Decision Analytics Journal 10 (2024) 100410

Contents lists available at ScienceDirect

Decision Analytics Journal

journal homepage: www.elsevier.com/locate/dajour

A systemic approach for stochastic reliability management in human–machine systems

F. Costantino, G. Di Gravio, R. Patriarca *, M. Tronci

Department of Mechanical and Aerospace Engineering, Sapienza University of Rome, Rome, Italy

ARTICLE INFO

Keywords:
Reliability
Human factor
Socio-technical systems
SPAR-H
Probabilistic reliability analysis
Human–machine systems

ABSTRACT

In today's complex engineered systems, comprising a multitude of interacting components, preserving system performance is of utmost importance. The challenge often lies in effectively prioritizing components with the highest potential to compromise system reliability, mainly when human interaction with technical artefacts is not negligible. This study proposes a systemic methodology for pragmatic reliability management within human–machine systems. The proposed approach combines a rule-based adaptation of the well-established Failure Mode, Effects, and Criticality Analysis (FMECA) with a probabilistic Fault Tree Analysis (FTA). Furthermore, the technical considerations are seamlessly integrated into a human-centric analysis, utilizing the Standardized Plant Analysis Risk – Human Reliability Analysis (SPAR-H). The proposed decision-support methodology is instantiated through Monte Carlo simulations to account for stochastic phenomena and uncertain operating conditions. The effectiveness and practicality of the proposed approach are elucidated through a case study involving a high-reliability system, specifically a high-mobility multi-wheeled vehicle. This study demonstrates the step-by-step application of the proposed approach and its implications in challenging operating scenarios, reaffirming its potential to enhance reliability management within human–machine systems.

1. Introduction

The relevance of a consistent reliability management strategy has been nowadays recognized and widely accepted for any industrial asset. Systems must be designed in a way that ensures reaching acceptable levels of performance: besides operational levels, both reliability and risk cover crucial aspects to ensure business continuity and safety. With respect to reliability, a robust initial product design should be integrated by continuous observations with the ultimate goal to develop preventive and mitigation maintenance strategies for the system at hand [1]. Technical artefacts require a precise estimation of reliability in a relevant time moment t, under certain operating conditions, for a specified mission time interval. Systems involving human operators require even additional assessments, considering cognitive and psycho-physiological characteristics [2].

Technical reliability assessments usually rely on well-established methods such as Failure Modes and Effect Analysis (FMEA), Fault Tree Analysis (FTA), Event Tree Analysis (ETA) [3]. These latter have been applied widely to manage human errors as well, in line with an interpretation of errors as situations in which a planned task sequence fails to accomplish its intended outcome. The field of Human Reliability Analysis (HRA) suggests additional methods capable of addressing the role of a human operator and the respective probability of human error [4]. Several approaches across three so-called generations of HRA methods have been proposed over years, to name a few: THERP (Technique for Human Error-Rate Prediction), ATHEANA (A Technique for Human Event Analysis), SPAR-H (Standardized Plant Analysis Risk - HRA), etc. [5] Regardless of their specific analytical nature, the ultimate purpose of any HRA approach consists of identifying the reliability of a human operator with respect to a task they have to conduct, and then integrate it in the failure analysis.

Whereas a FMEA provides an overview on possible single failure modes, an FTA can provide a quantitative appraisal for the chain of events that can lead to failure in individual failure analysis. Such techno-centric reliability analysis usually starts with the failure analysis of a specific component for which it is possible to assign credible reliability scores, in light of (e.g.) mechanical, physical or chemical parameters [6]. These reliability values can be used to evaluate system's reliability, through analytical steps with varying degrees of complication [7]. Extending the reliability analysis towards human agents, the reliability calculation is expected to reflect human propension to error, possibly influenced by operating and environmental conditions [8].

When coming to decision-making in real scenarios, the identification of critical components and their impact on system reliability can become puzzling [9,10]. This difficulty increases in complicated

* Correspondence to: Department of Mechanical and Aerospace Engineering, Sapienza University of Rome, Via Eudossiana, 18 00184, Rome, Italy.
E-mail address: riccardo.patriarca@uniroma1.it (R. Patriarca).

https://doi.org/10.1016/j.dajour.2024.100410
Received 23 September 2023; Received in revised form 12 January 2024; Accepted 30 January 2024
Available online 2 February 2024

systems that are made up of several tightly interconnected technical artefacts, where punctual assessments on failure modes must be coherently managed to ensure a holistic appraisal. When human actions are involved, the appraisal should be complemented with a human-centric perspective [11].

On these premises, *this manuscript aims to define a systemic reliability engineering methodology to account for both technical failures and human operations for the identification of critical elements in an engineered system.*

The manuscript defines a combined technical-human research methodology for pragmatical management of system reliability to inform decision-makers. The integration of a techno-centric perspective (encompassing FMECA and FTA) with a human-centred dimension of analysis (via SPAR-H) is actualized through a Monte Carlo simulation to capture stochastic phenomena by means of combinatorial modelling. The proposed methodology is expected to be usable for any industrial asset, but it acquires relevance especially for systems exposed to highly demanding and uncertain conditions, and whose reliability target levels are usually high. On this basis, the methodology has been presented both a theoretical level, and through a case study referred to a High Mobility Multi-Wheeled Vehicle (HMMVEE, also called HUMVEE), which can be employed in war, peacekeeping, or other cargo transportation scenarios that require high reliability. On this path, while the focus of the analysis could span over multiple types of human tasks, the proposed methodology refers to exploring post-failure maintenance and operations as performed by human operators. The normative dimension (how things should be, i.e. methodological steps) of this objective is indeed emphasized over a detailed numerical presentation of the results to stress the methodological contribution proposed. On the other hand, punctual numerical values have been omitted in order not to compromise the sensitivity and confidentiality of data, yet offering exemplary results wherever relevant.

The remainder of the paper is organized as follows. Section 2 provides some background on the methods used in this manuscript, proving their previous usage and significance in systemic reliability management. Section 3 details the steps of the proposed methodology, then applied in practice in Section 4. The final section summarizes the outcomes of the study and propose future research directions.

2. Literature review

Systemic reliability assessment for modern engineered systems should span over both technical and human aspects. Several methods have been proposed over time for technical reliability, where the most common ones refer to FMEA and FTA (cf. IEC 60812:2018, IEC 61025:2006). On the other hand, HRA comprises a wide variety of methods for human-related reliability assessment. This section describes some relevant contributions which can be used to ground the methodology proposed in this paper.

2.1. Failure modes, effects and criticality analysis

A milestone in reliability engineering has been set by the introduction of the FMEA, firstly developed as a design methodology in the 1949 by US Army to study problems related to military systems [12]. It was soon extended to include a criticality analysis, updating its acronym as FMECA (Failure Mode, Effects and Criticality Analysis), with the purpose of facilitating the identification of critical failure modes, causes and effects of different component failures [13]. The identification usually relies on a criticality assessment carried out through the development of a Risk Priority Number (RPN). The RPN is traditionally based on three risk factors, linked to severity (S), occurrence (O), and detectability (D), calculated to prioritize the failure modes deserving further investigation and dedicated management approaches. These risk factors are usually expressed into an expert-based 5- (or 10-) points Likert scale, whose selected values are then multiplied to obtain a synthetic RPN score [14].

Previous literature on the topic has however highlighted some criticalities in this assessment process [15]. As a first observation, the elicitation of factors is inherently subject to experts' bias, so a robust set of criteria is requested to facilitate consistent scoring. Then, it is worth noticing that the RPN obtained in this way is not a continuous function, causing possible mis-interpretation between different values [16]. Nevertheless, different evaluations of Severity, Occurrence, Detectability may lead to identical RPN values, compromising some interpretative knowledge as well [17]. Based on these observations, over recent years, the application of the FMECA has been largely reconsidered, mainly by means of dedicated mathematical programming, artificial intelligence approaches and multi-criteria decision making techniques [15]. All these techniques showed their validity under specific operating conditions, still creating concern when trying to bridge the gap between pure research and practice [12]. In particular, FMECA approaches have been criticized for their high level of subjectivity, being the results highly influenced by the analysts' judgements; as well as risk to have only incomplete set of identified failure modes, with emphasis on capturing especially the less frequent ones. Additional concerns refer to its static nature, requiring a lengthy time-consuming continuous update over time which limits the possibility to capture evolving risks in a systematic manner [18]. These concerns have been discussed over time, with scholars attempting integrated FMECA assessment to deal with high-risk and volatile scenarios (e.g., recently: cloud model theory [19] or best-worst methods [20]).

From a decision-making point of view, it remains helpful to adopt a more pragmatic solution, as the one identified by the adoption of logic rules for failure assessment. This choice implies that a set of conditional rules can replace the RPN mathematical product, largely criticized for RPN calculations [17]. In literature, several authors reflected on this aspect, proposing different systems for defining rules. One of the earliest approach in this area [21] proposes to set fuzzy if-then rules capable of fuzzify crisp ratings for Severity, Occurrence, Detectability into continuous scales to explore the full region of rule statements. Since then, this kind of logic has been adopted in various domains and at various granularity levels [22], from detailed product design towards larger scale architectures [23]. Nevertheless, the application of a fuzzy approach still demands time-consuming tasks, and requires a non-trivial analytical understanding about the inherent analytical steps for fuzzification/defuzzification [24]. Therefore, based on the same logic, simpler if-then logic rules can be constructed to relate different sets of Severity, Occurrence, Detectability for the generation of a RPN score. These constructs make the rule-based approach even more applicable by operators who do not have a specific background in fuzzy theory. The specific RPN that can be obtained remains more robust than traditional mathematical products, and at the same time, more interpretable by practitioners [25]. Using the rule-based calculation for RPN, it becomes thus possible to isolate the failure modes with the highest detrimental potential for system performance.

2.2. Fault tree analysis and dynamic fault tree analysis

Even considering more recent versions of the FMECA, they still do not offer a complete understanding of the failure mechanisms, as subjectivity and systematisms are not inherently built within the method, especially when a component decomposition is required [26]. For this purpose, the FMECA has been frequently integrated with another reliability method, the FTA [27], also in a recursive manner. This latter allows building logical and temporal relationships among different failures [28]. The FTA is a widely applied deductive failure analysis which focuses on identifying negative events. Since its development in 1970s, the FTA has been used to determine the various combinations of hardware and software – sometimes being extended to human errors – that could generate undesired events [29]. Relying on a graphical representation, it supports combinatorial reliability assessments through logic ports that formally describe a directed acyclic graph

(DAG) consisting of two types of nodes: events and gates [30]. Within the FTA, the usage of stochastic measures allows dealing with uncertain operating conditions [31]. Dynamicity has been used to model temporal failure behaviours, such as priority failure settings, sequence enforcing failures, functional dependent failures [32]. These dynamic FTA (DFTA) are currently widespread fore reliability assessment and risk management of industrial systems with temporal constrained behaviours [33,34]. The decomposability by FTA allows a flexible logic approach, supporting the analysis at different system levels and through different types of components [35]. Specific Monte Carlo simulations have been developed in literature for both continuous-time models and qualitative analysis, or single-time models, facilitating the management of stochastic settings within FTA and DFTA [34,36].

Even though some authors suggest performing both FMECA and FTA separately to expand the number of failure modes [37], a higher value has been recognized in case of a complementary approach [26]. The combined approach suggests to extend the results of the FMECA with the ones from FTA, or vice versa [38]. While both integrating directions are possible [39], when dealing with complicated systems, the FMECA then FTA logic might be preferable to reduce the burden on analysts. One can indeed firstly perform the FMECA to prioritize a set of failure modes at a component level, which are then explored in detail through the FTA [40].

