issues related to its risk analysis.

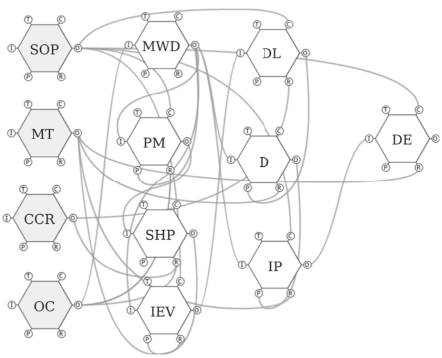


Fig. 1. FRAM model of the Maintenance operation

### 3.2. *FRAM graph model representation and analysis*

The FRAM graph instantiation is depicted in Figure 2 that includes 12 functions (nodes) and 28 couplings (edges). The graph representation has been developed by NetworkX (Hagberg et al., 2005), a Python package for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks.

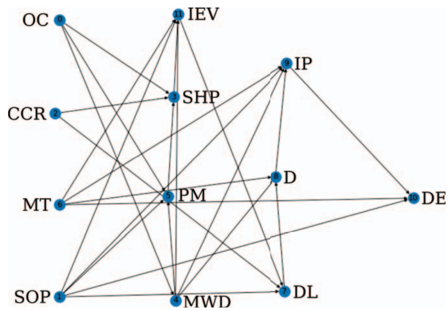


Fig. 2. Graph representation of the maintenance operation FRAM model

The variability assessment process defines a semi-quantitative variable through an ordinal measure to show the variability state of a function output. Table 3 shows the stated two operational scenarios, the score of the RIFs, and the corresponding primary edge(s) weight for the specific background function in each scenario.

Table 3. Details of the scenarios and calculated OV

| Scenario Description | $i$ | $j$ | $RIF_{ijk}$ | $S_{ijk}$ | $x_{ijk}$ | $M_{ijk}$ | $OV_i$ |
|---|---|---|---|---|---|---|---|
| Maintenance technician not competent | 2 | 1 | R211 | 0.33 | 6 | 1.0 | 4.54 |
| | | | R212 | 0.27 | 4 | | |
| | | | R213 | 0.27 | 5 | | |
| | | | R214 | 0.13 | 1 | | |
| Operation coordination not executed properly | 4 | 2 | R421 | 0.16 | 5 | 0.4 | 3.06 |
| | | | R422 | 0.21 | 3 | | |
| | | | R423 | 0.21 | 3 | | |
| | | | R424 | 0.26 | 2 | | |
| | | | R425 | 0.11 | 1 | | |
| | | | R426 | 0.05 | 1 | | |
| | | 4 | R441 | 0.45 | 4 | 0.6 | |
| | | | R442 | 0.36 | 3 | | |
| | | | R443 | 0.19 | 2 | | |

In scenario 1, the "Maintenance team" background function corresponds to the maintenance technician as a Resource for IEV, D, IP, and DE functions. According to Table 2, the MT function variability depends on RIFs that define the "characteristics of the personnel performing the tasks". In the alternative situation of scenario 2, the "Operation coordination" background function constitutes the work description, coordination with the control room, and requisites of resources and materials for the maintenance. The Output of this function is directly connected to MWD Input and Resources of PM and SHP functions.

The variability score in the remaining background functions of each scenario is considered as $OV_i = 1.0$. Remember that the weight 1.0 indicates a situation in which there is no variability. The corresponding edge weights for all downstream foreground functions are calculated based on Eq. (3), and the change in their performance variability state is reported in Figure 3. Generally, it is challenging to intercede a single activity in a socio-technical system without changing it in some way, partially or entirely (Falegnami et al., 2019). Therefore, when the initial conditions of a background function change, this functional variability propagates through the system and changes other downstream functions' variability scores toward the imprecise state.

