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A probabilistic tool for multi-hazard risk analysis using a bow-tie approach: application to environmental risk assessments for geo-resource development projects

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Abstract In this paper, we present a methodology and a computational tool for performing environmental risk assessments for geo-resource development projects. The main scope is to implement a quantitative model for performing highly specialised multi-hazard risk assessments in which risk pathway scenarios are structured using a bow-tie approach, which implies the integrated analysis of fault trees and event trees. Such a model needs to be defined in the interface between a natural/built/social environment and a geo-resource development activity perturbing it. The methodology presented in this paper is suitable for performing dynamic environmental risk assessments using state-of-the-art knowledge and is characterised by: (1) the bow-tie structure coupled with a wide range of probabilistic models flexible enough to consider different typologies of phenomena; (2) the Bayesian implementation for data assimilation; (3) the handling and propagation of modelling uncertainties; and (4) the possibility of integrating data derived form integrated assessment modelling. Beyond the stochastic models usually considered for reliability analyses, we discuss the integration of physical reliability models particularly relevant for considering the effects of external hazards and/or the interactions between industrial activities and the response of the environment in which such activities are performed. The performance of the proposed methodology is illustrated using a case study focused on the assessment of groundwater pollution scenarios associated with the management of flowback fluids after hydraulically fracturing a geologic formation. The results of the multi-hazard risk assessment are summarised using a risk matrix in which the quantitative assessments (likelihood and consequences) of the different risk pathway scenarios considered in the analysis can be compared. Finally, we introduce an open access, web-based, service called MERGER, which constitutes a functional tool able to quantitatively evaluate risk scenarios using a bow-tie approach.

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Abbreviations

Acronym	Definition
BE	Basic event (of a fault tree)
BT	Bow-tie analysis
EPOS-IP	European Plate Observing System - Implementation Phase (European project)
ERA	Environmental risk assessment
ET	Event tree
E(x)	Mean value of x
FT	Fault tree
HazMat	Hazardous materials
HPP	Homogeneous Poisson process
IAM	Integrated assessment modelling
IS-EPOS platform	Platform for Research into Anthropogenic Seismicity and other Anthropogenic Hazards, developed within IS-EPOS project
Λ	Equivalent sample size
MERGER	Simulator for Multi-hazard risk assessment in ExploRation/exploitation of GEoResources
MHR	Multi-hazard risk
PRM	Physical reliability model
SD(x)	Standard deviation of x
SHEER	Shale gas exploration and exploitation induced risks (European project)
TCS	Thematic core service (in EPOS-IP project)
TCS-AH	Anthropogenic hazards thematic core service
TE	Top event (in a fault tree)

1 Introduction

The term *geo-resources* is generally referred to any kind of geological resource (as, e.g. geo-energy, any kind of mineral resources, as well as underground space used to store or dispose materials) used by the modern human society. The exploration and exploitation of geo-resources may strongly impact the surrounding environment, and for this reason such industrial activities need to be carefully planned, including reliable environmental risk assessment (ERA) analyses. A multi-hazard risk (MHR) analysis aims at providing a theoretical framework for harmonising the methodologies employed and the results obtained from risk assessments (i.e. likelihood and consequences) considering different risk sources and taking into account possible interactions among events (e.g. Marzocchi et al 2012; Gasparini and Garcia-Aristizabal 2014; Liu et al 2015).

The implementation of a MHR assessment tailored to assess environmental risks associated with the development of geo-resources needs to be defined in the interface between a natural/built/social environment and an industrial activity perturbing it. This combination makes such a kind of application an interesting challenge that requires considering different specific issues as the following: (1) it has to take into account the possibility of multiple natural and anthropogenic hazards as possible triggering mechanisms; such hazards can be either of natural origin, occurring underground (as, e.g. natural earthquakes), in the atmosphere (as, e.g. extreme meteorological events) or at the air/ground interface, or anthropogenic events caused by the same industrial activities (as, e.g. subsidence, induced seismicity); (2) failures might propagate through the industrial elements, leading to complex scenarios according to the setting of the industrial site; (3) it has to consider the possibility of impacting different typologies of environmental (as, e.g. the air, soil, surface water, or groundwater) and man-made exposed elements (e.g. Garcia-Aristizabal et al 2017).

The adopted method for MHR assessment relies on the quantification of the likelihood and related consequences of identified risk pathway scenarios (e.g. Fig. 1a) structured using a *bow-tie* (BT, Fig. 1b) approach (e.g. Bedford and Cooke 2001; Rausand and Høyland 2004). The BT is widely used in reliability analysis and has been proposed for assessing risks in a number of geo-resource development applications, as for example in offshore oil and gas development (e.g. Khakzad et al 2013, 2014; Yang et al 2013) and for the mineral industry in general (e.g. Iannacchione 2008).