2.3. Standardized plant analysis risk - HRA

Both FMECA and FTA have been priorly used to model human error [41]. Traditionally a human error can be ascribed to be a cause, or it can be further decomposed through dedicated logic ports to further encompass a plethora of sub-factors (e.g. mental workload, physical stress, complexity of tasks, etc.) [42,43]. However, such perspective hardly captures the real complexity of an operator's psychophysiological conditions, which indeed require other types of modelling approach that consider human error as a symptom of a system's failure prescribed by more recent HRA methods [44]. This type of logic overcomes the limitations of using generic tables such as the ones in IEC 61511–3 that include standard human error probability [45]. For the majority of tasks, there is no previous recorded tests, or any functional understanding of human contribution to an accident sequence [46]. More recent HRA methods aims to fill this open gap, addressing potential human contribution to undesired events in a systematic and structured manner. The majority of HRA methods has been originally developed in the nuclear industry, following the pioneering work described in the WASH-1400 report [47]. Since the early HRA development, the first and most established HRA method, the THERP investigated human potential towards the development of specific performance shaping factors (PSFs), which are meant to describe the probability associated with human error [48]. One of the most recurring techniques, inspired by THERP, is SPAR-H, which refines and extends the treatment of the PSFs [49]. The SPAR-H method was initially developed to support the modelling of human performance at nuclear power plants [50], but it has been subsequently applied in other domains (e.g. oil and gas industry [51], process plants [52], surgical theatres [53]), discussing the need and role of different PSFs. It is worth noticing the pragmatical research dimension of SPAR-H aligned with the purpose of this research, as emphasized by an application in drilling operations that shows its positive impact for decision-makers [54]. The ultimate purpose of SPAR-H consists of defining a probability for human inability to correctly perform a certain task. This definition is task-specific, and influenced by operating and environmental conditions in which the operator is working [55]. The isolation of human tasks to be investigated via SPAR-H becomes a challenge for modelling. Additionally, each task should be studied in relation to the variables affecting other activities, to generate a coherent yet representative models of actual system performance.

2.4. The rationale for a technical-human integrated approach

In a systems-theoretic perspective, while SPAR-H has been documented to be useful for modelling diverse human errors, there is limited evidence of its methodological integration into other techno-centric analyses. This systemic integration is crucial to generate cost-effective and representative analyses of man-machine systems, as suggested by (e.g.) NASA man-machine integration design and analysis system (MIDAS) [56].

To this extent, in this manuscript we argue that human reliability values obtained through SPAR-H can complement pure technical reliability assessment derived by FMECA-FTA. This integration should lead to the calculation of man-machine system reliability considering a complex set of intertwined variables that acknowledge: (i) criticality levels (FMECA), (ii) dynamicity and combinatoriality (DFTA), along with (iii) human performance (SPAR-H). In turn, the usage of SPAR-H is here expanded by means of a modern socio-technical modelling techniques to delineate more precisely the tasks to be investigated. Among modern techniques for socio-technical modelling, the FRAM (Functional Resonance Analysis Method) [57] represents a viable alternative to capture human, technical, and organizational aspects of work.

Based on these observations, the research question of this paper is answered by developing of a multi-method approach that integrates a bottom-up FMECA, with a top-down FTA, where this latter is further extended towards an explicit assessment of human reliability, via SPAR-H and FRAM.

3. Methodology

This section describes the proposed methodology from a theoretical point of view, proposing firstly the FMECA, specialized through a system analysis and a systematic rule-based criticality assessment. Then, it suggests the adoption of the FTA, which relies on SPAR-H to assess human reliability (Fig. 1). Note that specific observations are proposed about the adoption of a stochastic calculation based on Monte Carlo simulation to fully capture stochastic conditions, even in case of limited data available. Monte Carlo simulation is used here as it relies on the generation of random samples from specific probability distributions to fully represent the inherent uncertainties into the system variables. By sampling data from these distributions, a Monte Carlo simulation is able to capture the range and probability of potential values for each input variable, thus modelling relationships between variables, via aggregation of results over multiple iterations, essentially numerically integrating the system's behaviour by averaging or summing the outcomes of each random sample [58].

To ensure the successful application of the methodology, all steps were executed with the agreement and participation of six selected experts with large experience in maintenance operations. Among them, two operators and the maintenance manager possessed a wealth of knowledge gained from their extensive involvement in HUMVEE operations, while the maintenance engineer and the two maintenance researchers brought diverse expertise from their work across various sectors. Table 1 provides additional details, offering a snapshot of the distinctive roles, experience levels in maintenance operations, and sector-specific backgrounds of the selected experts:

3.1. Prioritizing the failure modes: FMECA

The adoption of the FMECA includes two steps. The *first step* provides a complete failure analysis for relevant systems/sub-systems. The *second step* analyzes specific failure modes for criticality assessment: integrating severity, repeatability, and detectability evaluations, it allows a clear identification and comparison of relevant failure modes. All information on the system and its missions should be considered as a knowledge base for the next steps.

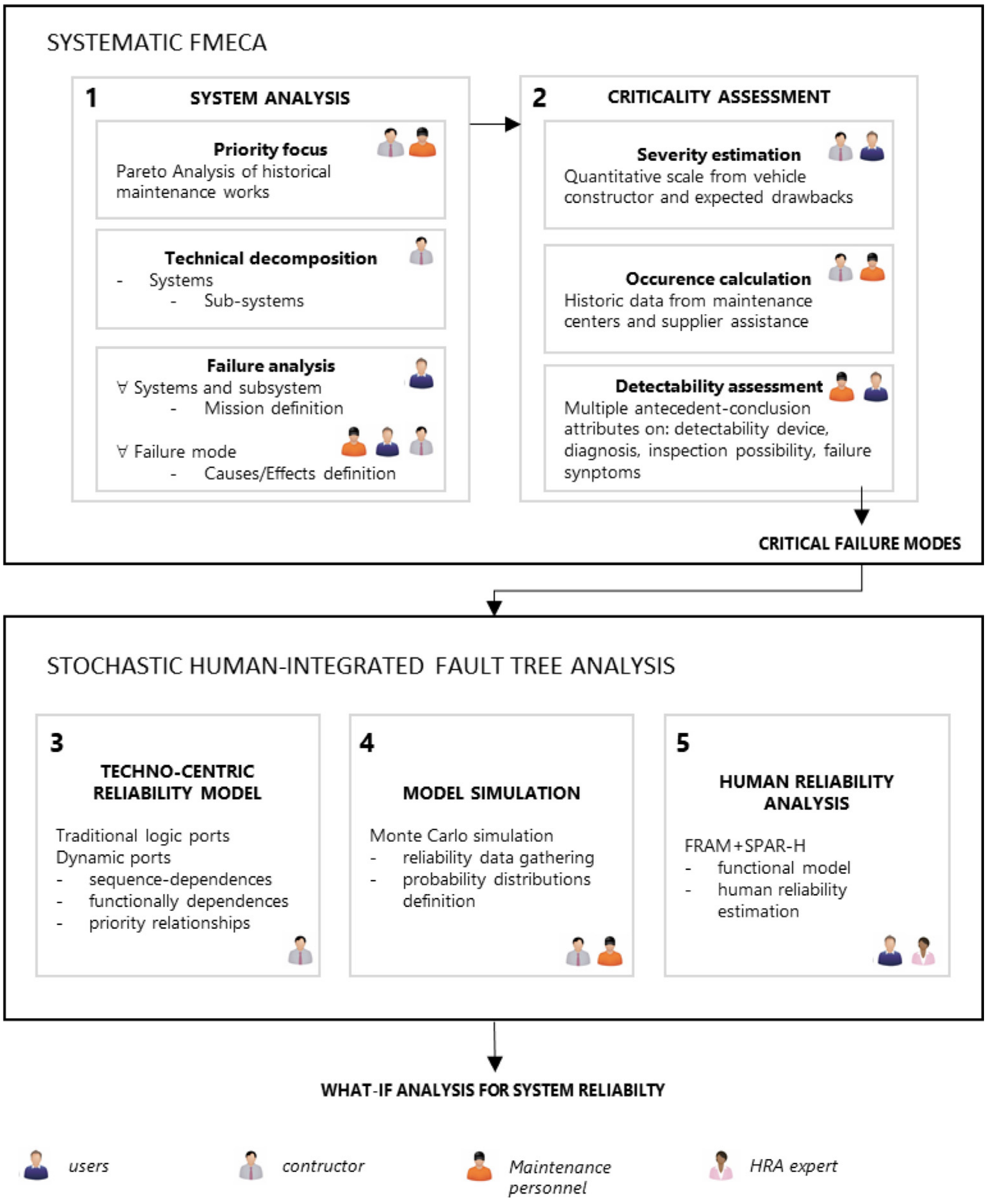

SYSTEMATIC FMECA
1
SYSTEM ANALYSIS
Priority focus
Pareto Analysis of historical maintenance works
Technical decomposition
- Systems
- Sub-systems
Failure analysis
∀ Systems and subsystem
- Mission definition
∀ Failure mode
- Causes/Effects definition
2
CRITICALITY ASSESSMENT
Severity estimation
Quantitative scale from vehicle constructor and expected drawbacks
Occurence calculation
Historic data from maintenance centers and supplier assistance
Detectability assessment
Multiple antecedent-conclusion attributes on: detectability device, diagnosis, inspection possibility, failure synptoms
CRITICAL FAILURE MODES
STOCHASTIC HUMAN-INTEGRATED FAULT TREE ANALYSIS
3
TECHNO-CENTRIC RELIABILITY MODEL
Traditional logic ports
Dynamic ports
- sequence-dependences
- functionally dependences
- priority relationships
4
MODEL SIMULATION
Monte Carlo simulation
- reliability data gathering
- probability distributions definition
5
HUMAN RELIABILITY ANALYSIS
FRAM+SPAR-H
- functional model
- human reliability estimation
WHAT-IF ANALYSIS FOR SYSTEM RELIABILTY
users
contructor
Maintenance personnel
HRA expert

Fig. 1. Methodology overview.

Table 1
Experts involved in the study.

Expert ID	Role	Years of experience	Sector
E-1	Maintenance engineer	8	Industrial plants, Automotive
E-2	Maintenance manager	10	HUMVEE
E-3	Maintenance researcher	12	Industrial plants, automotive
E-4	Maintenance researcher	10	Industrial plants, aerospace
E-5	Maintenance operator	10	HUMVEE
E-6	Maintenance operator	14	HUMVEE

The *first step* includes three tasks: the priority focus, the technical decomposition, and the failure analysis.

The **priority focus** consists of a Pareto analysis on the sub-systems considering the frequency of all maintenance works (repairs and overhauls). Since the breakdown into sub-systems for step 1 and its full analysis of failure modes is a complicated and time-consuming task, it remains significant just for those sub-systems playing a relevant role for system reliability (e.g., being involved in several previous maintenance works). The Pareto analysis on historic failure frequency allows a rough cut on the sub-systems to be prioritized. This technique has been recognized suitable in reliability management in literature [59]. Both constructor and maintenance personnel are involved in this step because both roles contribute to create such a knowledge base (e.g., the failure severity, warranty agreements, the place and time of the fault, the need for a fast repair).

The **technical decomposition** is the traditional breakdown of the (prioritized) sub-systems and basic technical components. The constructor is engaged to define the indenture of these items, using the bill of materials, CAD (Computer Aided Design) models, and exploded-view drawings of each system. Mechanical handbooks support the identification of failure modes for the mechanical components in the system.

Table 2
Severity assessment scheme.

Antecedent				Conclusions
Safety	Mission target	Mean time to repair	Cost	Severity level
Safety issue	Irrelevant	Irrelevant	Irrelevant	9
No safety issue	Mission abort	Irrelevant	Irrelevant	7
No safety issue	Mission not compromised	MTTR>T_{cutoff}	Irrelevant	5
No safety issue	Mission not compromised	MTTR<T_{cutoff}	Cost>C_{cutoff}	3
No safety issue	Mission not compromised	MTTR<T_{cutoff}	Cost<C_{cutoff}	1
Failure out of scope				0

Table 3
Occurrence assessment.

Probability of occurrence	Occurrence class	Occurrence level
Greater than 0.20 of the overall probability of failure during the item operating time interval	Frequent	9
More than 0.10 but less than 0.20 of the overall probability of failure during the item operating tine	Reasonably probable	7
More than 0.01 but less than 0.10 of the overall probability of failure during the item operating time	Occasional	5
More than 0.001 but less than 0.01 of the overall probability of failure during the item operating time	Remote	3
Less than 0.001 of the overall probability of failure during the item operating time.	Extremely unlikely	1

The **failure analysis** describes each failure mode with its mission, historical recorded or expected causes and effects. This stage involves both constructor personnel, maintenance technicians, and users to ensure a comprehensive multi-perspective knowledge gathering from all the agents involved in the product's life cycle (i.e., the design process, the repair activities, or the everyday usage, also considering its real mission environments).

The *second step* starts from the specific knowledge about failure modes and provides a criticality comparison, enhancing the canonical S · O · D approach. The expected output of this step consists of a list of the most critical failure modes in the system. At this stage, a dedicated calculation procedure has been developed to ensure a formal and reliable analysis of each index.