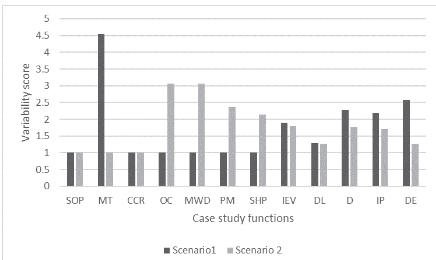


Fig. 3. Functional variability (OV) score of the maintenance operation

Furthermore, Katz centrality algorithm is used when the initial edge weight of the corresponding background functions is assigned to calculated $OV_i$ in the defined scenarios from Table 3 and also in an ideal situation when all the weights are equal to 1.0. The results are represented in Figure 4, where the vertical axis is the Katz values, and the horizontal axis represents the functions (graph nodes). In the "Ideal" situation when all the RIFs have better than average performance, the Katz value increases at each step of the maintenance process. This indicates that the later stages of the maintenance process are more critical than the previous ones.

The next step was the identification of highly critical functional couplings. The evaluation is based on the analysis of edge "e" (i.e., specific coupling) betweenness centrality, which is the sum of the fraction of all the shortest paths that pass through "$e$". Figure 5 shows the relative importance of the functional couplings (graph edges) over the FRAM graph model. Each functional coupling represents a specific interaction in the process. The high-priority couplings in both scenarios are mostly identical, as the graph's topology (number of the nodes and edge locations)

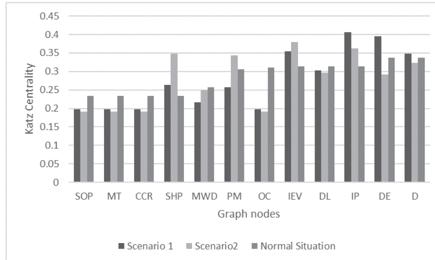


Fig. 4. Evaluated Katz centrality for the FRAM graph model nodes

remained unchanged.

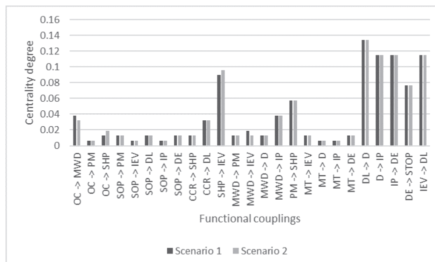


Fig. 5. Edge betweenness centrality-degree for the FRAM graph model edges

Since the algorithm only considers the relative number of shortest path going through an edge, only the weights that change the shortest paths will affect the edge centrality. According to the results in Figure 5, the critical couplings that may have more effect on the risk of hydrocarbon release accidents are exemplified: From output of SHP function to precondition entrance of IEV function; From output of IEV to input of DL function; From output DL function to precondition entrance of D function; From output of D function to precondition IP function; From output of IP function to input of DE function.

## 4. Discussion

This section discusses how the provided information by the FRAM graph model supports risk-informed decision-making. Unlike the QRA methods, the developed FRAM graph model provides a complete overview of the socio-technical process through understanding the relationship of the functions and their dependencies. In the case of risk assessment, it visualizes the link between changes of RIFs' value and their effect on every part of the system. This plays a major role in preventing accidents during operation.

In a specific situation, as discussed earlier in the scenarios of the case study, there is a specific knowledge regarding the status of the system (i.e., background function performance variability score) and how it propagates through the process and influences other parts. The risk associated with the situation can be expressed implicitly, by considering what parts of the system are affected most and use this information providing measures and preventing possible resonances. Moreover, the graph model topological indices (Katz and Edge betweenness) can be used as useful indicators for sharp-end personnel's action risk.

Operators need concrete indicators to look into, rather than too much information that emphasis on the risk value. Therefore, in APR, instantaneous decisions need monitoring of early warning indicators to detect and prevent deviations from developing into hazardous situation (Yang and Haugen, 2015). For instance, when an operational manager asks about the risk associate with maintenance of the pump, this can be interpreted by using the FRAM graph model to answer what can go wrong during each step of the maintenance. It will also enable the control of the activity and supports the maintenance operational team to optimize work process while minimizing risk.

The analysis encourages a proactive approach to risk reduction measures by understanding the critical functions during maintenance and by better organizing the resources and barriers. For example according to the results of Table 3, scenario 1 shows a situation in which, although the work environment is in a perfect condition, the technician lacks training (low competence) and is tired and stressed at work. This affects the Maintenance team (MT) function's variability from precise to imprecise state (Table 1), and it is possible to observe this effect on the overall network in Figure 3. This functional resonance has the highest variability effect on DE, D, IP and IEV functions accordingly.