The BT analysis, in particular, provides an adequate structure to perform detailed assess-

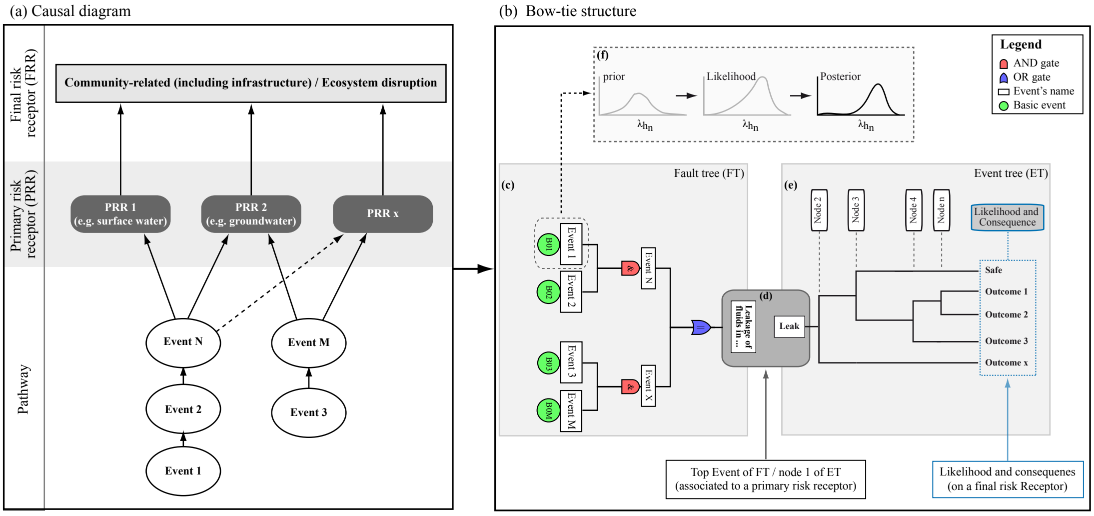

Fig. 1 (a) generic causal diagram used for qualitative structuring of a set of scenarios; (b) bow-tie structure for a determined scenario of interest (modified from Garcia-Aristizabal et al 2017); (c) fault tree component of the bow-tie structure; (d) critical event linking the fault tree and the event tree; (e) event tree component of the bow-tie structure; (f) Bayesian inference of the parameters of the probabilistic models used to define basic events in fault trees and nodes in event trees.

ments of the probability of occurrence of events or chains of events in a given accident scenario. It is targeted to assess the causes and effects of specific critical events; it is composed of a *fault tree* (FT, Fig. 1c), which is set by identifying the possible events causing the critical or *top event* (TE, Fig. 1d), and an *event tree* (ET, Fig. 1e), which is set by identifying possible consequences associated with the occurrence of the defined TE (e.g. Rausand and Høyland 2004). Therefore, in the BT structure, the top event of the FT constitutes the initiating event for an ET analysis.

The FT is a graphical representation of various combinations of basic events that lead to the occurrence of the undesirable critical situation defined as the TE (e.g. Bedford and Cooke 2001). Starting with the TE, all possible ways for this event to occur are systematically deduced until the required level of detail is reached. Events whose causes have been further developed are *intermediate events*, and events that terminate branches are *basic events* (BE). The FT implementation is based on three assumptions: (1) events are binary events (do occur/ don't occur); (2) basic events are statistically independent; and (3) relationships between events are represented by means of logical Boolean gates (mainly AND, OR). The probability of occurrence of the TE is calculated from the occurrence probabilities of the BEs.

The ET is an inductive analytic diagram in which an event is analysed using logical series of subsequent events or consequences. The overall goal of the ET analysis in this context is to determine the probability of possible consequences resulting from the occurrence of a determined initiating event. Moreover, most industrial systems include various barriers and safety functions that have been installed to stop the development of accidental events or to reduce their consequences; these elements should be considered in the consequence analysis.

The quantitative assessment of the scenarios implemented in a BT structure is based on the probabilities assigned to the basic events of the FT and to the nodes of the ET. In this work, the BT logic structure is coupled with a wide range of probabilistic tools that are flexible enough to make it possible to consider in the analyses different typologies of phenomena. Furthermore, since the risk scenarios associated with geo-resource development activities are likely to include events closely related to geological, hydrogeological, and geomechanical processes in underground rock formations and with limited access to direct measurements, alternative modelling mechanisms for retrieving reliable data need to be considered.