The **severity assessment** considers a multi-criteria quantitative scale to estimate the expected drawbacks, with a set of criteria ranked in decreasing order of significance, starting with safety issue, level of operability degradation (mission target), time to repair, and costs (Table 2).

Some reflections on the severity levels can be added to clarify the extent and validity of the proposed assumptions for post-failure assessments.

- Any occupational safety issue (a minor or serious injury, or even death) acquires the highest severity level. Other dimensions such as repair time, or cost, as well as mission target become irrelevant.
- Time to repair is accounted for severity via the mean time to repair (MTTR) value, i.e., the average of the total time to restore the required function considering the transportation time (i.e., the time to bring the system to the maintenance centre or the maintainer to the system), the inspection time, the diagnosis time, the spare parts supply time, and the intervention time. MTTR measures the complete system's downtime after a failure. The severity estimation needs a cut-off value (T_{cutoff}, cfr. Table 2), which is dependent on the system at hand.
- The maintenance cost is obtained as the sum of the labour cost, spare parts cost, and logistics cost. Even in this case, it is expected to have a cut-off value (C_{cutoff}, cfr. Table 2) which depends on the system at hand.
- A failure is out of scope in the analysis if, regardless of the consequences on the system, it is caused by factors not attributable to the system, (e.g.) external maintenance operations, incorrect driving.

Table 4
Detectability antecedent-conclusion assessment (extract).

Antecedent				Conclusion
Devices	Time	Inspection	Warnings	Detectability level
Yes	1	Yes	Yes	1
Yes	3	Yes	Yes	3
Yes	5	Yes	Yes	3
Yes	7	Yes	Yes	3
No	1	Yes	Yes	3
No	3	Yes	Yes	3
No	5	Yes	Yes	3
No	7	Yes	Yes	5
No	1	Yes	Yes	5
No	3	Yes	Yes	5
No	5	Yes	Yes	5
Yes	1	Yes	No	3
Yes	3	Yes	No	3
Yes	5	Yes	No	3
Yes	7	Yes	No	3
No	1	Yes	No	3
No	3	Yes	No	5
No	5	Yes	No	5
No	7	Yes	No	5
No	1	Yes	No	5
No	7	Yes	No	7
…	…	…	…	…

The **occurrence** calculation uses historic data from maintenance centres, as well as assistance by the constructor to calculate the frequency of occurrences for each failure mode. The probability of occurrence levels are defined as frequent, reasonably probable, occasional, remote, extremely unlikely, referring to the MIL-STD-1629 A [60] (Table 3). As for the previous dimensions, fine-tuning of the thresholds have been proposed by the six experts involved in the case study.

The methodology defines **detectability** for each failure mode to assess the users' capability of recognizing a specific failure. The maintenance personnel are involved at this stage because of their expertise in fault diagnosis. Cost and time for the fault detection during the corrective maintenance activities are not considered in detectability, because they already play a role in the prioritization logic via the severity level. The detectability definition combines the availability of devices to detect the failure, the time for the user to get the diagnosis, the possibility for inspection, the availability of warning signals. All the combinations of these 4 elements are the antecedents of the conclusive score, where the conclusion is the detectability level, built by the pool of the six subject matter experts. An extraction of this rule-based logic is reported in Table 4 (note that "Time" values are 1 if time for the inspection can be measured in seconds, 3 if in minutes, 5 if in hours, 7 if in days). The values have been obtained after a focus group with the three subject matter expertise in HUMVEE (cf. Table 1).

As a final stage for the FMECA analysis, high-risk priority numbers RPN = S · O · D highlight the most critical failure modes of the system. The failure modes with the highest RPN value represent the input values for the FTA, which is used to further extend the overall picture offered by the FMECA. Please note that a complete list of these results is omitted in order not to violate data confidentiality and data sharing policies.

3.2. Detailed component analysis: stochastic human integrated FTA

The FTA has been used to provide insights into the effects of components' failures that threaten system's functionality. The methodology extends the applicability of the FTA into a human integrated FTA to account for human related issues and unexpected combinations of performance variability within a probabilistic simulated reliability model.

The *third step* of the methodology introduces dynamic ports to the traditional FTA, to consider sequence, functional, and priority dependencies. Dynamic ports are introduced to handle states or time dependencies, (e.g.): a PAND (*Priority* AND) gate represents the situation of an output event occurring if its input events occur in a specific sequence; a SEQ (*Sequence enforcing*) gate models the situation in which the output event occurs if all events occur in a specific sequence; a SPARE (*Standby or spare*) gate represents the situation in which the output event occurs if the number of spares is less than required; lastly a FDEP (*Functional Dependency*) gate represents a situation for a trigger event forcing a dependent event [34].

The *fourth step* of the methodology introduces Monte Carlo simulation to enrich the FTA model via probabilistic distribution of components' reliability. The introduction of Monte Carlo simulation requires the definition of probability distribution for each failure rate. This activity depends on the availability of historical data for the specific factor, or at least the component's similarity with other items, even considering handbooks. More specifically, this step has been conceived as follows:

- **No data sample**: handbooks provide the failure rate analytical expression of the component considering physical variables. For each expression, the most significant factors are identified in the specific system and intended mission. Considering the expected characteristics of the mission, the significant parameters are set to address the probability distribution of the contributing factors, identifying the historical lower value, higher value, and mode, leading to a triangular probability distribution.
- **Limited data sample**: the failure rate is assumed with a triangular probability distribution, whose mean μ and standard deviation σ can be expressed as follows:

  $$\mu = \frac{a+b+c}{3}$$

  $$\sigma = \sqrt{\frac{(a^2+b^2+c^2)-(ab+ac+bc)}{18}}$$

  where a = minimum value, b = maximum value, c = mode. This distribution is used to reduce the extent of necessary assumptions. It is worth noticing the adoption of triangular distributions to reduce the number of assumptions requested for the analysis, providing at the same time something that could be easily interpreted by the personnel involved in the maintenance tasks [61].
- **Large data sample**: inductive inference returns the probability distribution for failure rate by traditional distribution fitting methods based on estimators such as the Akaike Information Criterion, AIC [62].

When referring to Monte Carlo simulation, it should be discussed the definition of the number of iterations for each simulation. Too few iterations may lead to inadequate accuracy and confidence, too many iterations require long computational overload and a long time to get the results. The concept of pivotal quantity is applied to calculate the n minimal value of iterations [63]:

$$n > \left(\frac{\sigma\phi^{-1}\left(\frac{1+\alpha}{2}\right)}{\delta}\right)^2$$

where δ is the desired accuracy level (whether the confidence interval contains the true population), $\boldsymbol{\phi}$ is the probability distribution, α is the required confidence level (the percentage of all samples that can be expected to include the true population), σ is the standard deviation of the simulated parameter. Since many reliability values are necessary in the FTA calculation, a conservative approach suggests to set the number of model iterations as for the most critical components [64].

The *fifth step* of the methodology integrates human reliability in the techno-centric FTA developed so far, with a two sub-steps process. Stage 1 aims to identify human activities that should be modelled as FTA blocks, studying actions and tasks related to operations. This stage is performed using the Functional Resonance Analysis Method (FRAM) [65], a promising method from resilience engineering [66] that overcomes the limits of traditional linearism via a functional-based approach. The FRAM is a method capable of unveiling key functions in socio-technical systems [67] and it has been successfully used in combination with other methods to model the functional properties of a system [57].

FRAM deconstructs the system in terms of the functions that agents conduct. The system is modelled via the functions performed by technological units, humans or organizations; each function is analysed to understand and represent how its output inference to all the other functions, in terms of six aspects, put at the corner of an hexagon (Fig. 2):

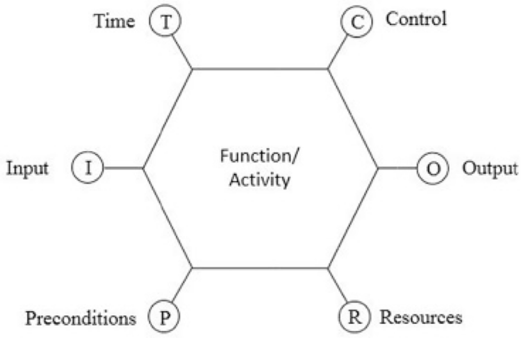


Fig. 2. A generic FRAM function.

- Input. Whatever starts the function or is transformed to produce the output.
- Precondition. Condition that must be fulfilled before a function can be conducted.
- Time. Temporal conditions that affect how the function is conducted.
- Control. Whatever supervises or regulates the function.
- Resource. Whatever is needed or consumed by the function.

Considering the proposed reliability model, the FRAM introduces the concept that a failure mode happens as a combined interaction of variable functional outputs. In other terms, FRAM emphasizes the identification of how a system adapts to variations and disturbances, thus investigating normal work. By integrating FRAM with other traditional methods (such as FTA, or used as a basis for SPAR-H), this methodology aims to gain insights into not only potential failure pathways but also the system's ability to adapt in the face of these failures.

The FRAM analysis of the system produces a model of connected functions. The FRAM model is here restricted to the conditions affecting the critical failure mode. This is a preliminary step to integrate

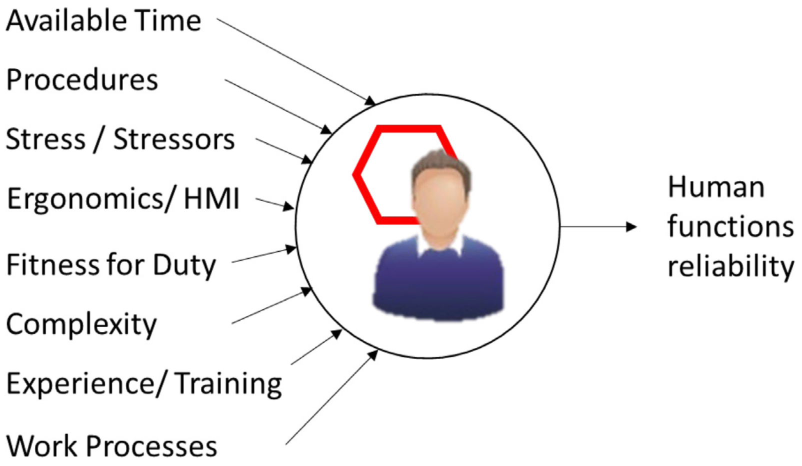


Fig. 3. SPAR-H influencing factors for the determination of reliability in human functions.

the human aspect into the traditional FTA. Once the methodology points out which human functions contribute to system's reliability, an HRA approach is used to model performance shaping factors. One should note that the FRAM could be even substituted with another functional approach, such as a Hierarchical Task Analysis (HTA), or other techniques within human factors engineering [68].

The Standardized Plant Analysis Risk Human Reliability Assessment (SPAR-H) [50,69] recognizes eight performance shaping factors (PFS) that influence the human performance. These factors are combined to properly quantify the human error probability (HEP), that in the methodology is the reliability value for the human function (Fig. 3). Even though, initially designed for the nuclear industry, SPAR-H demonstrated adaptability to a range of high-risk domains, including aviation, healthcare, and process industries. Its flexibility makes it a versatile tool that can be applied to diverse contexts, emphasizing the transferability of its principles. In particular, it has been selected as it remains easy-to-use, and versatile enough to recognize the influence of task complexity and contextual factors on human performance [70,71]. By considering such factors explicitly, the technique provides a nuanced understanding of how human reliability varies across different tasks and operational contexts, making it applicable to high-risk and dynamic work environments [72–74].

The reliability calculation requires the analysis of the PSFs level for each function, in line with Table 5 [50]. The formula to calculate each HEP is:

$$HEP = \frac{NHEP \cdot PSF_{COMPOSITE}}{NHEP \cdot \left(PSF_{COMPOSITE} - 1\right) + 1}$$

where $NHEP$ is the nominal HEP: $NHEP$ equals 0.01 for diagnosis, and $NHEP$ equals 0.001 for action. $PSF_{COMPOSITE}$ is the product of multipliers from the selected level of PSF. The methodology uses HEP values for the reliability of human functions.

The last step of the methodology is the development of the integrated fault tree, combining the produced technical and human models, via a Monte Carlo simulation. A step-by-step clarification is illustrated in the proposed case studied.

