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TECHNICAL ARTICLE—PEER-REVIEWED

# A Hybrid Probabilistic Model for Evaluating and Simulating Human Error in Industrial Emergency Conditions (HEIE)

**Antonella Petrillo · Fabio De Felice · Domenico Falcone · Alessandro Silvestri · Federico Zomparelli**

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**Abstract** Over the years, many techniques have been developed for human reliability analysis (HRA). The main weakness of traditional HRA approaches is the use of a simple classification scheme without a link to a model of cognition in terms of mental processes. The present work is an attempt in this direction through a particular hybrid probabilistic model. The human error in industrial emergency model aims to develop an integrated methodological approach useful in critical infrastructures during an emergency condition. The proposed method, starting from the integration of existing techniques, develops a very flexible tool, able to take into account the main external and internal factors responsible of human error in emergency conditions. The model is able to estimate the evolution of human behavior and error following the evolution of the emergency scenario. The final result is a simulation model that calculates the contextualized human error probability, through which it is possible to estimate a realistic and detailed scenario of the conditions during the emergency management.

**Keywords** Human reliability analysis · Cognitive simulation · Disaster · Failure analysis · Industrial plant

A. Petrillo (✉)
University of Naples "Parthenope", Isola C4 - Centro Direzionale Napoli, 80143 Naples, Italy
e-mail: antonella.petrillo@uniparthenope.it

F. De Felice · D. Falcone · A. Silvestri · F. Zomparelli
University of Cassino and Southern Lazio, Via G. Di Biasio 43, 03043 Cassino, Italy

## Introduction

For many years, the risk analyses have been carried out in a mere technical field, simply aiming at the improvement of system reliability by acting on its "mechanical" parts. However, in recent years, it has spread the awareness that work accidents prevention must necessarily involve an accurate risk assessment that considers the human factor. To manage risk is evident that it is necessary to know what are the accidents that may occur and what are the causes that trigger them [8]. Therefore, a model for risk assessment is needed to identify and quantify risks associated with operations or activities carried out by man. Only by knowing the causes that trigger the mechanisms of error, accidents can be prevented. To mitigate the risk associated with emergencies means avoiding, or at least stopping, the chain of that, given an initial event, can lead to a probable disaster [4, 12]. The risk management puts in place all necessary measures to control the factors of uncertainty linked to activity and limit the effects of potential adverse events. Such reasoning can and should be extended to all activities where there is the human factor, which is the cause of the majority of incidental events. The contribution of human factor plays a fundamental role in accident dynamics, not only at a probabilistic level, but rather in terms of seriousness of the expected effects [10]. HRA could be regarded as the set of a number of techniques which come together to describe the conditions of the operator during the work, evaluating errors and unsafe actions, also taking count of relative skills, training and abilities required for the given task. HRA techniques can be used for the design of work tools and environments, in personnel management, in procedures planning and so on. Due to the uncertainty related to the human error, this particular group of techniques, although it is already widely adopted, cannot yet be fully exploited. The HRA methods were first born for applications in the nuclear field, for which the risk related to an accident clearly appears most relevant [22]. Therefore, a lot of HRA techniques were developed to provide human error probabilities associated with the operator's tasks; these probabilities should then be included within the wider framework of risk assessment of the considered system. Thus, they are originally aimed at reducing probabilities and frequencies of occurrence of unsafe events [5].

In a few words, human reliability studies all those factors (both external and internal with respect to the man) which affect the worker's performance [33]. The "*external*" factors are random technical malfunctioning events, or organizational and environmental factors substantially modifying the working conditions and thus leading to errors. The "internal" factors are those related to the individual's characteristics and therefore related to individual psycho-physical conditions of the operator [39]. The development of this new model is necessary, because analyzing the literature has shown that there are multiple human reliability analysis. In fact, there are no models that integrate the analysis model HRA with the surrounding environment and implement the system in a simulation model. As analyzed by Hollnagel and Marsden [20], the main weakness of traditional HRA approaches is the use of a simple classification scheme without a link to a model of cognition in terms of mental processes. The present work is an attempt in this direction through a particular hybrid probabilist model.

The purpose of this study is to propose an *integrated* hybrid model to evaluate Human Error in Industrial Emergency conditions (HEIE) through a probabilistic approach. The model includes a simulation algorithm that allow to assess different scenarios. The result of the simulation is used both to predict error rates and to identify criticalities.

The model aims to integrate the cognitive aspects of operator analysis and the reliability analysis of actions.

This rest of the paper is organized as follows. "Literature Review: State of the Art and Related Work" section analyzes the state of art on human reliability methods. "Description of the HEIE Model: The Rationale" section describes the HEIE model. "Case Study: The Experimental Design" section presents a case study concerning a petrochemical industry. "Discussion" section presents a discussion about the model, and the main result is presented. Finally, "Conclusions" section summarizes the contribution of the research and future developments.

## Literature Review: State of the Art and Related Work

The principle of human error study dates back to the accident at Three Mile Island that occurred on March 28, 1979, the most serious nuclear accident in the USA [18]. After this event, it became clear how the action, even a single operator, can be a challenge to the safety of the entire system and its productivity [6]. Already in [2], Baron states that, on average, about 80% of industrial accidents are caused wholly or partly by human actions, while a few years later Dhillon [13] collected the following data of failures due to human error in different organizations: 20–53% of failures of the US Air Force missile system; over 90% of air traffic control system errors; 82% of production errors in one unnamed company; 50–70% of all electronic equipment failures; and 25.8% of maintenance malfunctions.

In this context, HRA is a system of techniques that describe the physical and environmental conditions in which the operator is to carry out its tasks, assessing errors and taking into account the skills, experience and ability [15, 41]. Over the years, many techniques have been developed HRA. Each technique is characterized by advantages and disadvantages. Historically the development of human reliability analysis methods occurred in three phases [9].

The first phase (1970–1990) gave rise to the *first-generation* methods, focused on the assessment of the likelihood of human error and not very sensitive to the causes of observable behaviors. Examples of first-generation methods are: Technique for Human Error Rate Prediction—THERP [26]; the empirical technique to estimate the operator's error—TESEO [3]; Systematic Human Action Reliability—SHARP (Hannaman and Spurgin [17]; Success Likelihood Index Method—SLIM [32]; Human Cognitive Reliability Correlation—HCR [37] and; human error assessment and reduction technique—HEART [43]. The second phase (1990–2005) generated the *second-generation* methods, which focus more on internal and external factors affecting human performance (workload, stress level, psychological and sociological issues related to the environment working, disorders and diseases, etc.) and on cognitive processes. During this phase, advanced cognitive models have been developed that represent the logical processes of the operators and summarize the dependence on personal and individual factors. In the second-generation models of the factors that shape the performance (PSFS) they are derived by focusing on the impact of the environment on the cognitive level [27]. Examples of second-generation methods are: A Technique for Human Event Analysis—ATHEANA [1]; Cognitive Reliability and Error Analysis Method—CREAM [21] and Standardized Plant Analysis Risk—Human RA—SPAR-H [16]. The third phase, began in 2005 and still in progress, is related to production methods that focus on mutual dependency relationships between the various factors of human performance. Some specialists have focused on the development of the methods of third generation, namely "*Nuclear Action Reliability Assessment*" (NARA) and Bayesian networks, while other authors and experts have conducted extensive studies on dynamic simulation and modeling methods for the analysis of human reliability (dynamic HRA methods) [28].