In this paper, we present a MHR assessment approach to assess environmental risks related to geo-resource development projects.

The performance of the proposed methodology is illustrated using a synthetic case study focused on the assessment of groundwater pollution scenarios associated with the management of flowback fluids resulting from the hydraulic fracturing of a geologic formation. Finally, we introduce a web-based service that provides a functional tool able to quantitatively evaluate, from bottom to top, risk pathway scenarios using a bow-tie approach.

2 Methodology

A quantitative MHR analysis applied to assess environmental risks associated with georesource development activities can be implemented following a similar approach as usually adopted in reliability analysis (see, e.g. Rausand and Høyland 2004). In summary, it relies on the following main elements: (a) the identification and description of potential accidental scenarios (Fig. 2a); (b) the structuring of identified scenarios using a bow-tie approach (Fig. 2b); (c) the probabilistic assessment of the structured scenarios, which rely on the probability models assigned to basic events of the fault trees and the nodes of the event trees (Fig. 2c); and (d) for each structured scenario, assessment of the consequences associated with the outcome of each path of the ET.

The output of the probabilistic analysis, combined with the consequence assessment, provides as result a detailed ERA. In the following paragraphs, we describe the main characteristics of probabilistic analysis of the MHR approach for ERA proposed in this paper. Furthermore, a practical implementation of the consequence assessment that complements the BT analysis is illustrated in the case study presented in sections 3 and 4.

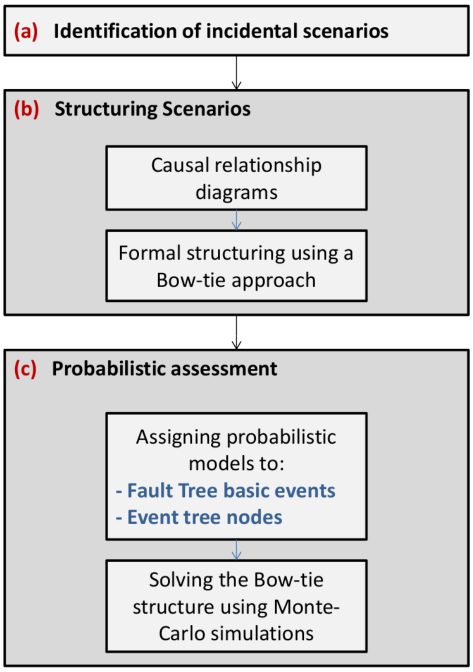

Fig. 2 General approach for quantitative multi-hazard risk assessments. (a) identification of incidental scenarios; (b) structuring incident scenarios using a bow-tie approach; (c) assigning probabilistic models to basic events (FT) and event tree nodes, and solving the bow-tie structure to obtain the results.

2.1 Identification of risk pathway scenarios

This step is referred to the identification and description of potential accidental events in the analysed system (Fig. 2a). An accidental event is usually defined as a significant deviation from normal operating conditions that may lead to unwanted consequences. In the oil/gas industry, for example, an oil leak on a surface water body may be considered an accidental event. The scenario identification process is generally based on a deep analysis of the system as well as a literature review of potential impacts in different risk receptors of interest. The results of such screening are condensed in causal diagrams as the one shown in Fig. 1a, which constitute the base to assemble risk pathway scenarios in a bow-tie structure. A detailed example of the process of risk pathway scenarios identification and causal diagram preparation applied to shale gas development can be found in Garcia-Aristizabal et al (2017).

2.2 Structuring risk pathway scenarios using a bow-tie approach

The core of the quantitative MHR analysis is performed structuring the risk pathway scenarios using a BT approach (Fig. 1b). The BT approach may provide a qualitative and a quantitative representation of a given scenario. Qualitatively, a BT clearly illustrates the logical relationships among the components of an accident scenario; moreover, quantitative analyses can be performed by assigning probabilities to the BEs of the FT and the nodes of the ET.

In the following sections of this paper, we discuss different probabilistic models necessary to represent different processes of interest for the quantitative analysis of risk scenarios related to geo-resource development projects.

For convenience in the modelling process, the possible risk receptors are divided in two groups (for details, see Garcia-Aristizabal et al 2017): *primary risk receptors* and *final risk receptors* (Fig. 1). The primary risk receptors are basically the environmental elements that potentially might be affected by the industrial activity associated with a given geo-resource development project. Examples of primary risk receptors are therefore the groundwater, surface water, air, soil, the solid rock matrix (e.g. by transient or permanent deformations), etc. Conversely, the final risk receptors are elements that can be potentially impacted indirectly through the impacts in a primary risk receptor. Clearly, there are two main categories of final risk receptors: the communities (that includes e.g. the building environment and the socio-economic elements) and the ecosystems localised in the surroundings of a geo-resource development project.