4. Case study

A High Mobility Multipurpose Wheeled Vehicle (HMMWV, also called HUMVEE), is a technical automotive system used mainly in military scenarios. Military missions are usually highly demanding and exposed to tough operating conditions requiring thus a vehicle capable of bringing people and materials on different and impracticable terrains, ensuring crew protection, high mobility, and responsiveness to abrupt manoeuvres. The major HUMVEE features refer to the heavy weight of the vehicle to increase chassis survivability, the presence of a three-axles drive to achieve a greater load-carrying capacity and better off-road performance, the off-road access to rough, mountainous, or sandy terrain. These features make the vehicle highly suitable for several types of operating conditions, but at the same time, require a thorough reliability analysis to ensure the feasibility of the system mission. An exemplar HUMVEE is presented in Fig. 4.

Table 5
Levels for performance shaping factors in SPAR-H.
Source: Adapted from [50].

PSF	PSF Levels	Multipliers
Available time	Inadequate time	P(failure) = 1.0
	Time available = time required	10
	Nominal time	1
	Time available ≥ 5 × time required	.1
	Time available > 50 × time required	0.01
Stress/Stressors	Extreme	5
	High	2
	Nominal	1
Complexity	Highly complex	5
	Moderately complex	2
	Nominal	1
Experience/Training	Low	3
	Nominal	1
	High	0.5
Procedures	Not available	50
	Incomplete	20
	Available, but poor	5
	Nominal	1
Ergonomics/HMI	Missing/Misleading	50
	Poor	10
	Nominal	1
	Good	0.5
Fitness for duty	Unfit	P(failure) = 1.0
	Degraded Fitness	5
	Nominal	1
Work processes	Poor	2
	Nominal	1
	Good	0.8

The maintenance activities on the technical system require considering human contribution beyond the drivers' conduct. When dealing with a HUMVEE, the vehicle availability depends on planned and unplanned human interventions like inspection, cleaning, tuning, and sometimes repair or part replacement. These maintenance activities could be done in different moments (even during the mission), shifting respectively the responsibility level: on the user (if performed during mission), or on the maintenance personnel (if performed in the military technical maintenance centre), or on the constructor (if performed in

Table 6
Simulated scenarios.

Scenario	Description	Major impacts on parameters
S1	Thermal stress of the system, considering a wide range of the ambient temperature, e.g., studying the system behaviour from night and winter mission to daytime and summer mission	O-rings seal (C_{T}) Electric engine (α_B, α_W)
S2	Wide range of shock condition, from uniform load to moderate, heavy, and extreme shock (e.g., for different ground surfaces)	Internal drivers (C_{SF}) Human reliability (range of stress level)
S3	Long mission	Internal drivers (C_{SF}) Human reliability (extremely high stress level)
S4	Combat conditions	Human reliability (extreme stress level, little available time)

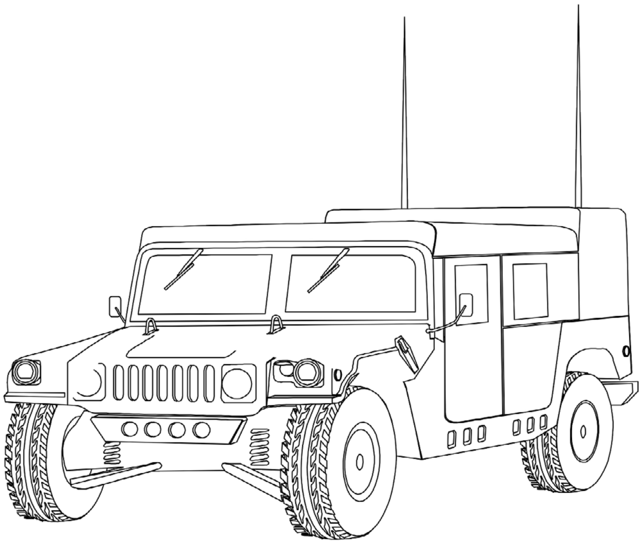


Fig. 4. Simplified graphical representation of an HUMVEE.

the producing company assistance centre). On these premises, the next sections detail the application of the proposed methodology to a real HUMVEE with specific focus on human activities performed during a mission by the user themselves. The methodology would remain valid to include other maintenance interventions, extending the respective analyses accordingly. Note that punctual numerical data have been manipulated in order not to break the intellectual property of the company involved in the study.

The FMECA requires the vehicle analysis starting with a priority focus, using the Pareto analysis of historical maintenance works, from a database of over 3000 historical maintenance interventions recorded in a three-year period. Fig. 5 shows the Pareto analysis, presented in relative terms.

This Pareto analysis requires a cut-off value for the percentage of cumulative interventions to be considered: three vehicle systems are responsible to explain the requested features on the system (explaining over 60% of the entire maintenance intervention): the suspension system, the fuel system, and the electrical system.

Each one of them require a technical decomposition into its respective subsystems: the decomposition identifies 23 relevant subsystems. Every subsystem requires a further failure analysis, with the definition of its mission, a list of failure modes, and the related cause and effect to feed the FMECA. A total of 48 failure modes completes the FMECA, since the subsystems analysis includes from 1 to 6 failure modes for each subsystem, depending on recorded historic interventions.

The criticality assessment requires performing the severity, occurrence, and detectability assessments, as shown respectively in Tables 1, 2 and 3. Note that, with respect to Table 2, the $\mathrm{T}_{\mathrm{cutoff}}$ has been set as follows: repair within an hour (simple diagnosis, spare parts in stock), repair within 8 h (difficulty of diagnosis, spare parts in stock), repair within the week (difficulty of diagnosis, spare parts not in stock), repair within the month (vehicle to be sent to the manufacturer). From the calculation, the most critical failure mode using the S · O · D comparison is the failure of the fuel electric pump.

The Stochastic Human Integrated Fault Tree Analysis starts from this evidence. Firstly, a techno-centric reliability model outlines the specific subsystem (the fuel electric pump) and its failure mode, using traditional and dynamic logic ports. Fig. 6 presents the FTA model at a high abstraction level.

Once developed the FTA structure, Step 4 introduces the Monte Carlo simulation. Failure rates and probability distributions are defined in line with the respective methodological step. The reliability focus for the HUMVEE under examination has been considered in peculiar scenarios, reflecting severe conditions affecting the mission.

Technical devices and human behaviour are thus considered in a combat setting, during night activities, in high/low temperature, with prolonged service duration, over a rough terrain. Table 6 details four operating scenarios, and the majorly impacted parameters.

Then, the methodology continues defining the probability distribution functions for each element, reflecting on the respective availability of data.

More specifically, no historical data is available for the internal drivers. In this case, a handbook of mechanical reliability [75] provides the failure rate analytical expression of the component as $\lambda_{\mathrm{FD}} = \lambda_{\mathrm{FD,B}} \cdot \mathrm{C}_{\mathrm{PF}} \cdot \mathrm{C}_{\mathrm{PS}} \cdot \mathrm{C}_{\mathrm{C}} \cdot \mathrm{C}_{\mathrm{SF}}$.

More specifically, $\lambda_{\mathrm{FD,B}}$ is the basic failure rate: $\lambda_{\mathrm{FD,B}} = 0.20$ considering the pump technical characteristics (Fig. 6-a).

CPF is the multiplying factor set by the ratio of actual operating pump flow Q and the specified maximum pump flow Q_r (Fig. 6-b). In the identified scenarios, the probability distribution of the λ_{FD} mostly depends on the pump's capacity. According to the methodological steps defined in Section 3.2, a triangular probability distribution for C_{PF} is set in a [0.7; 1.0; 2.5] range, from a [0.8–1.2] range of Q/Q_r.

C_{PS} is the pump speed multiplying factor set by the ratio of the operating speed V_O and the maximum allowable design speed V_D (Fig. 6-c): a conservative approach suggests setting $V_O \ / \ V_D = 1$. This assumption is anyway coherent with the generic mission requirements where full speed might be required.

C_{C} is the multiplying factor for fluid contaminants and handbook suggests $\mathrm{C}_{\mathrm{C}} = 0.6 + 0.05 \cdot F_{AC}$; The constructor assumes $F_{AC} = 10\mu$, thus $\mathrm{C}_{\mathrm{C}} = 1.1$. C_{SF} is the multiplying factor depending on the duration service of the component. In scenario S1 and S4 the HUMVEE exceeds 3 h a day, in scenario S2 a discrete uniform probability of values {1, 1.25, 1.50, 1.75} represents the wide range of shock levels, in scenario S3 the value 1.50 considers a mission over 10 h (Fig. 7-d). Table 7 shows the probability distribution of the λ_{FD} for scenario S1 and S4.

A limited data sample was available for the O-rings, but since they are common components, some respective statistics are available from the constructor. The failure rate of an O-ring between mechanical elements can be calculated [75]: $\lambda = \lambda_0 \cdot \mathrm{C}_{\mathrm{P}} \cdot \mathrm{C}_{\mathrm{Q}} \cdot \mathrm{C}_{\mathrm{DL}} \cdot \mathrm{C}_{\mathrm{H}} \cdot \mathrm{C}_{\mathrm{F}} \cdot \mathrm{C}_{\mathrm{V}} \cdot \mathrm{C}_{\mathrm{T}} \cdot \mathrm{C}_{\mathrm{N}}$, where every C-term considers specific operative conditions (C_{P} for pressure, C_{Q} for allowable leakage, C_{DL} and C_{H} and C_{F} for dimensions, C_{V} for fluid viscosity, C_{T} for temperature, C_{N} for contaminations).

The scenario S1 identifies in C_{T} the contributing factor of greatest relevance. Historic data report the difference between the T_{R} reference temperature and T_{O} operative temperature occasionally reach the -20°F during night and winter missions, and +20°F values in elevated temperature conditions. These values represent the range for S1. Consequently,

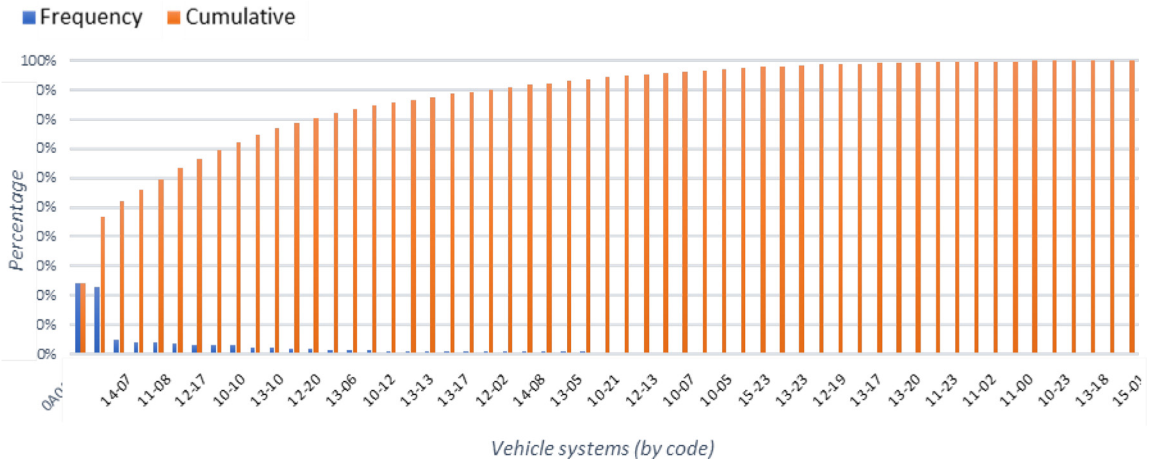


Fig. 5. Pareto analysis of interventions by vehicle systems.