Table 1 summarizes the main HRA methods, as analyzed by [11].

In the last few years, there are interesting studies that analyze the human reliability analysis applied in the emergency conditions. For a comprehensive survey of the phenomenon an investigation on Scopus data base, the largest abstract and citation database of peer-reviewed literature, was carried out. Search string used in the literature survey was "*human reliability analysis.*" String was defined according to the standards of Scopus database. We applied the main criterion to select articles. Only articles in which the string *"human reliability analysis"* was found in article title were analyzed. The analysis on Scopus pointed out that from 1952 (the first year in which it was published the first article on Scopus) until March 2017 (the time of the investigation) a set of 463 documents have been published divided in 197 articles, 237 conference papers and the remaining part on books, editorials, letters, etc. The research highlighted a growth in the number of publications. The most of them have been published in 2014 (in total 45), as shown in Fig. 1. Furthermore, it is interesting to note that most of the publications (155) have been published in the USA.

Considering our specific field of interest, we refined our search applying a preliminary filter. Search string used was "*human reliability analysis AND human error*" considering the criterion article title. Out of 463, we identified 45 articles from 1969 (the first year in which it was published the first article on Scopus) to 2016 (the last article published Scopus).

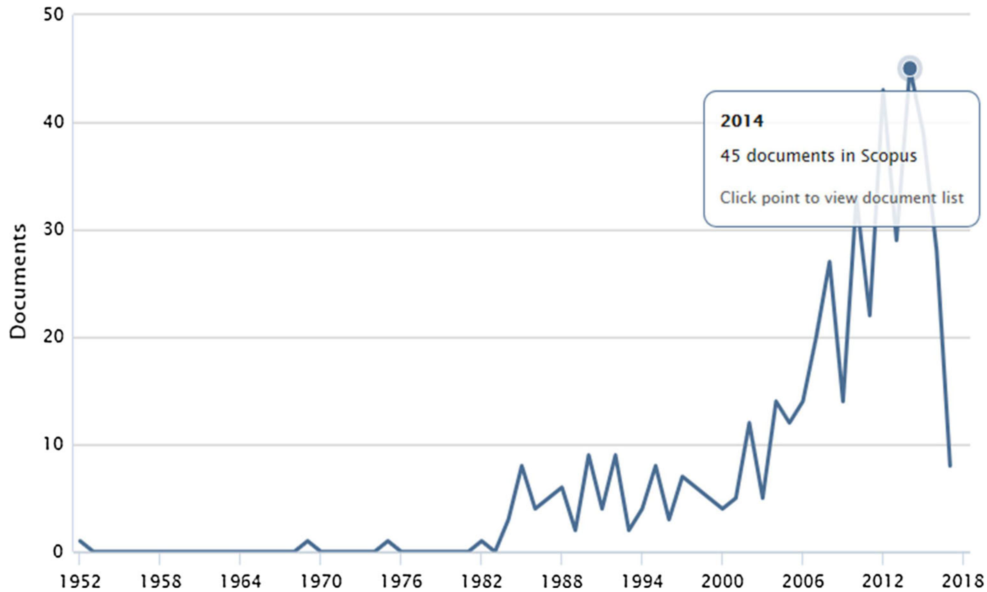
As a result of the previous research analysis, we decided to examine some relevant studies in which the direct relationship between human reliability analysis and emergency condition in critical infrastructure has been explored.

Recently, Kim et al. [24] propose a study to quantify the weightings of performance shaping factors (PSFs) when performing HRA during low-power and shutdown (LPSD) operation. In 2016, Ribeiro et al. [38] develop a HRA model that allows the incorporation of features related to facility conditions to determine human error probabilities (HEPs) used in probabilistic safety analyses of process plants. The model was applied to the accident that occurred

**Table 1** Benchmarking grid comparing HRA methods

| Method | Main theoretical framework | Predefined data | Nature of data | Processing approach | Analysis target | Coverage of PSF |
|---|---|---|---|---|---|---|
| THERP | Behavioral | TRC curves and tables | Quantitative | Frequentist | Operator | Human task |
| SLM-MAUD | Behavioral | PSF coefficients | Quantitative | Bayesian | Operator | Human task |
| HCR/ORE | Cognitive | Curves | Quantitative | Frequentist | Operator | Human task |
| HEART | Cognitive | Tables | Quantitative | Frequentist | Operator and crew | Human task |
| CREAM | Cognitive | Nominal HEP | Quantitative | Frequentist | Operator and Crew | Human task System |
| ATHENA | Behavioral and cognitive | Nominal HEP | Quantitative Qualitative | Frequentist | System | Human task system environment |
| SPAR-H | Cognitive | Nominal HEP | Quantitative | Frequentist | System | Task system |

Fig. 1 Documents by year. Source Scopus database




in 1999 in Tokai-Mura, Japan. Cheng and Hwang [7] in their research outline the human error identification (HEI) techniques that currently exist to assess latent human errors. A case study concerning the operational process of changing chemical cylinders in a factory is analyzed. An interesting study is carried out by Joe and Boring [23]. They develop a research to model and quantify the team work in the control room of a nuclear power plant in order to improve the standard techniques of the HRA that in most cases do not provide group dynamics. Always in [31], Kosmowski proposes a model based on human error probability (HEP) to monitor human error within control rooms of industrial hazardous plants, while in their paper MacLeod et al. [34] proposes a method for estimating the component of the human error probability (HEP) associated with the deployment of portable equipment. An interesting study to quantify and to identify causes that influence human reliability is developed by Park et al. [36]. But, this study does not take into full consideration the environmental effects that can affect the operator.

In 2008, Meel et al. [35] examine the analysis of management actions, human behavior and process reliability in chemical plants. A different approach is proposed by Trucco and Leva [42]. In their study, a simulator, based on "first-generation" human reliability assessment for approaching human errors in complex operational frameworks (e.g., plant commissioning), is developed. In [30], Konstandinidou et al. propose a fuzzy classification system for human reliability analysis in order to calculate the probability of erroneous actions according to CREAM in specific contexts. A pilot application demonstrates the successful "translation" of CREAM into a fuzzy logic model. A theoretical and empirical development for an error prediction methodology called task analysis for error identification (TAFEI) is proposed by Stanton and Baber [40].