Furthermore, the highest Katz value in scenario 1 is associated with IP and DE functions, which shows that the maintenance performance has the highest effect on these two stages of the process and increases their criticality in terms of hydrocarbon release risk. This risk information helps the decision maker to plan an additional coordination with maintenance supervisor during the critical stages of operation to avoid possible shortcomings due to manual intervention and complying with the requirements and instructions. In scenario 2, when there is a change in the task procedure, the fluctuation of RIFs is related to "administrative control of procedure" and the "characteristics of the performed task". This can cause variability in Operation coordination (OC) function as calculated in Table 3. The task complexity, complicated organizational procedures, and drawn-up work permit in a stressful situation affect the efficiency of maintenance coordination. Figure 3 shows this functional resonance causes the highest variability in MWD, PM, SHP and IEV functions. Whereas based on the results of Figure 4, IEV has the highest Katz value and is thus the most critical function.

The manner in which risk information is presented in this scenario helps the decision makers to be aware of possible conflicting activities that occur simultaneously or in overlap with each other. In other words, it will reduce the risk of verification error during operation.

The presented results in Figure 5 indicate the priority couplings, that can be used for a better understanding of the potential functional resonances in the system. The functional variability of the background functions in both scenarios does not affect the highly critical couplings of the FRAM model, as shown in Figure 5. In this sense, after analysis of the different resonant links of the case study, the dampening of functional resonance should primarily consider modifications in coordination between maintenance technician, operational manager, and control room operator. Since their collaboration has a direct or indirect effect on most of the functions. Therefore, control measures should be in place to monitor the effectiveness of coordination performance, and new indicators need to be introduced as a basis for monitoring.

## 5. Conclusion

This paper presents an alternative approach by using a dynamic FRAM graph model for assessing operational risks arisen from maintenance. The dynamic FRAM graph model proved both to systematically manage the couplings and functional variability information and to lessen the effort needed for identifying possible resonance propagations.

FRAM allows a systematic analysis of systems, providing a clearer and systemic description of system functions and their interactions. The inherent functional nature of FRAM allows identifying static and transient links among the human, organizational, and technological factors while describing the normal functioning of the system. However, the graphical representation of FRAM in the case of complex processes and systems may quickly become highly interconnected and thus overwhelming to interpret. Therefore, this work shows a way of capturing the dynamicity feature of operational risk analysis and a better understanding of the FRAM model by using the dynamic graph approach.

Furthermore, to assess the APR risk in the maintenance operation by FRAM, the only way to know how the output of a function is actually variated is when the operating conditions are changed. To capture this concept, RIFs that are related to the source of functional variability are defined to evaluate the functional variability score in background and foreground functions. This approach captures the effect of changes within the system and provides a systematic prioritization of critical stages and interactions during maintenance work through graph topological analysis by considering Katz centrality and Edge betweenness algorithms in two different operational situations.

## References


Aven, T., S. Sklet, and J. E. Vinnem (2006). Barrier and operational risk analysis of hydrocarbon releases (bora-release): Part i. method description. *Journal of hazardous Materials 137*(2), 681–691.

Bellini, E., P. Nesi, G. Pantaleo, and A. Venturi (2016). Functional resonance analysis method based-decision support tool for urban transport system resilience management. In *2016 IEEE International Smart Cities Conference (ISC2)*, pp. 1–7. IEEE.

Bjerga, T., T. Aven, and E. Zio (2016). Uncertainty treatment in risk analysis of complex systems: The cases of stamp and fram. *Reliability Engineering & System Safety 156*, 203–209.

Bubbico, R., S. Lee, D. Moscati, and N. Paltrinieri (2020). Dynamic assessment of safety barriers preventing escalation in offshore oil&gas. *Safety Science 121*, 319–330.

Bucelli, M., N. Paltrinieri, and G. Landucci (2018). Integrated risk assessment for oil and gas installations in sensitive areas. *Ocean Engineering 150*, 377–390.