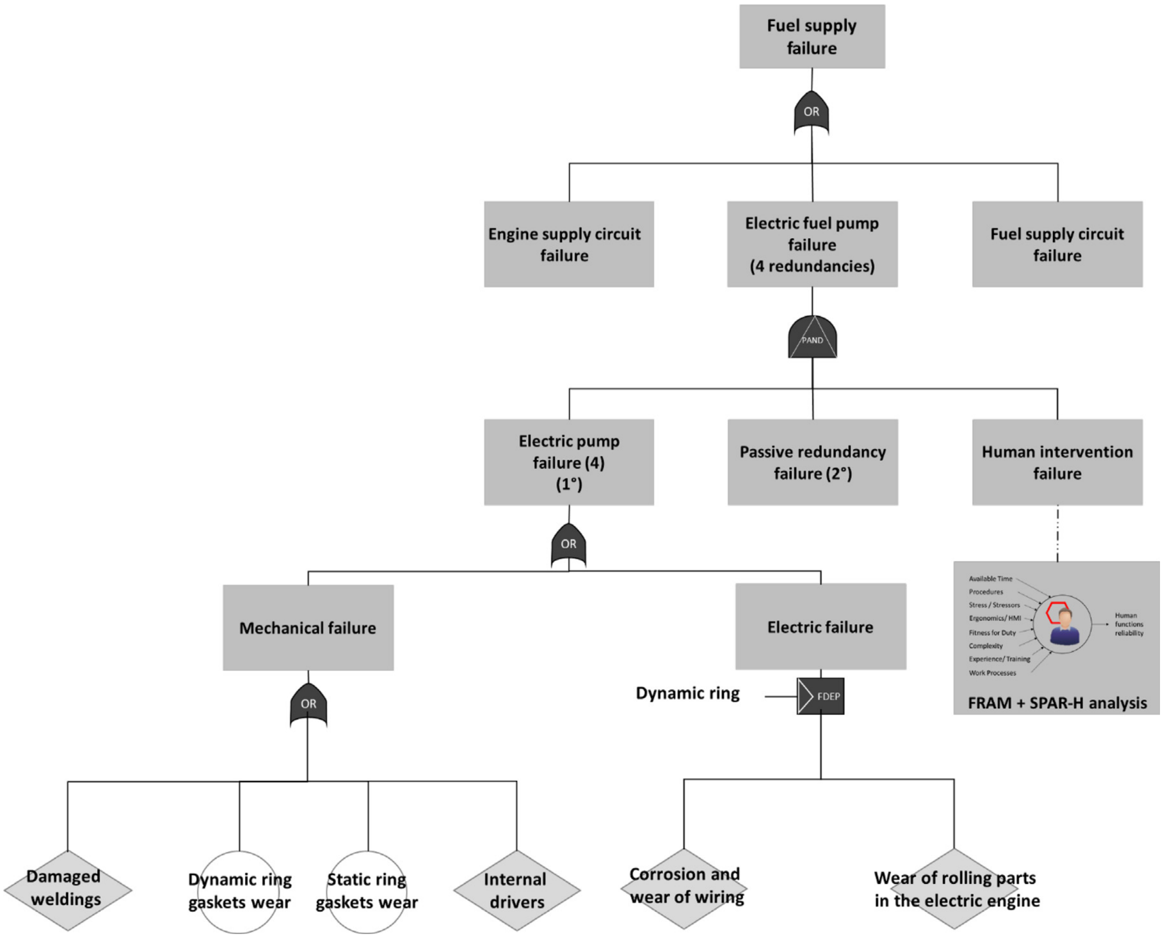

Fuel supply failure
OR
Engine supply circuit failure
Electric fuel pump failure (4 redundancies)
Fuel supply circuit failure
PAND
Electric pump failure (4) (1°)
Passive redundancy failure (2°)
Human intervention failure
OR
Mechanical failure
Electric failure
Available Time
Procedures
Stress / Stressors
Ergonomics/ HMI
Fitness for Duty
Complexity
Experience/ Training
Work Processes
Human functions reliability
FRAM + SPAR-H analysis
OR
Dynamic ring
FDEP
Damaged weldings
Dynamic ring gaskets wear
Static ring gaskets wear
Internal drivers
Corrosion and wear of wiring
Wear of rolling parts in the electric engine

Fig. 6. Techno-centric reliability model for the fuel supply failure.

a triangular probability distribution of C_T is defined by a=0.46, b=1.00, c=2.16 (Fig. 8). The calculated probability distribution of λ for dynamic rings and for static rings are provided in Table 7.

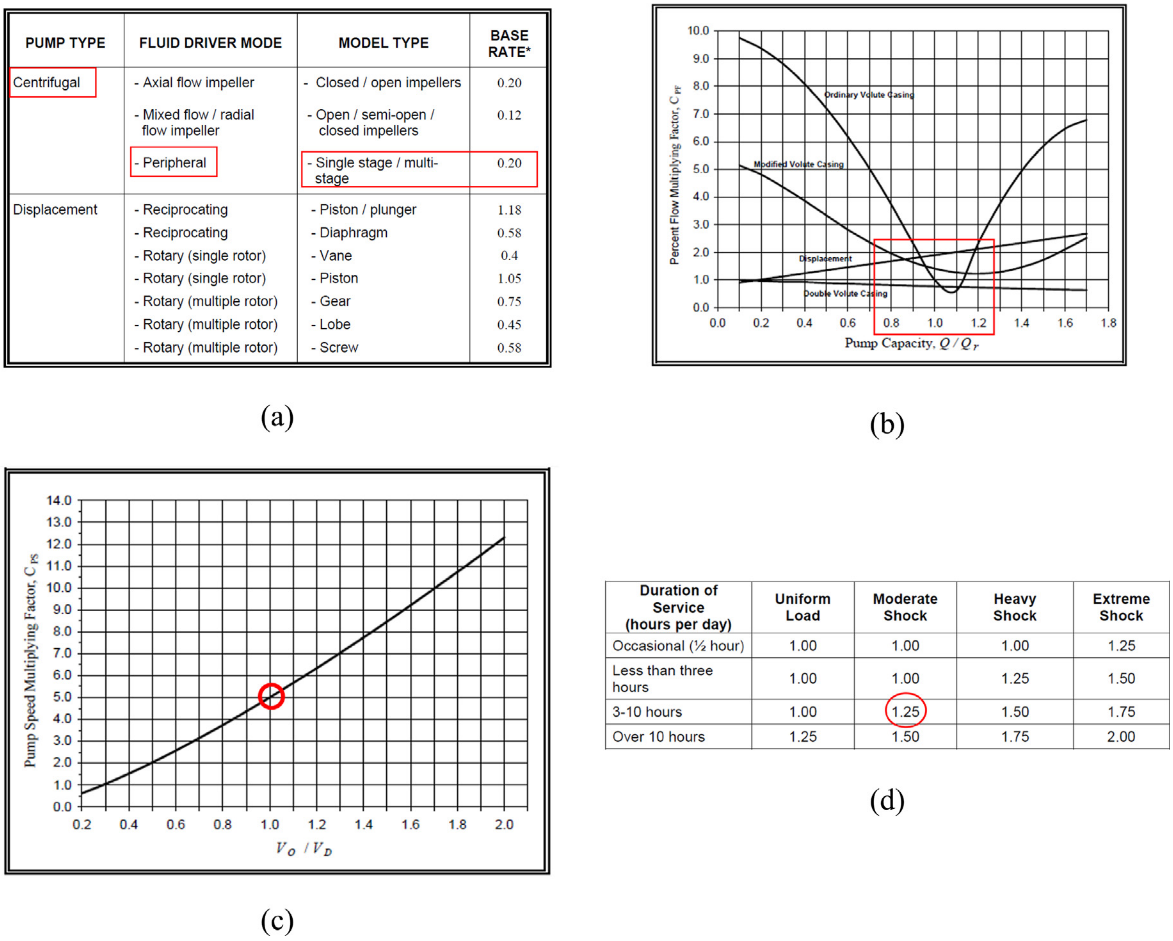
The electric engine belongs to motors with power ratings below one horsepower and its failure rate model is dictated by two failure modes, bearing failures and winding failures [76]:

$$\lambda_p = \left[\frac{t^2}{{\alpha_B}^3} + \frac{1}{\alpha_W}\right] \cdot 10^6 \text{ Failures}/10^6 \text{ h}$$

$$\alpha_B = \left[10^{\left(2.534 - \frac{2357}{T_A+273}\right)} + \frac{1}{10^{\left(20 - \frac{4500}{T_A+273}\right)} + 300}\right]^{-1}$$

$$\alpha_W = 10^{\left(\frac{2357}{T_A+273} - 1.83\right)}$$

where α_B is Weibull characteristic life for the motor bearing, α_W is Weibull characteristic life for the motor windings, T_A is the ambient temperature (°C), t is the operating time. The scenario S1 encompasses a wide temperature range: between 0 °C and 48 °C, with an expected



PUMP TYPE	FLUID DRIVER MODE	MODEL TYPE	BASE RATE*
Centrifugal	- Axial flow impeller	- Closed / open impellers	0.20
	- Mixed flow / radial flow impeller	- Open / semi-open / closed impellers	0.12
	- Peripheral	- Single stage / multi-stage	0.20
Displacement	- Reciprocating	- Piston / plunger	1.18
	- Reciprocating	- Diaphragm	0.58
	- Rotary (single rotor)	- Vane	0.4
	- Rotary (single rotor)	- Piston	1.05
	- Rotary (multiple rotor)	- Gear	0.75
	- Rotary (multiple rotor)	- Lobe	0.45
	- Rotary (multiple rotor)	- Screw	0.58

(a)

(b)

(c)

Duration of Service (hours per day)	Uniform Load	Moderate Shock	Heavy Shock	Extreme Shock
Occasional (½ hour)	1.00	1.00	1.00	1.25
Less than three hours	1.00	1.00	1.25	1.50
3-10 hours	1.00	1.25	1.50	1.75
Over 10 hours	1.25	1.50	1.75	2.00

(d)

Fig. 7. Example of failure rate from handbook: λ_{FD}.

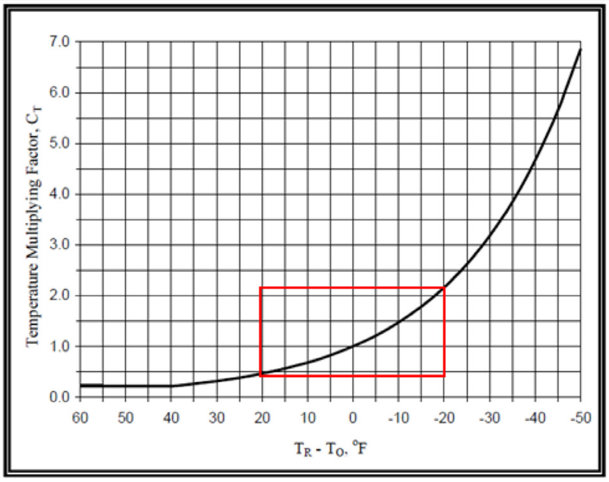


Fig. 8. Operative temperature range and C_T values for scenario S1.

value of 22 °C. Temperature affects the α_B and the α_W coefficients and leads to a triangular distribution for the failure rate λ_p (Table 7). A similar analysis leads to the probability distribution referred to welding, and wirings of Table 7. Since also in this case, only a limited data sample was available, the adoption of a triangular distribution is preferred to a distribution fitting method.

The number of Monte Carlo simulation is set to 5000, to reach a minimum value of the desired accuracy level $\delta = 0.5$, the required confidence level $\alpha = 95\%$.