The literature review highlighted that, although several studies on human reliability analysis are proposed by several authors, it is evident that the main weakness of traditional HRA approaches is the use of a simple classification scheme without a link to a model of cognition in terms of mental processes. The present research aims to cover this gap.

## Description of the HEIE Model: The Rationale

The HEIE model introduces the quantification of the probability associated with each accident scenario, defined by a particular sequence of human errors. The development of HEIE model is based on typical procedures characterizing first- and second-generation methods.

In detail, the model is a hybrid algorithm-based HEART and SPAR-H methodology. The first one is used for the purposes of evaluating the probability of a human error occurring throughout the completion of a specific task. Furthermore, the choice of HEART as the primary source of error rates is based on the consideration that this technique incorporates the most widely used estimates of error rates of generic tasks [19].

The main weakness of HEART methodology is that it does not consider the external environment and the influence of the operator. For this reason, the HEART method is integrated using SPAR-H methodology that defines a set of

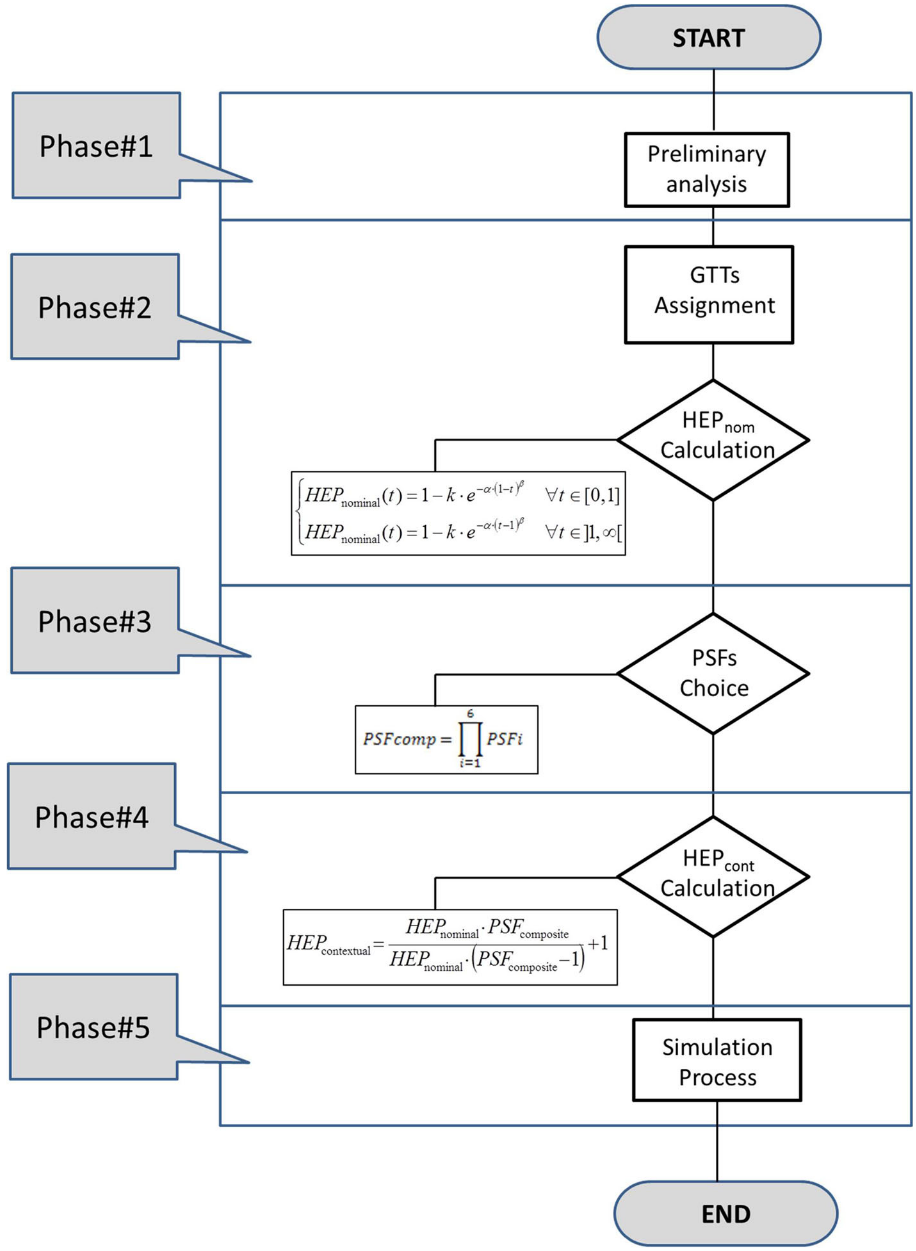



Fig. 2 Methodological approach

performance shaping factors (PSFs) or in other words identifies the external environment and the influence of environment on the operator.

Figure 2 shows the rationale of HEIE model.

The model is characterized by 5 major phases, as described below.

Phase#1: Preliminary Analysis

HEIE model starts by considering all useful information of the scenario under study. In particular, the most important information is related to all emergency procedures that must be performed by operator during an emergency condition.

Phase#2: Generic Tasks—Nominal HEP Calculation

The present phase aims to select generic tasks (GTTs) or in other words types of emergency tasks that characterized by some sense of urgency. The generic tasks are presented with estimated human error probabilities (HEPs) based on and extrapolated from the HRA literature [29].

The probability distribution that best describes the error distribution is the Weibull. In particular, according to Di Pasquale et al. [14], the human error probability (HEP) distribution is defined by Eq 1:

$$\begin{cases} \mathrm{HEP}_{\mathrm{nominal}}(t) = 1 - k \cdot e^{-\alpha\cdot(1-t)^{\beta}} & \forall\, t \in [0,1] \\ \mathrm{HEP}_{\mathrm{nominal}}(t) = 1 - k \cdot e^{-\alpha\cdot(t-1)^{\beta}} & \forall\, t \in ]1,\infty[ \end{cases} \qquad \text{(Eq 1)}$$