Falegnami, A., F. Costantino, G. Di Gravio, and R. Patriarca (2019). Unveil key functions in socio-technical systems: mapping fram into a multilayer network. *Cognition, Technology & Work*, 1–23.

Girvan, M. and M. E. Newman (2002). Community structure in social and biological networks. *Proceedings of the national academy of sciences 99*(12), 7821–7826.

Hagberg, A., D. Schult, and P. Swart (2005). Networkx: Python software for the analysis of networks. *Mathematical Modeling and Analysis, Los Alamos National Laboratory*.

Halseth, I. K. (2012). Modeling process leaks using fram. Master's thesis, Institutt for produksjons-og kvalitetsteknikk.

Harary, F. and G. Gupta (1997). Dynamic graph models. *Mathematical and Computer Modelling 25*(7), 79–87.

Hollnagel, E. (2012). *FRAM: the functional resonance analysis method: modelling complex socio-technical systems*. CRC Press.

Hollnagel, E. and O. Goteman (2004). The functional resonance accident model. *Proceedings of cognitive system engineering in process plant 2004*, 155–161.

Hollnagel, E., R. L. Wears, and J. Braithwaite (2015). From safety-i to safety-ii: a white paper. *The resilient health care net: published simultaneously by the University of Southern Denmark, University of Florida, USA, and Macquarie University, Australia*.

Hosseinnia, B., N. Khakzad, R. Patriarca, and N. Paltrinieri (2019). Modeling risk influencing factors of hydrocarbon release accidents in maintenance operations using fram. In *2019 4th International Conference on System Reliability and Safety (ICSRS)*, pp. 290–294. IEEE.

Lee, J. and H. Chung (2018). A new methodology for accident analysis with human and system interaction based on fram: case studies in maritime domain. *Safety science 109*, 57–66.

Lee, S., G. Landucci, G. Reniers, and N. Paltrinieri (2019). Validation of dynamic risk analysis supporting integrated operations across systems. *Sustainability 11*(23), 6745.

Patriarca, R., G. Di Gravio, and F. Costantino (2017). myfram: An open tool support for the functional resonance analysis method. In *2017 2nd International Conference on System Reliability and Safety (ICSRS)*, pp. 439–443. IEEE.

Patriarca, R., G. Di Gravio, R. Woltjer, F. Costantino, G. Praetorius, P. Ferreira, and E. Hollnagel (2020). Framing the fram: A literature review on the functional resonance analysis method. *Safety Science 129*, 104827.

Skogdalen, J. E. and J. E. Vinnem (2011). Quantitative risk analysis offshore—human and organizational factors. *Reliability Engineering & System Safety 96*(4), 468–479.

Vinnem, J., R. Bye, B. Gran, T. Kongsvik, O. Nyheim, E. Okstad, J. Seljelid, and J. Vatn (2012). Risk modelling of maintenance work on major process equipment on offshore petroleum installations. *Journal of Loss Prevention in the Process Industries 25*(2), 274–292.

Vinnem, J., J. Seljelid, S. Haugen, S. Sklet, and T. Aven (2009). Generalized methodology for operational risk analysis of offshore installations. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 223*(1), 87–97.

Vinnem, J. E. and W. Røed (2015). Root causes of hydrocarbon leaks on offshore petroleum installations. *Journal of Loss Prevention in the Process Industries 36*, 54–62.

Vinnem, J.-E., W. Røed, et al. (2014). Norwegian oil and gas industry project to reduce hydrocarbon leaks. *SPE Economics & Management 6*(02), 88–99.

Woltjer, R. and E. Hollnagel (2008). Functional modeling for risk assessment of automation in a changing air traffic management environment. In *Proceedings of the 4th international conference working on safety*, Volume 30.

Yang, X. and S. Haugen (2015). Classification of risk to support decision-making in hazardous processes. *Safety science 80*, 115–126.

Zhen, X., J. E. Vinnem, C. Peng, and Y. Huang (2018). Quantitative risk modelling of maintenance work on major offshore process equipment. *Journal of Loss Prevention in the Process Industries 56*, 430–443.