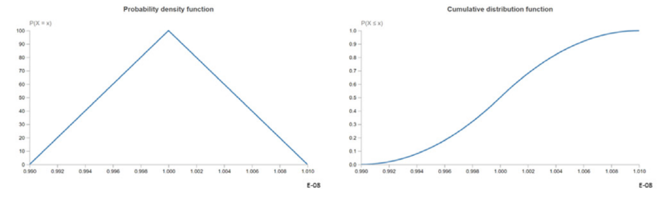
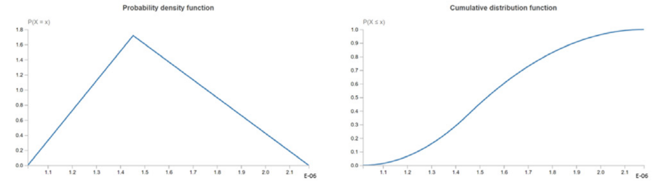
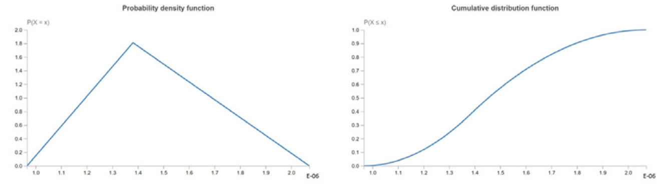
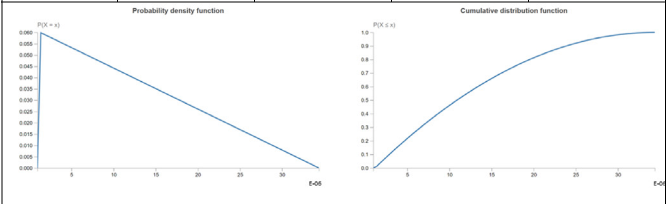
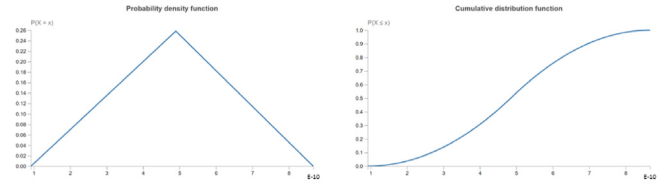
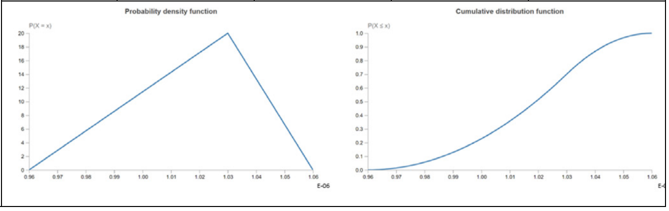
Then, it is expected to extend the techno-centric dimension towards an assessment of human actions. In line with the methodological steps defined in Section 3.2, the SPAR-H method is adopted in combination with FRAM. More specifically, a model of the human activities is developed using FRAM, with the results depicted in Fig. 9. Information to develop the FRAM model has been obtained interviewing maintenance personnel and users to highlight several types of functions. Since the most critical failure mode concerns the fuel electric pump failure, the FRAM modelling focuses on the operating activities to check, recognize, anticipate, and respond to the fuel electric pump failure, as expected by usage procedure.

The first background function (background source) refers to mission's planning and feeds the actual start of the mission and the procedural tests and power on. It activates further an availability request for the HUMVEE and the planned usage of the fuel electric pump. Other background functions consider the outputs of the mission, which could be aborted or continued.

Some human functions are marked "out of scope", since they are present in the procedure, but not specifically linked with the failure mode (e.g., to evaluate the fuel level). Other functions are technical elements already included in the FTA (red hexagons) or human activities to add in the reliability assessment (blue hexagons) (cfr. Fig. 9).

From this modelling, the SPAR-H step application for the human functions within the scope is numerically summarized in Table 8. As detailed in the SPAR-H methodology, there is a difference between action failure probability and diagnosis failure probability for the NHEP

Table 7
Examples of probability distributions of failure rate in the Monte Carlo simulation.

Components	Probability distribution of λ parameters				
	a	b	c	μ	σ
Welding	0.99E-08	1.00E-08	1.01E-08	1.00E-08	4.082E-11
					
Dynamic rings	6.39E-07	1.38E-06	2.980E-06	4.89E-07	1.67E-06
					
Static rings	6.729E-08	1.45E-07	3.14E-07	5.15E-08	1.76E-07
					
Internal drivers	0.962E-06	1.375E-06	3.4375E-06	1.925E-06	5.413E-07
					
Wiring	9.24E-11	4.90E-10	8.67E-10	4.832E-10	1.582E-10
					
Electric engine	0.96E-06	1.03E-06	1.06E-06	4.107E-06	2.190E-06
					

value. The results are the human error probabilities (HEPs) to put inside the Stochastic Human Integrated Fault Tree Analysis. The five functions should be considered in an OR gate condition for human error probability calculation because each of those functions' failure represents a potential minimal cut set. Human error here refers to a task that is not performed as for the expectations by a human operator.

The simulation of human reliability remains of interest in scenarios S2, S3, and S4. The range of shock levels changes not only the reliability of internal drivers but also the value of the PSF "Stress/Stressors". The stress level was increased from "nominal" to "high" if shock levels are heavy or extreme. In scenario S3, stress levels are always "high", and in scenario S4, stress levels are always "Extreme": these scenarios impact all the $PSF_{COMPOSITE}$ values and consequently the human intervention failure probabilities.

The four scenarios were assessed in terms of conditional what-if settings for system's reliability, whose Monte Carlo based results are shown in Fig. 10. This latter proves that the system remains quite reliable considering external possible perturbations (low/high

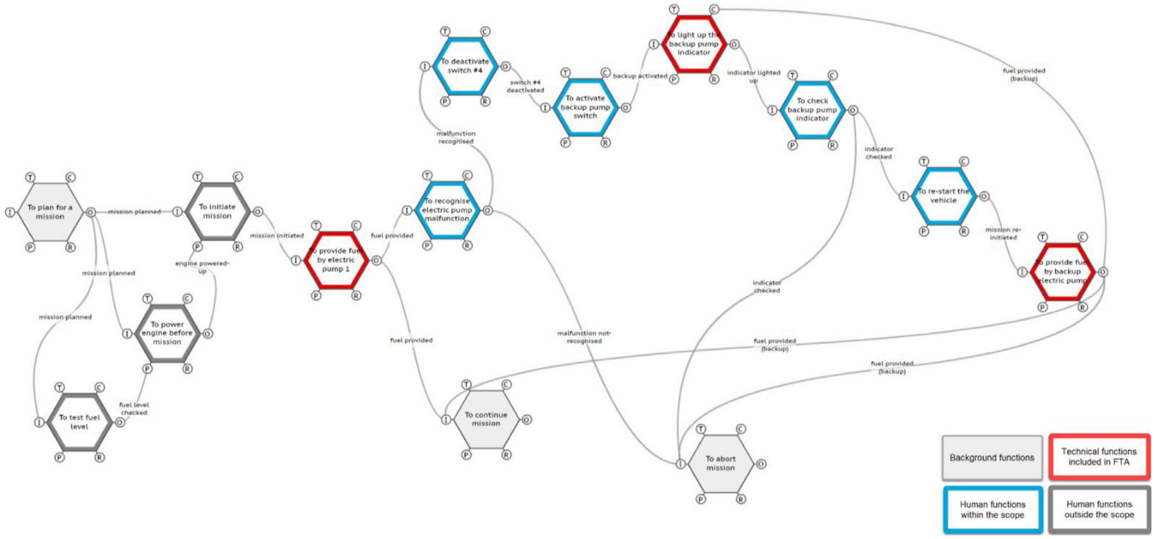


Fig. 9. FRAM model of the human-technical intervention for the HUMVEE critical failure mode. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

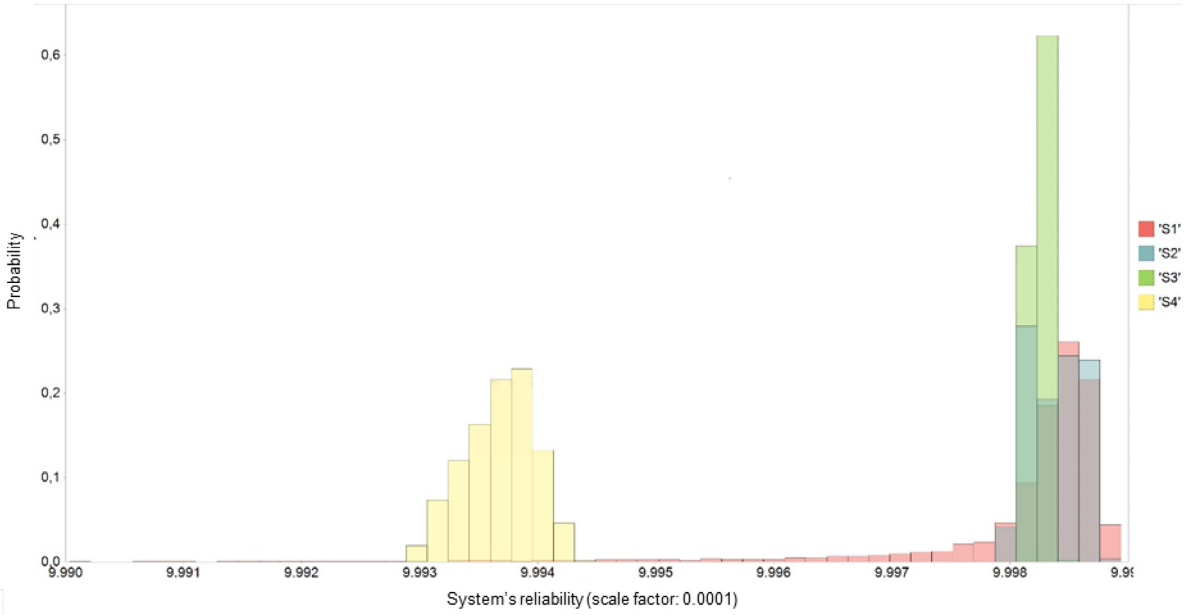


Fig. 10. Monte Carlo simulation results: system reliability.

Table 8
Levels for performance shaping factors in SPAR-H.

Function	NHEP (Action or Diagnosis)		PSFcomposite	HEP
To recognize electric pump malfunction	Diagnosis	0.01	1 ·2 ·1 ·0.5 ·1 ·1 ·1 ·1 = 1	0.01
To deactivate switch #4	Action	0.001	1 ·2 ·1 ·0.5 ·1 ·0.5 ·1 ·1 = 0.5	0.00050025
To activate backup pump switch	Action	0.001	1 ·2 ·1 ·0.5 ·1 ·0.5 ·1 ·1 = 0.5	0.00050025
To check backup pump indicator	Action	0.001	1 ·1 ·1 ·0.5 ·1 ·0.5 ·1 ·1 = 0.5	0.000250188
To re-start the vehicle	Action	0.001	0.1 ·1 ·1 ·2 ·1 ·0.5 ·1 ·1 = 0.1	0,00010009

temperature, tough ground surfaces) and stressful situations (long mission, combat). Indeed each probability distribution is presenting the expected system reliability states, as obtained from the Monte Carlo simulation, in the conditions being examined. The higher the mean value of the distribution, the higher the reliability, especially if paired with a lower variance. In this context, Scenario S4 shows the largest weakness, having the lowest mean value (the one distribution centred more on the left side of the x-axis). However, even in this scenario, it might be expected that human operators will be capable of responding to emergencies, if there would be a reasonable time available to perform the task. For example, it could be worth developing here an alternative leaner procedure to further shorten the operational time required. The integration of FRAM with FTA supports a more comprehensive understanding of system safety, fostering a culture that values not only the identification (beyond blame) of failure modes but also the understanding of how the system adapts to ensure continued operations. Anyway, the reliability of the system in scenario S4 remains still high, and satisfactory for the system at hand.

If this should have not been the case, it could have been possible to restart analysing the fault propagation, and verifying possible changes to the technical factors, or to the PSF affecting human performance.

5. Discussion

The methodology proposed in this paper supports systemic reliability management for systems encompassing both technical and human elements. The results pointed out to system's criticalities from an integrated analysis perspective and supported the development of what-if scenarios through which, it is possible to model potential system performance and to gain wider understanding of reliability issues.

On one hand, the extension of FMECA with FTA is a topic largely debated in previous literature (cf. Section 2). On the other hand, FTA is here proved to be compatible with human factor modelling, as exploited through the proposed integration with SPAR-H. In this sense, the calculation of human error rate can be straightforwardly linked to a failure probability for dedicated events mapped in a FTA, or even in a DFTA, if dynamicity is added to the system's model. In our approach, uncertainty and dynamics are modelled via the usage of Monte Carlo simulations. Nonetheless, when using SPAR-H, it becomes necessary to identify what are the tasks that require in-depth investigations. At this stage, the proposed methodology avails of FRAM to capture the complexity of the performed functions and activities. FRAM is normally used for socio-technical systems, but it does not have a built-in integration with reliability data. The proposed combination instead creates novel staging areas for complementing human error methods with modern resilience engineering tools [66]. Currently, the proposed methodology acknowledges FRAM to be used for mapping system functions, to be then explored via the SPAR-H taxonomy. Nonetheless, this choice generates other viable possibilities of analysis creating room for non-linear interactions at different man-machine scales. This last development is out of scope for this paper, but it may represent a path for future research. We believe that this combination evolves from other approaches such as CREAM (Cognitive Reliability and Error Analysis Method, a precursor of the FRAM) [77], and while effective, might not offer the same level of integration between system functions and human actions, as critically discussed also with reference to the Gaylean simplification of the performance shaping factors [78].