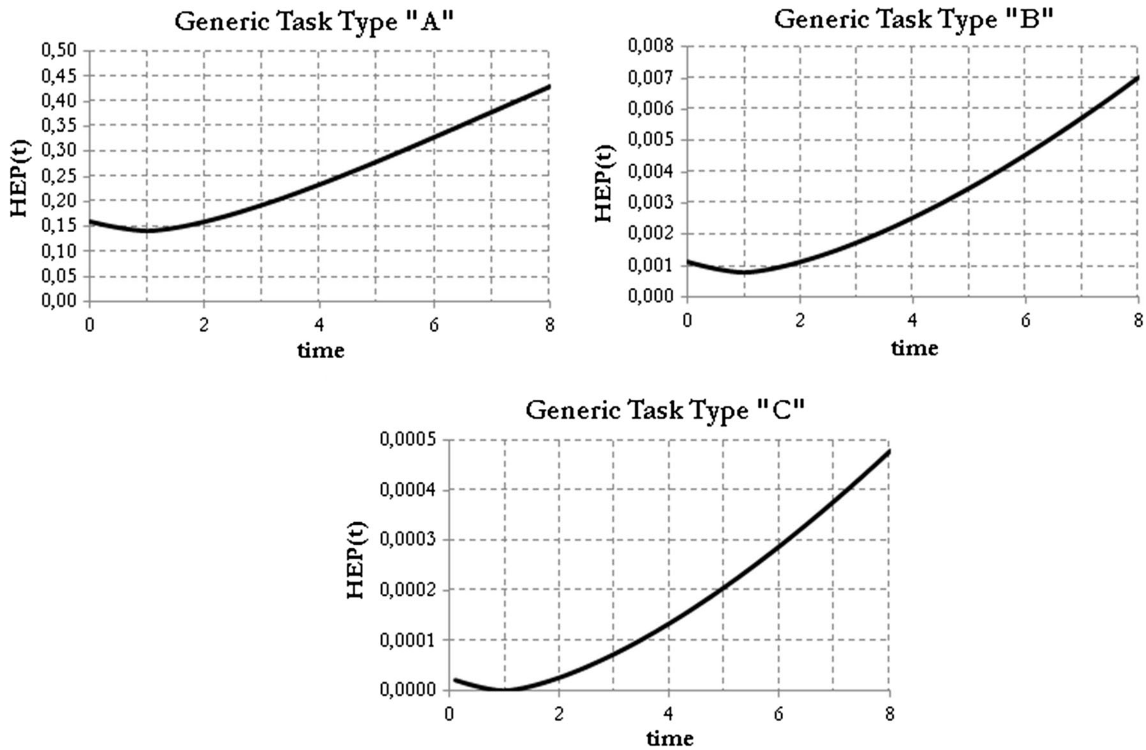



**Fig. 3** Trend of Weibull-modified function

The function has also been assumed to have a minimum value of error probability in the first hour of processing and a maximum value at the 8 h of work during an 8-h shift.

The model calculates the nominal rate of error at time $t$. The parameters of the mathematical function ($\alpha$, $\beta$, $k$) vary according to the generic tasks.

The $k$ parameter is calculated considering the minimum probability condition at $t = 1$.

The $\beta$ parameter is chosen in function to the shape that is to be assigned to the curve.

The $\alpha$ parameter is calculated imposing the maximum value of the function for $t = 8$ and an intermediate value for $t = 4.5$.

The HEP of values taken as a reference for the calibrations is the percentiles dependent on the individual generic task, proposed by HEART technique.

The $\beta$ parameter of the function is set at 1,5.

The maximum reliability condition at $t = 1$ is given by Eq 2:

$$f(t) = 1 - k \qquad \text{(Eq 2)}$$

The function is matched to the reference value of HEP (5% percentile). See Eq 3:

$$f(t) = 1 - k = \mathrm{HEP}_{\mathrm{ref}} \Rightarrow k = 1 - \mathrm{HEP}_{\mathrm{ref}} \qquad \text{(Eq 3)}$$

**Table 2** List of PSFs

| PSFs | Description |
|---|---|
| 1 Available time | Time to receive, check and process the information and make a decision on the required actions |
| 2 Stress | Level of unwanted conditions and circumstances which prevent the operator to successively carry out an activity |
| 3 Task complexity | Complexity of executing a task in a given context. Activity aspects and environment aspect are considered |
| 4 Information management | Quality, quantity, reliability and effectiveness of the information available in the control room and the relative difficulty, for the operator, to process them and to take appropriate decisions |
| 5 Complexity of scenario | Number of people present at the site of the accident. Classified as “normal,” “high” or “critical” |
| 6 Level of critical emergency | Level of difficulty of the emergency situation. Classified as “low,” “medium” or “high” |

**Table 3** Numerical values of PSFs

| PSF | Levels | Multipliers for actions | Multipliers for diagnosis |
|---|---|---|---|
| Available time | Inadequate | HEP = 1 | HEP = 1 |
| | Available time = time required | 10 | 10 |
| | Nominal | 1 | 1 |
| | Available time >5 time required | 0.1 | 0.1 |
| | Available time >50 time required | 0.01 | 0.01 |
| Stress | Extreme | 5 | 5 |
| | High | 2 | 2 |
| | Nominal | 1 | 1 |
| Task complexity | Very complex | 5 | 5 |
| | Low complex | 2 | 2 |
| | Nominal | 1 | 1 |
| | Obvious diagnosis | – | 0.1 |
| Information management | Insufficient | 11.9 | 14 |
| | Enough | 2.6 | 2.6 |
| | Good | 1 | 1 |
| Complexity of scenario | Number of person ≥50 (critical) | 1.6 | 3.7 |
| | Number of person <50 (high) | 1.25 | 3.5 |
| | Number of person <20 (normal) | 1 | 1 |
| Level of critical emergency | High | 9.4 | 9.4 |
| | Medium | 2.2 | 2.2 |
| | Low | 1 | 1 |

For each generic task considered, the HEP reference is equal to 5% percentile. For the conditions $t = 4.5$ and for the conditions $t = 8$. See Eqs 4 and 5, respectively:

$$f(t) = 1 - k \cdot e^{-\alpha\cdot(3,5)^{\beta}}(t = 4.5) \quad \text{(Eq 4)}$$

$$f(t) = 1 - k \cdot e^{-\alpha\cdot(7)^{\beta}}(t = 8) \quad \text{(Eq 5)}$$

From previous expressions, matching the respective reference HEP (50% percentile and 95%) obtains the value of $\alpha$ for $t = 4.5$ and for $t = 7$. See Eqs 6 and 7, respectively:

$$\alpha = -\ln\left(\frac{1 - \mathrm{HEP}}{k}\right) \cdot (3.5)^{-\beta} \quad \text{(Eq 6)}$$

$$\alpha = -\ln\left(\frac{1 - \mathrm{HEP}}{k}\right) \cdot (7)^{-\beta} \quad \text{(Eq 7)}$$

The final value for $\alpha$ is the average of the two values determined.

Figure 3 shows the trend of the Weibull function modified, with the parameters calibrated according to the HEIE method for each considered generic task.

Phase#3: Determination of the Performance Shaping Factors (PSFs)

This is a crucial phase. It is based on the consideration that human reliability is estimated as function of the performed task, the performance shaping factors (PSFs) and the time worked. The aim is to consider how reliability depends not only on the task and working context, but also on the time that the operator has already spent on the work. Thus, it is important to consider the PSFs that best describe the condition of the system. The *average time for decision*, *stress* and *task complexity* is 3 PSFs cited by SPAR-H methodology and that we have considered in the HEIE model. In our opinion, the mentioned PSFs are not sufficient to represent a complex system. Therefore, we have proposed 3 new PSFs: the *management of information*, the *complexity of the situation* and the *emergency level*. In this way, the generic tasks balance the design aspects.

Table 2 shows the complete list of PSFs involved in the process of changing nominal HEP, with a brief description [25].

In Table 3, numerical values, assigned to each level defined for each PSFs, are reported. Values are based on the literature review.

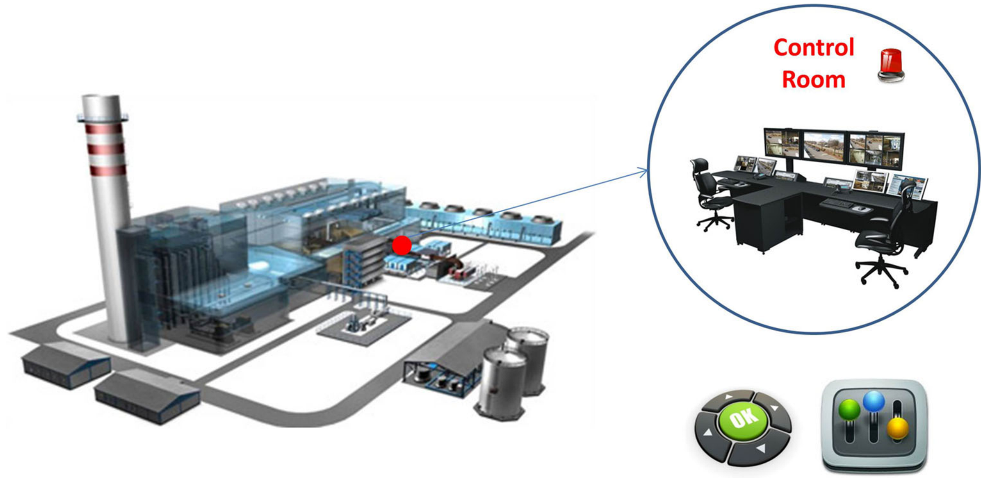



**Fig. 4** Control room at the petrochemical plant

**Table 4** Generic Tasks description [26]

| Generic tasks (GTs) | Limitation of unreliability for operation (5th–95th percentile) |
|---|---|
| Shift or restore the system without procedures | 0.26 (0.14 ÷ 0.42) |
| Shift or restore the system following procedures | 0.003 (0.0008 ÷ 0.007) |
| Respond correctly to system command when there is an automated supervisory system | 0.00002 (0.0000001 ÷ 0.0009) |

**Table 5** Nominally HEP in function of generic tasks

| | $t = 1$ (percentile 5%) | $t = 4, 5$ (percentile 50%) | $t = 8$ (percentile 95%) |
|---|---|---|---|
| GT "A" | 0.14 | 0.26 | 0.42 |
| GT "B" | $8 \times 10^{-4}$ | $3 \times 10^{-3}$ | $7 \times 10^{-3}$ |
| GT "C" | $1 \times 10^{-7}$ | $2 \times 10^{-5}$ | $9 \times 10^{-4}$ |

Of course, others PSFs could be added to conduct a more detailed analysis, according the scenario under study. The possibility of changing and adding PSFs according to the analyzed contest and scenario makes the method flexible.

Phase#4: Contextualized HEP Calculation

Mathematically, the contextualized HEP is calculated as following (see Eq 8):

$$\mathrm{HEP}_{\mathrm{contextual}} = \frac{\mathrm{HEP}_{\mathrm{nominal}} \cdot \mathrm{PSF}_{\mathrm{composite}}}{\mathrm{HEP}_{\mathrm{nominal}} \cdot \left(\mathrm{PSF}_{\mathrm{composite}} - 1\right) + 1} \quad \text{(Eq 8)}$$

where the $\mathrm{PSF}_{\mathrm{composite}}$ factor is the product of all the values assigned to the six PSFs (see Eq 9):

$$\begin{aligned}\mathrm{PSF}_{\mathrm{composite}} &= (\mathrm{PSF}_1 \times \mathrm{PSF}_2 \times \cdots \times \mathrm{PSF}_6)/100 \\ &= \prod \mathrm{PSF}_i/100 \end{aligned} \quad \text{(Eq 9)}$$

Some tasks of the desk operator are considered both actions and diagnosis. This involves a double possibility of error. For this reason, they add up the multipliers associated with actions and diagnosis. This fact is equivalent to considering the possibility of two parallel error.

Phase#5: Simulation Process

The simulation process defines all the possible events associated with an emergency. The system is described by a logical tree representing the possible scenarios.

The simulation calculates the probabilities associated with different outcomes ($E_1$, $E_2$,…,$E_N$), through the conditional probabilities. The criticality of the system is defined as follows, see Eq 10:

$$C_{\mathrm{imp}} = \sum_{i=1}^{n} P(E_i) \cdot V_i = \sum_{i=1}^{n} C_i \quad \text{(Eq 10)}$$

where $P(E_i)$ is the probability associated with the event; $V$ is the system vulnerability associated with the event; $n$ is the number of scenarios.

The human reliability of the system is defined as follows, see Eq 11:

$$R_{\text{imp}} = \sum_{i=1}^{n} \{[1 - P(E_i)] \cdot V_i + (1 - V_i)\} = \sum_{i=1}^{n} (1 - C_i) \quad \text{(Eq 11)}$$

where $P(Ei)$ is the probability associated with the event; $V$ is the system vulnerability; $n$ is the number of scenarios; $Ci$ is criticality of the system.

## Case Study: The Experimental Design

### Phase#1: Preliminary Analysis

A company that operates in the petrochemical sector is analyzed. In particular, the case study concerns the emergency management procedures within a control room. Figure 4 shows the scenario under study.

Precisely, case study is related to emergency during a fire. The model aims to identify incorrect choices and inadequate actions.

**Table 6** Basic parameters in function of generic tasks

| | $k$ | $\alpha$ | $\beta$ |
|---|---|---|---|
| GT "A" | 0.86 | $2.211 \times 10^{-2}$ | 1.5 |
| GT "B" | 0.9992 | $3.364 \times 10^{-4}$ | 1.5 |
| GT "C" | $1–10^{-7}$ | $2.583 \times 10^{-5}$ | 1.5 |

**Table 7** PSFs case study

| PSFs | Value |
|---|---|
| Available time | 10 |
| Stress | 5 |
| Task complexity | 1 |
| Information management | 2.6 |
| Complexity of scenario | 1.25 |
| Level of critical emergency | 2.2 |
| PSFcomp | 3.575 |

The team that operates in the control room is formed by 1 engineer, 1 safety engineer and 3 operators.