While the proposed methodology provides a holistic picture for systemic management of reliability, it could be also integrated with additional data sources, such as sensors placed on the system itself. The possibility to gather data from the field to feed machine learning algorithms remains indeed a viable solution to improve the probability estimations currently based on experts or scarce data [79]. This is an open research dimension, but it could be particularly helpful especially for rare events estimation [80]. In this specific regard, the translation of the DFTA into a Bayesian Network may become necessary to model more complex structures and relationships among variables. It has been demonstrated [81] that any fault tree can be automatically transformed into its corresponding Bayesian network, by creating binary Bayesian representation for each event in the fault tree. The usage of field data and expert judgements can be ascribed to prior/posterior probabilities and thus allows an effective modelling of joint technical-human aspects [82].

Other observations can be added about the limitations of the current FMECA usage. For example, the proposed rule system at the basis of the FMECA could be enlarged with other artificial intelligence approaches [83]. This opens the path to the need for a comparison and validation of different techniques, possibly through evidence-based assessments, and application feasibility tested with practitioners, in form of workshops and hands-on tutorials. About the rule-based logic suggested for the FMECA, it should be noted that the proposed approach prioritizes mission success over maintenance costs. This concept remains valid for high-reliability settings, as a war or peacekeeping scenario proposed in the case study. In this sense, mission's importance acquires a higher priority than time to repair or repair costs. Of course, the methodology can easily fit other functional priorities, adapting the rule-based logic to deal with the peculiar features of the system at hand.

6. Conclusion

In line with the research question of this paper, the proposed methodology follows a pragmatic research dimension to be applicable primarily in systems with strict reliability performance. Even if referring to the same basis of system properties, the proposed cumbersome elaboration of several methods (FMECA, FTA, SPAR-H) is expected to be beneficial for the revelation of potential deficiencies in system design. The bottom-up FMECA prioritizes failure modes that are then explored from a top-down perspective offered by the FTA. This latter is then complemented with a human reliability analysis where a deconstructed functional description of work via FRAM is used to reduce over-simplistic assessments in the taxonomy of SPAR-H. The evidence from the case study in a military HUMVEE confirms the relevance of the proposed approach. While a quantitative approach for reliability management offers numerous advantage in terms of supported decision-making, and resource allocation for maintenance operations, the availability or the quality of data remains a puzzling item. The integration of human and organizational factors remains limited. In this case study, indeed, the integration just resembles a limited, fairly simple, procedure. Larger organizational context, balancing maintenance management at large, tactics, strategies, and human resource management may not be equally described by the proposed approach. These challenges call for wider interdisciplinary collaboration to leverage diverse expertise (reliability analysts, data scientists, human factors experts) into a unique assessment, possibly pairing the quantitative assessment with larger qualitative scores [84].

Open endeavours remain, as the ones that could emerge adopting a different paradigm view for technical-human systems, or more sophisticated analytical calculation. These research directions remain relevant especially in case of human tasks that span over different layers, (e.g.) including team maintenance interventions, coordination for organizational tasks on logistics and training. In these cases, when the complexity of human actions exceeds the execution of an individual task (as for the proposed case study), the need for a systemic approach should be prioritized as a foundation for any reliability assessment. We believe integrated man-machine-organizational assessment are indeed necessary to deal with large scale system lifecycles.

Declaration of competing interest

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

Data availability

Data will be made available on request.

References

[1] A.M. Smith, G.R. Hinchcliffe, RCM: Gateway to world class maintenance, 2003, http://dx.doi.org/10.1016/B978-0-7506-7461-4.X5000-X.

[2] N.J. Ekanem, A. Mosleh, S.-H. Shen, Phoenix - A model-based human reliability analysis methodology: Qualitative analysis procedure, Reliab. Eng. Syst. Saf. 145 (2016) 301–315, http://dx.doi.org/10.1016/j.ress.2015.07.009.

[3] A.H.A. Melani, C.A. Murad, A. Caminada Netto, G.F.M. de Souza, S.I. Nabeta, Criticality-based maintenance of a coal-fired power plant, Energy 147 (2018) 767–781, http://dx.doi.org/10.1016/j.energy.2018.01.048.

[4] S. French, T. Bedford, S.J.T. Pollard, E. Soane, Human reliability analysis: A critique and review for managers, Saf. Sci. 49 (6) (2011) 753–763, http://dx.doi.org/10.1016/j.ssci.2011.02.008.

[5] Y. Li, L. Zhu, Risk analysis of human error in interaction design by using a hybrid approach based on FMEA, SHERPA, and fuzzy TOPSIS, Qual. Reliab. Eng. Int. 36 (5) (2020) 1657–1677, http://dx.doi.org/10.1002/qre.2652.

[6] N.W. Ozarin, Bridging software and hardware FMEA in complex systems, in: Proceedings - Annual Reliability and Maintainability Symposium, 2013, http://dx.doi.org/10.1109/RAMS.2013.6517739.

[7] S. Kabir, An overview of fault tree analysis and its application in model based dependability analysis, Expert Syst. Appl. 77 (2017) 114–135, http://dx.doi.org/10.1016/j.eswa.2017.01.058.

[8] C.D. Griffith, S. Mahadevan, Use of Meta-Analysis To Derive PSF Multipliers for HRA, Vol. 2, Vanderbilt University, Nashville, United States, 2008, pp. 1242–1249.

[9] G. Di Bona, A. Forcina, A. Petrillo, F. De Felice, A. Silvestri, A-IFM reliability allocation model based on multicriteria approach, Int. J. Qual. Reliab. Manag. 33 (5) (2016) 676–698, http://dx.doi.org/10.1108/IJQRM-05-2015-0082.

[10] S. Gupta, J. Bhattacharya, J. Barabady, U. Kumar, Cost-effective importance measure: A new approach for resource prioritization in a production plant, Int. J. Qual. Reliab. Manag. 30 (4) (2013) 379–386, http://dx.doi.org/10.1108/02656711311308376.

[11] S. Dekker, J. Bergström, I. Amer-Wåhlin, P. Cilliers, Complicated, complex, and compliant: Best practice in obstetrics, Cogn. Technol. Work 15 (2) (2013) 189–195, http://dx.doi.org/10.1007/s10111-011-0211-6.

[12] C. Spreafico, D. Russo, C. Rizzi, A state-of-the-art review of FMEA/FMECA including patents, Comput. Sci. Rev. 25 (2017) 19–28, http://dx.doi.org/10.1016/j.cosrev.2017.05.002.

[13] A. Bouti, D.A. Kadi, A state-of-the-art review of FMEA/FMECA, Int. J. Reliab. Qual. Saf. Eng. 1 (4) (1994) 515–543.

[14] US MIL-STD-1629A, Procedures for Performing a Failure Modes and Effects Criticality Analysis, Washington, DC, 1980.

[15] H.-C. Liu, L. Liu, N. Liu, Risk evaluation approaches in failure mode and effects analysis: A literature review, Expert Syst. Appl. 40 (2) (2013) 828–838, http://dx.doi.org/10.1016/j.eswa.2012.08.010.

[16] G. Huang, L. Xiao, W. Zhang, J. Li, G. Zhang, Y. Ran, An improving approach for failure mode and effect analysis under uncertainty environment: A case study of critical function component, Qual. Reliab. Eng. Int. 36 (6) (2020) 2119–2145, http://dx.doi.org/10.1002/qre.2686.

[17] V.R. Renjith, M. Jose kalathil, P.H. Kumar, D. Madhavan, Fuzzy FMECA (failure mode effect and criticality analysis) of LNG storage facility, J. Loss Prev. Process Ind. 56 (2018) 537–547, http://dx.doi.org/10.1016/j.jlp.2018.01.002.

[18] J. Lee, I. Cameron, M. Hassall, Dynamic simulation for process hazard analysis: Affordances and limitations in the application to complex process systems, J. Loss Prev. Process Ind. 87 (2024) http://dx.doi.org/10.1016/j.jlp.2023.105232.

[19] M.J. Akhtar, A. Naseem, F. Ahsan, A novel hybrid approach to explore the interaction among faults in production process with extended FMEA model using DEMATEL and cloud model theory, Eng. Fail. Anal. 157 (2024) http://dx.doi.org/10.1016/j.engfailanal.2023.107876.

[20] Y. Ju, Q. Zhao, M. Luis, Y. Liang, J. Dong, P. Dong, M. Giannakis, A novel framework for FMEA using evidential BWM and SMAA-MARCOS method, Expert Syst. Appl. 243 (2024) http://dx.doi.org/10.1016/j.eswa.2023.122796.

[21] J.B. Bowles, C.E. Peláez, Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis, Reliab. Eng. Syst. Saf. (1995) http://dx.doi.org/10.1016/0951-8320(95)00068-D.

[22] H. Soltanali, A. Rohani, M. Tabasizadeh, M.H. Abbaspour-Fard, A. Parida, An improved fuzzy inference system-based risk analysis approach with application to automotive production line, Neural Comput. Appl. 32 (14) (2020) 10573–10591, http://dx.doi.org/10.1007/s00521-019-04593-z.

[23] H. Shi, L. Wang, X.-Y. Li, H.-C. Liu, A novel method for failure mode and effects analysis using fuzzy evidential reasoning and fuzzy Petri nets, J. Ambient Intell. Humaniz. Comput. 11 (6) (2020) 2381–2395, http://dx.doi.org/10.1007/s12652-019-01262-w.

[24] M. Braglia, M. Bevilacqua, Fuzzy modelling and analytic hierarchy processing as a means to quantify risk levels associated with failure modes in production systems, Technol. Law Insur. 5 (3–4) (2000) 125–134.

[25] N.R. Sankar, B.S. Prabhu, Modified approach for prioritization of failures in a system failure mode and effects analysis, Int. J. Qual. Reliab. Manag. 18 (2001) 324–336, http://dx.doi.org/10.1108/02656710110383737.

[26] J.F.W. Peeters, R.J.I. Basten, T. Tinga, Improving failure analysis efficiency by combining FTA and FMEA in a recursive manner, Reliab. Eng. Syst. Saf. 172 (2018) 36–44, http://dx.doi.org/10.1016/j.ress.2017.11.024.

[27] J. Castet, M. Bareh, J. Nunes, S. Okon, L. Garner, E. Chacko, M. Izygon, Failure analysis and products in a model-based environment, in: 2018 IEEE Aerospace Conference, 2018, pp. 1–13, http://dx.doi.org/10.1109/AERO.2018.8396736.

[28] M. Rauschenbach, J. Nuffer, Quantitative FMEA and functional safety metrics evaluation in Bayesian networks, in: M.Z.E. Beer (Ed.), Proceedings of the 29th European Safety and Reliability Conference, ESREL 2019, Research Publishing Services, 2020, pp. 2475–2482, http://dx.doi.org/10.3850/978-981-11-2724-3.0509-cd.

[29] M. Yazdi, S. Kabir, M. Walker, Uncertainty handling in fault tree based risk assessment: State of the art and future perspectives, Process Saf. Environ. Prot. 131 (2019) 89–104, http://dx.doi.org/10.1016/j.psep.2019.09.003.

[30] E. Ruijters, M. Stoelinga, Fault tree analysis: A survey of the state-of-the-art in modeling, analysis and tools, Comput. Sci. Rev. 15–16 (2015) 29–62, http://dx.doi.org/10.1016/j.cosrev.2015.03.001.

[31] D. Guo, M. Yang, H. Wu, D. Ge, X. Cao, Dynamic reliability evaluation of diesel generator system of one Chinese 1000 MWe NPP considering temporal failure effects, Front. Energy Res. 9 (2021) http://dx.doi.org/10.3389/fenrg.2021.793577.

[32] R. Manian, J. Bechta Dugan, D. Coppit, K.J. Sullivan, Combining various solution techniques for dynamic fault tree analysis of computer systems, in: Proceedings Third IEEE International High-Assurance Systems Engineering Symposium (Cat. No. 98EX231), 1998, pp. 21–28, http://dx.doi.org/10.1109/HASE.1998.731591.

[33] Y. Ren, J. Bechta Dugan, Design of reliable systems using static and dynamic fault trees, IEEE Trans. Reliab. 47 (3) (1998) 234–244, http://dx.doi.org/10.1109/24.740491.

[34] K. Durga Rao, V. Gopika, V.V.S. Sanyasi Rao, H.S. Kushwaha, A.K. Verma, A. Srividya, Dynamic fault tree analysis using Monte Carlo simulation in probabilistic safety assessment, Reliab. Eng. Syst. Saf. 94 (4) (2009) 872–883, http://dx.doi.org/10.1016/j.ress.2008.09.007.