The emergency procedure involves the following actions:

1. Total blockade of the ovens;
2. Closure of all turbines;
3. Closing the propane valve;
4. Sequence block of propane handling;
5. Closure of the flow control valves;
6. Close the control room and join the rest of the fire team.

### Phase#2: Generic Tasks—Nominal Hep Calculation

Considering the operations that may be performed by an operator in the control room, three different classes of generic tasks are defined:

1. Bring the system to a new state or to its original state without use of procedures;
2. Bring the system to a new state or to its original state following the procedures;
3. Respond correctly to system commands when there is a supervisory system enhanced.

In Table 4 are reported the limit values for the nominal probability of error. These values correspond to the 5% and the 95% percentile of the probability distribution.

It is assumed that the categories of generic tasks considered in Table 4 are sufficient to represent the scenario under study.

Table 5 shows the nominal HEP has taken as reference for the calibration $t = 1$, $t = 4, 5$ and $t = 8$, respectively, for the three generic tasks defined in Table 4. The values of nominal HEP are obtained by Eq 1. In Table 6, the values obtained are collected for the parameters $k$ and $\alpha$. The values of nominal $k$, $\alpha$ and $\beta$ are obtained by using equations from 2 to 7.

### Phase#3: Determination of the Performance Shaping Factors

Weighted values of PSFs are defined to represent the model as close as possible to reality. Table 7 shows the values of the PSF and the value of PSF composite.

**Table 8** Contextualized HEP in function of generic tasks

| | $t = 1$ (percentile 5%) | $t = 4.5$ (percentile 50%) | $t = 8$ (percentile 95%) |
|---|---|---|---|
| GT "A" | 0.368 | 0.557 | 0.721 |
| GT "B" | $2.85 \times 10^{-3}$ | $1.06 \times 10^{-2}$ | $3.97 \times 10^{-2}$ |
| GT "C" | $3.57 \times 10^{-7}$ | $7.15 \times 10^{-5}$ | $3.21 \times 10^{-3}$ |

The value of PSF composite is calculated by Eq 9.

Phase#4: Contextualized HEP Calculation

The contextualized HEP is calculated from Eq 8. The input values of the nominal HEP and composite PSF are shown, respectively, in Tables 5 and 7. The values of contextualized HEP are shown in Table 8.

Phase 5: Simulation Process

The emergency management involves leaving the building at the end of the recovery operations. At the time of emergency signaling, the operator is inside the control room. His/her main task is to control the blocking of facilities and join the rest of the team at the end of the emergency management operations. The algorithm of the operator's interaction with the sequence of operations required by the procedure is divided into three decision blocks: *diagnosis*, *sequence of actions* and *verification*.

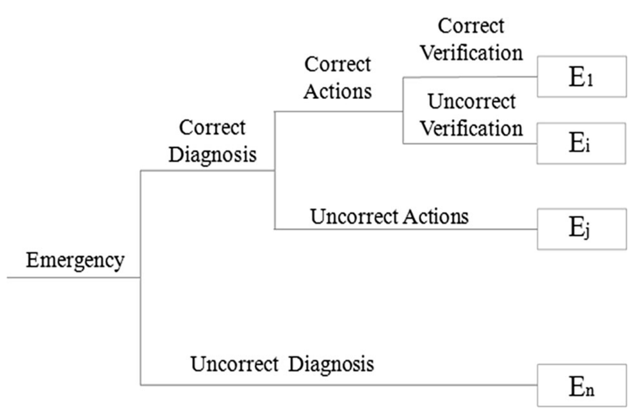



**Fig. 5** Logical tree of emergency management process

Each of these blocks has a given probability of error that will be calculated subsequently.

In the preliminary phase, the operator must perform a correct diagnosis of the emergency level, according the received reports. This task should be performed in the initial phase of emergency management, and this depends on the subsequent decisions and outcomes of the emergency operations team. An initial mis-diagnosis or not timely activation of the emergency procedure undermines the work of the entire team, and it can lead to serious consequences.

- If the actions to be taken are mutually independent, the probability of occurrence of a non-optimal outcome is equal to the sum of the individual probabilities of failure.
- If the actions are dependent, it needs to consider the conditional probability of each error related to the previous.
- If the execution of all operations is correct, it passes to the next of the verification node.

The verification is configured as an operation composed of "action + diagnosis," which involves the development of a "parallel system" in the tree logical diagram. The possibility of error is double, both linked to an incorrect confirmation (error in action), both at an incorrect assessment of the control parameters (error in diagnosis). The overall error probability is the sum of the individual error probability associated with the two possibilities.

The failure of the verification operation in the control room will lead to the definition of a no optimal scenario with low probability of occurrence. The success will provide optimal final outcome, however, corresponding to the best emergency management.

**Fig. 6** Logical tree of emergency management process in detail of closing maneuvers

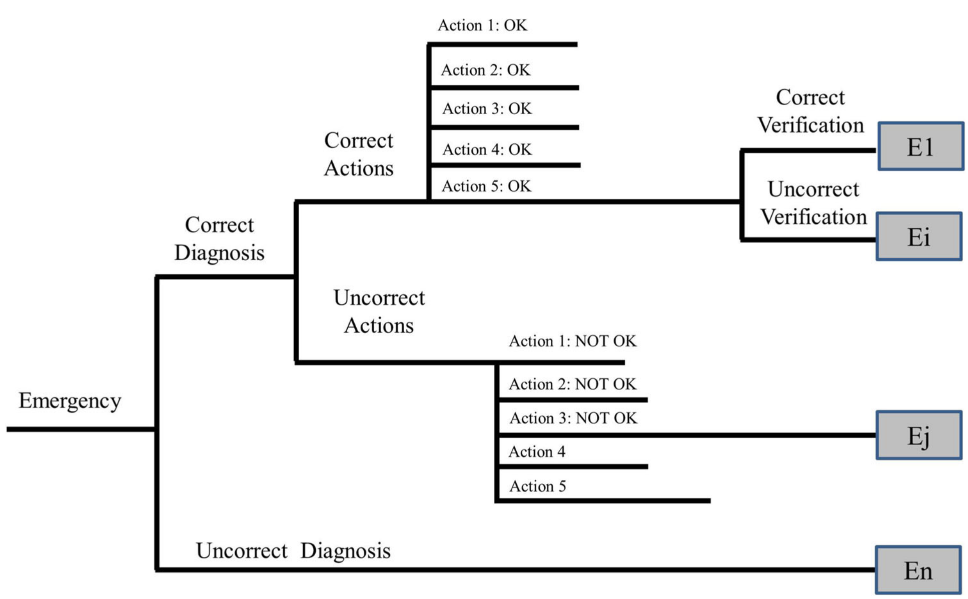


**Table 9** Numerical simulation results

| Outcomes | Dangerousness ($P$) | Vulnerability ($V$) | Critical index ($C$) |
|---|---|---|---|
| $E_1$ | $51.93 \times 10^{-2}$ | 0.05 | $2.60 \times 10^{-2}$ |
| $E_2 + E_3$ | $23.30 \times 10^{-2}$ | 0.1 | $2.33 \times 10^{-2}$ |
| $E_4 +\cdots+ E_8$ | $18.81 \times 10^{-2}$ | 0.2 | $3.76 \times 10^{-2}$ |
| $E_9 +\cdots+ E_{18}$ | $1.88 \times 10^{-2}$ | 0.4 | $7.53 \times 10^{-3}$ |
| $E_{19} +\cdots+ E_{28}$ | $9.41 \times 10^{-4}$ | 0.6 | $5.65 \times 10^{-4}$ |
| $E_{29} +\cdots+ E_{33}$ | $2.35 \times 10^{-5}$ | 0.8 | $1.88 \times 10^{-5}$ |
| $E_{34}$ | $2.35 \times 10^{-7}$ | 1 | $2.35 \times 10^{-7}$ |
| $E_{35}$ | $3.97 \times 10^{-2}$ | 1 | $3.97 \times 10^{-2}$ |

Figure 5 shows the logical tree of the emergency management process. Developing the tree diagrams gives a scenario with their possible outcomes. The activities linked to the closing operations of the plant are considered independent, the errors can be considered equally probable, and conditional probabilities to others errors remain unchanged compared to the probabilities of the individual errors.

Figure 6 shows in detail the decomposition of the elementary actions that constitute the set of the closing maneuvers.

The tree event provides 35 results. The worst case scenario of all is the one related to the error in the initial diagnosis. This gives rise, in an increase in the situation. All this leads us to consider a HEP = 1, the onset of the emergency condition and inadequate initial diagnosis.

The total probability of this scenario is therefore equal to the product of the probability of error in diagnosis, for HEP conditioning in this first error.

The 35th final outcome is defined as follows, see Eq 12:

$$P(E_{35}) = \mathrm{HEP}_{\mathrm{diag}} \quad \text{(Eq 12)}$$

If the initial diagnosis is correct, the next node is represented by the execution of closing operations through the commands of the console. With these assumptions, if the probability of error, associated with the single command, is called $p$, there are a series of variable entity scenarios. Equations from 13 to 17 represent the extremes of the ranges of variation of the probabilities associated with outcomes that provide for errors.

1. 5 scenarios consisting of a single error of 5 possible maneuvering commands, each scenario having a probability of occurrence (see Eq 13).

$$p \cdot (1-p)^4 \quad \text{(Eq 13)}$$

2. 10 scenarios consisting of 2 errors of 5 possible maneuvering commands, each scenario having a probability of occurrence (see Eq 14).

$$p^2 \cdot (1-p)^3 \quad \text{(Eq 14)}$$

3. 10 scenarios consisting of 3 errors of 5 possible maneuvering commands, each scenario having a probability of occurrence (see Eq 15).

$$p^3 \cdot (1-p)^2 \quad \text{(Eq 15)}$$

4. 5 scenarios consisting of 4 errors of 5 possible maneuvering commands, each scenario having a probability of occurrence (see Eq 16).

$$p^4 \cdot (1-p) \quad \text{(Eq 16)}$$

5. One scenario consisting of 5 errors of 5 possible maneuvering commands, each scenario having a probability of occurrence described (see Eq 17).

$$p^5 \quad \text{(Eq 17)}$$

The number of equivalent scenarios is determined by calculating the number of possible errors combinations in the commands associated with the block operations (Fig. 6).

The scenarios are equally likely to groups, and then the individual probability of error can be added together for each group, obtaining the probability of five errors (see Eq 18), the probability of four errors (see Eq 19), the probability of three errors (see Eq 20), the probability of two errors (see Eq 21) and the probability of one error (see Eq 22).

$$P(E_{34}) = (1-\mathrm{HEP}_{\mathrm{diag}}) \cdot p^5 \quad \text{(Eq 18)}$$

$$P(E_{29}) + \cdots + P(E_{33}) = (1-\mathrm{HEP}_{\mathrm{diag}}) \cdot 5 \cdot p^4 \cdot (1-p) \quad \text{(Eq 19)}$$

$$P(E_{19}) + \cdots + P(E_{28}) = (1-\mathrm{HEP}_{\mathrm{diag}}) \cdot 10 \cdot p^3 \cdot (1-p)^2 \quad \text{(Eq 20)}$$

$$P(E_9) + \cdots + P(E_{18}) = (1-\mathrm{HEP}_{\mathrm{diag}}) \cdot 10 \cdot p^2 \cdot (1-p)^3 \quad \text{(Eq 21)}$$

$$P(E_4) + \cdots + P(E_8) = (1 - \mathrm{HEP_{diag}}) \cdot 5 \cdot p \cdot (1-p)^4 \quad \text{(Eq 22)}$$

It is necessary to define the first three emergency scenarios. If all operations are correctly carried out, it is skipped to the next node, represented by the verification of the correct execution of maneuvers on the display.

The starting hypothesis is that the emergency arises at the end of the fifth hour worked, so $t = 5$.

To be able to calculate all probabilities (conditional and total) and to assign a value to each outcome hazard, it is important to calculate the error probability for all possible scenarios.

The verification can fail due to an "action" error or a "diagnosis" error. These two events, which define the final results $E_2$ and $E_3$, form a scenario that worsens the losing time management.

The two scenarios are independent, and the overall probability of error will be given by the sum of the two error probabilities associated with individual errors.

If the probability of failing the verification operation in the control room is shown, respectively, with $\pi_A$ to the error in action and with $\pi_D$ to the error in the diagnosis, it can calculate the probability of check error (see Eq 23).

$$P(E_2) + P(E_3) = (1 - \mathrm{HEP_{diag}}) \cdot (1-p)^5 \cdot (\pi_a + \pi_d) \quad \text{(Eq 23)}$$

The first outcome is reported to the highest branch of the tree chart, corresponding to the best scenario. For such scenario, the function becomes, see Eq 24:

$$P(E_1) = (1 - \mathrm{HEP_{diag}}) \cdot (1-p)^5 \cdot (1 - \pi_a - \pi_d) \quad \text{(Eq 24)}$$

If the blocking actions are dependent can not only indicate a probability value for such results, but to indicate a range of values.