[35] M. Leimeister, A. Kolios, A review of reliability-based methods for risk analysis and their application in the offshore wind industry, Renew. Sustain. Energy Rev. 91 (2018) 1065–1076, http://dx.doi.org/10.1016/j.rser.2018.04.004.

[36] H. Aliee, H.R. Zarandi, A fast and accurate fault tree analysis based on stochastic logic implemented on field-programmable gate arrays, IEEE Trans. Reliab. 62 (2013) 13–22, http://dx.doi.org/10.1109/TR.2012.2221012.

[37] B. Bertsche, Reliability in automotive and mechanical engineering: Determination of component and system reliability, 2008.

[38] S. Yu, Q. Yang, J. Liu, M. Pan, A comparison of FMEA, AFMEA and FTA, in: ICRMS'2011 - Safety First, Reliability Primary: Proceedings of 2011 9th International Conference on Reliability, Maintainability and Safety, 2011, pp. 954–960, http://dx.doi.org/10.1109/ICRMS.2011.5979423.

[39] I. Mzougui, Z. Elfelsoufi, Improvement of failure mode, effects, and criticality analysis by using fault tree analysis and analytical hierarchy process, J. Fail. Anal. Prev. 19 (2019) 942–949, http://dx.doi.org/10.1007/s11668-019-00681-3.

[40] NUREG-0492 Fault Tree Handbook, USNRC, Washington DC, US, 1981.

[41] C.E. Kim, Y.J. Ju, M. Gen, Multilevel fault tree analysis using fuzzy numbers, Comput. Oper. Res. 23 (7) (1996) 695–703, http://dx.doi.org/10.1016/0305-0548(95)00070-4.

[42] L. Podofillini, J. Park, V.N. Dang, Measuring the influence of task complexity on human error probability: An empirical evaluation, Nucl. Eng. Technol. 45 (2) (2013) 151–164, http://dx.doi.org/10.5516/NET.04.2013.702.

[43] J. Park, W. Jung, Identifying objective criterion to determine a complicated task - A comparative study, Ann. Nucl. Energy 85 (2015) 205–212, http://dx.doi.org/10.1016/j.anucene.2015.05.012.

[44] R. Patriarca, M. Ramos, N. Paltrinieri, S. Massaiu, F. Costantino, G. Di Gravio, R.L. Boring, Human reliability analysis: Exploring the intellectual structure of a research field, Reliab. Eng. Syst. Saf. 203 (2020) 107102, http://dx.doi.org/10.1016/j.ress.2020.107102.

[45] IEC 61511-3 Functional Safety - Safety Instrumented Systems for the Process Industry Sector - Part 3, IEC, 2004.

[46] C. Taylor, S. Øie, K. Gould, Lessons learned from applying a new HRA method for the petroleum industry, Reliab. Eng. Syst. Saf. 194 (2020) http://dx.doi.org/10.1016/j.ress.2018.10.001.

[47] Reactor Safety Study. an Assessment of Accident Risks in U. S. Commercial Nuclear Power Plants. Executive Summary: Main Report, USNRC, 1975, http://dx.doi.org/10.2172/7134131.

[48] H. Bubb, Human reliability: A key to improved quality in manufacturing, Hum. Factors Ergon. Manuf. 15 (4) (2005) 353–368, http://dx.doi.org/10.1002/hfm.20032.

[49] J. Liu, Y. Zou, W. Wang, L. Zhang, X. Liu, Q. Ding, Z. Qin, M. Čepin, Analysis of dependencies among performance shaping factors in human reliability analysis based on a system dynamics approach, Reliab. Eng. Syst. Saf. 215 (2021) 107890, http://dx.doi.org/10.1016/j.ress.2021.107890.

[50] H.S. Blackman, D.I. Gertman, R.L. Boring, Human error quantification using performance shaping factors in the SPAR-H method, in: Proceedings of the Human Factors and Ergonomics Society, Vol. 3, 2008, pp. 1733–1737, http://dx.doi.org/10.1177/154193120805202109.

[51] A. Bye, K. Laumann, C. Taylor, M. Rasmussen, S. Øie, K. van de Merwe, K. Øien, R. Boring, N. Paltrinieri, I. Wærø, The petro-HRA guideline, 2017.

[52] Z.S. Nezamodini, Z. Rezvani, Z. Mosavianasl, in: M, C, R, B (Eds.), SPAR-H Method for Human Error Assessment: A Case Study in Control Room of an Alcohol Plant, CRC Press/Balkema: Occupational Health and Safety Group, Ahvaz Jundishapur University of Medical Sciences, Ahvaz, Iran, 2017, pp. 283–290, http://dx.doi.org/10.1201/9781315210469-38.

[53] K.T. Chenani, R.J. Nodoushan, M. Jahangiri, F. Madadizadeh, H. Fallah, Adaptation of the standardized plant analysis–risk human reliability analysis technique for the surgical setting: Expert judgment approach, Int. J. Occup. Saf. Ergon. (2022) http://dx.doi.org/10.1080/10803548.2021.2018856.

[54] K. Van De Merwe, S. Øie, K. Gould, The Application of the SPAR-H Method in Managed-Pressure Drilling Operations, Det Norske Veritas, Norway, 2012, pp. 2021–2025, http://dx.doi.org/10.1177/1071181312561422.

[55] R.L. Boring, H.S. Blackman, The Origins of the SPAR-H Method's Performance Shaping Factor Multipliers, Idaho National Laboratory, Idaho Falls, ID, United States, 2007, pp. 177–184, http://dx.doi.org/10.1109/HFPP.2007.4413202.

[56] R.L. Boring, Modeling Human Reliability Analysis using MIDAS; Human Factors, Vol. 2006, Instrumentation and Control Systems Department, Idaho National Laboratory, Idaho Falls, ID 83415, United States, 2006, pp. 1270–1274.

[57] R. Patriarca, G. Di Gravio, R. Woltjer, F. Costantino, G. Praetorius, P. Ferreira, E. Hollnagel, Framing the FRAM: A literature review on the functional resonance analysis method, Saf. Sci. (2020) http://dx.doi.org/10.1016/j.ssci.2020.104827.

[58] A.A. Jaoudé, The Monte Carlo Methods, IntechOpen, Rijeka, 2022, http://dx.doi.org/10.5772/intechopen.96413.

[59] Richard Denning, Applied R & M manual for defence systems (GR-77), 2012.

[60] Procedures for Performing a Failure Mode, Effects and Criticality Analysis, Vol. MIL-STD-16, US Department of Defence, 1980.

[61] H. Zheng, Y. Tang, A novel failure mode and effects analysis model using triangular distribution-based basic probability assignment in the evidence theory, IEEE Access 8 (2020) 66813–66827, http://dx.doi.org/10.1109/ACCESS.2020.2986807.

[62] G. Di Gravio, M. Mancini, R. Patriarca, F. Costantino, Overall safety performance of air traffic management system: Forecasting and monitoring, Saf. Sci. 72 (2015) 351–362, http://dx.doi.org/10.1016/j.ssci.2014.10.003.

[63] M.R. Driels, Y.S. Shin, Determining the number of iterations for Monte Carlo simulations of weapon effectiveness, 2004, http://dx.doi.org/10.1109/37.642974.

[64] C.M. Wang, J. Hannig, H.K. Iyer, Pivotal methods in the propagation of distributions, Metrologia (2012) http://dx.doi.org/10.1088/0026-1394/49/3/382.

[65] E. Hollnagel, FRAM: The Functional Resonance Analysis Method: Modelling Complex Socio-Technical Systems, Ashgate Publishing, 2012, http://dx.doi.org/10.1017/CBO9781107415324.004.

[66] R. Patriarca, J. Bergström, G. Di Gravio, F. Costantino, Resilience engineering: Current status of the research and future challenges, Saf. Sci. 102 (December 2016) (2018) 79–100, http://dx.doi.org/10.1016/j.ssci.2017.10.005.

[67] A. Falegnami, F. Costantino, G. Di Gravio, R. Patriarca, Unveil key functions in socio-technical systems: Mapping FRAM into a multilayer network, Cogn. Technol. Work 22 (2020) 877–899, http://dx.doi.org/10.1007/s10111-019-00612-0.

[68] M. Holman, G. Walker, T. Lansdown, Analysing dynamic work systems using DynEAST: A demonstration of concept, Ergonomics 66 (2023) 377–405, http://dx.doi.org/10.1080/00140139.2022.2092217.

[69] H. Blackman, J. Byers, ASP Human Reliability Methodology Development, INEL-95/0139, 1995.

[70] E. Uflaz, E. Akyuz, O. Arslan, P. Gardoni, O. Turan, M. Aydin, Analysing human error contribution to ship collision risk in congested waters under the evidential reasoning SPAR-H extended fault tree analysis, Ocean Eng. 287 (2023) http://dx.doi.org/10.1016/j.oceaneng.2023.115758.

[71] Z. Xu, S. Shang, X. Su, H. Qian, X. Pan, Handling dependencies among performance shaping factors in SPAR-H through DEMATEL method, Nucl. Eng. Technol. 55 (8) (2023) 2897–2904, http://dx.doi.org/10.1016/j.net.2023.04.017.

[72] T. Xiao, Q. Yongping, Z. Yucheng, L. Wenjing, H. Juntao, Study of Application Optimization of SPAR-H Human Reliability Analysis Method, Vol. 284 SPPHY, 2023, pp. 91–102, http://dx.doi.org/10.1007/978-981-19-8780-9_10.

[73] C.P.M. de Morais, Human reliability analysis of a pig receiver operation: A case study using petro-HRA, 2023, http://dx.doi.org/10.4043/32749-MS.

[74] Y. Qiao, X. Zhang, H. Wang, D. Chen, Dynamic assessment method for human factor risk of manned deep submergence operation system based on SPAR-H and SD, Reliab. Eng. Syst. Saf. 243 (2024) http://dx.doi.org/10.1016/j.ress.2023.109865.

[75] N. Logistics Technology Support Group, S.W.C. (CDNSWC), Handbook of reliability prediction procedures for mechanical equipment, 2010.

[76] Reliability Prediction of Electronic Equipment, Mil. Handb. MIL-HDBK-217F, Department of Defense of the USA, 1991.

[77] D. Chen, Y. Fan, C. Ye, S. Zhang, Human reliability analysis for manned submersible diving process based on CREAM and Bayesian network, Qual. Reliab. Eng. Int. 35 (7) (2019) 2261–2277, http://dx.doi.org/10.1002/qre.2501.

[78] R.L. Boring, How Many Performance Shaping Factors are Necessary for Human Reliability Analysis?, INL/CON-10-18620, Idaho National Laboratory, 2010.

[79] W. Du, Y. Wang, Y. Luo, A reliability-based fatigue design for mechanical components under material variability, Qual. Reliab. Eng. Int. 36 (1) (2020) 388–402, http://dx.doi.org/10.1002/qre.2586.

[80] E.-H. Yeh, P. Lin, X.-X. Lin, J.-Y. Jeng, Y. Fang, System error prediction for business support systems in telecommunications networks, IEEE Trans. Parallel Distrib. Syst. 31 (11) (2020) 2723–2733, http://dx.doi.org/10.1109/TPDS.2020.3001593.

[81] S. Montani, L. Portinale, A. Bobbio, D. Codetta-Raiteri, Automatically translating dynamic fault trees into dynamic Bayesian networks by means of a software tool, in: First International Conference on Availability, Reliability and Security, ARES'06, 2006, pp. 6–809, http://dx.doi.org/10.1109/ARES.2006.34.

[82] T. Parhizkar, S. Hogenboom, J.E. Vinnem, I.B. Utne, Data driven approach to risk management and decision support for dynamic positioning systems, Reliab. Eng. Syst. Saf. 201 (2020) http://dx.doi.org/10.1016/j.ress.2020.106964.

[83] J. Freiesleben, J. Keim, M. Grutsch, Machine learning and design of experiments: Alternative approaches or complementary methodologies for quality improvement? Qual. Reliab. Eng. Int. 36 (6) (2020) 1837–1848, http://dx.doi.org/10.1002/qre.2579.

[84] L.A. Derdowski, G.E. Mathisen, Psychosocial factors and safety in high-risk industries: A systematic literature review, Saf. Sci. 157 (2023) http://dx.doi.org/10.1016/j.ssci.2022.105948.