The following are the details of the ranges of the probabilities associated with outcomes that provide for closure actions, see equation from (25) to (33)

$$5 \text{ errors} \Rightarrow P(E_{34}) = (1 - \mathrm{HEP_{diag}}) \cdot p \cdot (p^*)^4 \quad \text{(Eq 25)}$$

$$4 \text{ errors} \Rightarrow P_{\max}(E_{29} \div E_{33}) = (1 - \mathrm{HEP_{diag}}) \cdot (1-p) \cdot p \cdot (p^*)^3 \quad \text{(Eq 26)}$$

$$4 \text{ errors} \Rightarrow P_{\min}(E_{29} \div E_{33}) = (1 - \mathrm{HEP_{diag}}) \cdot p \cdot (p^*)^3 \cdot (1-p^*) \quad \text{(Eq 27)}$$

$$3 \text{ errors} \Rightarrow P_{\max}(E_{19} \div E_{28}) = (1 - \mathrm{HEP_{diag}}) \cdot (1-p)^2 \cdot p \cdot (p^*)^2 \quad \text{(Eq 28)}$$

$$3 \text{ errors} \Rightarrow P_{\min}(E_{19} \div E_{28}) = (1 - \mathrm{HEP_{diag}}) \cdot p \cdot (p^*)^2 \cdot (1-p*)^2 \quad \text{(Eq 29)}$$

$$2 \text{ errors} \Rightarrow P_{\max}(E_9 \div E_{18}) = (1 - \mathrm{HEP_{diag}}) \cdot (1-p)^3 \cdot p \cdot p^* \quad \text{(Eq 30)}$$

$$2 \text{ errors} \Rightarrow P_{\min}(E_9 \div E_{18}) = (1 - \mathrm{HEP_{diag}}) \cdot p \cdot p^* \cdot (1-p^*)^3 \quad \text{(Eq 31)}$$

$$1 \text{ error} \Rightarrow P_{\max}(E_4 \div E_8) = (1 - \mathrm{HEP_{diag}}) \cdot (1-p)^4 \cdot p \quad \text{(Eq 32)}$$

$$1 \text{ error} \Rightarrow P_{\min}(E_4 \div E_8) = (1 - \mathrm{HEP_{diag}}) \cdot p \cdot (1-p^*)^4 \quad \text{(Eq 33)}$$

On the 34th outcome, it is associated a vulnerability equals 1 resulting from mis-diagnosis, while for the other outcomes it is associated a vulnerability proportional to the number of operating errors.

The simulation is related to generic task B with $t = 8$.

The dangerousness is given by Eqs 23 and 24. The critical indices are given by Eq 10.

Table 9 describes the synthesis of the numerical simulation results.

The critical index of the overall system is 0.1347 (see Eq 34).

$$C_{\mathrm{imp}} = \sum_{i=1}^{n} P(E_i) \cdot V_i = \sum_{i=1}^{n} C_i = 13.47 \cdot 10^{-2} \quad \text{(Eq 34)}$$

The human reliability of the overall system is 7.8653 (see Eq 35).

$$R_{\mathrm{imp}} = \sum_{i=1}^{n} \{[1 - P(E_i)] \cdot V_i + (1 - V_i)\} = 786.53 \cdot 10^{-2} \quad \text{(Eq 35)}$$

The value of the system human reliability is 786.53%, because the entire system value is added in eight scenarios. Thus, the human reliability value of the system is subtracted from 800 (representing the 8 scenarios considered). This means that the 13.47% is the total expected loss, that is, the unreliability of the system.

## Discussion

The purpose of HEIE method is twofold. The first one is to carry out a critical assessment of different emergency scenario. The second one is to evaluate the obtained numerical results in order to make corrections and improvements. The criticality index increases with increasing of occurrence. So two scenarios with different hazards can be comparable in terms of criticality. Table 9 shows that four groups of scenarios associated with outcomes from 9° to 34° are not particularly significant critical for the structure. In fact, some of these events are so improbable as not to lead to significant values of the criticality index, despite their vulnerability.

The most criticalities are identified in the outcomes 1st, 2nd + 3rd, 35th and 4th + 8th. In fact, for all of these scenarios (or groupings of scenarios), the index of criticality of the system settles around the values of $(2\text{–}4)\cdot 10^{-2}$. The high criticality of the E35 scenario (wrong initial diagnosis) is not related to the probability of error in the diagnosis process, but to the conditional failure probability equal to 1 and therefore cannot recover this error. The vulnerability associated with this scenario is 1, the maximum. It is clear that the gravity diagnosis in the emergency operation is critical to the safety of plant and the success of the management recovery operations. The optimal outcome $E_1$ has a high criticality, because it has a high probability of occurrence. Therefore, in this criticality, it must be reduced by decreasing the vulnerability. Switch from a value of 0.05 as that suggested to the value of 0.01 would reduce the criticality of 5 times. This can be achieved by adopting organizational and logistics attentions inside the plant. $E_2 + E_3$ outcomes correspond to errors in the verification phase in the control room, after successful execution of the closing operations of the plants. The vulnerability is low, because the closure has been successful. However, the criticality value is high due to an overall hazard of 23.30%, mainly due to the danger connected with the diagnosis error. Some logistical improvements may limit the vulnerability. It is important to act on the dangers by strengthening the instrumentation of the control room, and especially, improving the man-machine interaction. A proper distribution of breaks could reduce the individual probability of error, especially during the last hours of the session. The group that sum scenarios $E_4 + \cdots + E_8$ has a total hazard of 19.00%. The vulnerability is low, so it has to act on the ergonomics of workstations and on the man-machine interaction. The probability of error of 3.76% is a fairly high value. It needs to lower the error rate over time with an appropriate distribution of work breaks, after the 3rd–4th hour. This fact would produce a discontinuity in Weibull function, leading to the most acceptable error rate values.

The obtained results make it possible to highlight the following improvement areas:

- Adoption of correction and improvement measures of activities and work processes (work breaks, improved ergonomics, strengthening the instruments for controlling, logistics improvements, reduced danger associated with the error in the initial diagnosis);
- Investments to process improvement;
- Introduction of organizational measures to improve safety in the plant;
- Upgrades of the analytical method and the scenario simulator;
- Refinement of the method of analysis, introducing additional site-specific parameters.

## Conclusions

The aim of this work was to develop a new methodological approach based on Human Reliability Analysis to evaluate human error during an emergency condition. The model is applied in a real case study concerning emergency activities in the control room of a petrochemical plant. Based on a hybrid approach that integrates HEART and SPAR-H techniques, the HEIE method represents a new way to evaluate the human error. The proposed method involves the use of performance shaping factors, which allow the inclusion of all environmental and behavioral factors that influence the decisions and the actions of man. Results show that it is possible to obtain a realistic analysis according to the conditions in which the operations are carried out during the emergency management. The numerical results can be used to formulate considerations about the continuous improvement of the processes and the reduction of occupational risk. The calibration of the mathematical model and the characterization of the parameters have been proposed by the HEIE methodology, with the aim of producing, as a final result, a quantification of the contextualized probability of error, that is an error rate comprising all the factors considered to be of influence on the operator's performance. The HEIE model can be effectively used to evaluate changes in human error probability when changes occur in type of activity. The generality of the method and the flexibility of the tools make it theoretically applicable to a wide range of productive activities.

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