Given the different categories of risk receptors of interest, in this kind of application we suggest the following general criteria for structuring the MHR scenarios in a BT:

1. Impacts to primary risk receptors can be chosen as critical TEs for constructing fault trees. It is worth noting that TEs have to be well-specified events (e.g. what and where it happens?); an example of a specific top event definition (TEx) is: *pollution of groundwater due to the leakage on-site of hazardous materials (HazMat).*
2. Identification of the boundary conditions with respect to external stresses. In this way, we define the type of hazards that need to be included in the analysis. Following the example in the previous point, the TEx critical event can occur, e.g. due to a failure in a HazMat containment element (e.g. a tank). The failure of such an element can be assessed considering different cases, as, e.g. failures caused by material fatigue, impacts form external hazards as earthquakes, extreme meteorological events, terrorism, etc. Therefore, the level of detail reached while developing the scenario determines the boundaries for the analysis.
3. For each TE identified, a deductive technique is used to identify the possible causes of such a critical event, considering the boundary conditions defined and the level of resolution of the analysis.
4. The identified TEs are also the starting points of consequence analysis, which can be evaluated for considering both, the *magnitude* of the impact on the primary risk receptor, and the impacts on final risk receptors of interest.

2.3 Probabilistic models for defining basic events in fault trees

The quantitative assessment of the scenarios implemented in a BT structure is based on the probabilistic models assigned to the basic events of the FT and to the nodes of the ET. It is worth noting that major risks are rare events for which scarce or no data are usually available. It is therefore useful to adopt a probabilistic framework that allows us to coherently integrate all the useful information and to update assessments as site-specific data are retrieved. The approach presented in this paper is designed so that the results can be updated as new data becomes available; in this way, the assessments can be adjusted to the dynamic environment that usually characterises operations for the development of geo-resources.

The MHR assessment approach presented in this paper includes the following five classes of probabilistic models for implementing the stochastic characteristics of FT's basic events:

- Homogeneous Poisson process;
- Binomial model;
- Weibull model;
- Static physical reliability models;
- Dynamic physical reliability models;

Most of these models have been implemented using Bayesian data analysis techniques. Bayesian methods have gained some popularity in probabilistic risk assessment (e.g. Siu and Kelly 1998); the advantage of such a formulation is that it is possible to set a *prior* state of knowledge and to define a likelihood function using site-specific data, to produce an *updated* posterior state of knowledge (for each BE of the FT or node of the ET) combining prior and likelihood functions (see, e.g. Fig. 1f).

In practice, considering a given BE (or ET node) of interest, a *prior* state of knowledge can be set using generic information as, for example, data from similar cases, the use of integrated assessment modelling, and/or by the elicitation of experts. The probabilities obtained from the initial generic data can be then updated using the Bayes' theorem (through a likelihood function) as site-specific new data becomes available.

In this section, we briefly indicate the main features of the implemented models, as well as the input/output parameters required for defining a given BE according to these models. A detailed description of the mathematical background is presented in Appendixes A and B.

2.3.1 Homogeneous Poisson process (HPP)

A constant event rate implies that events are generated by a Poisson process. In this case, the inference problem is to estimate the rate of event occurrence (λ) per time unit. For simplicity, we adopt the conjugate pair Poisson likelihood / gamma prior (e.g. Gelman et al 1995), which is one of the most frequent models used in risk assessment applications (e.g. Siu and Kelly 1998). A prior distribution for λ can be developed from other generic data (as, e.g. data from similar cases or components, or from expert opinion elicitation).

The prior state of knowledge can be defined using the actual analyst's knowledge of a best prior estimate of the rate [which is set as the *mean* prior value, $E(\lambda)$] and a standard deviation, $\mathrm{SD}(\lambda)$, as a measure of the uncertainty in the prior best value. These two estimates are then used for setting the parameters of the gamma prior distribution (for details see the section A.1 in Appendix A). The (Poisson) likelihood function is set for encoding the site-specific data which, for a HPP is basically the number of events r occurred in a time interval $\Delta t = [0, t]$. Table 1 summarises the data required for defining a basic event as a homogeneous Poisson process.

Once the posterior distribution for λ, $\pi_1(\lambda|E)$, has been calculated (see Eq. 8 in Appendix A), samples of λ are drawn from the posterior distribution and used to calculate the probability of at least one event occurring in a determined period of time of interest (according to Eq. 10 in Appendix A) which, by default, is set to 1 year.

2.3.2 Binomial model

The standard solution for events occurring out of a number of trials uses the binomial distribution (e.g. Siu and Kelly 1998). This model assumes that the probability ϕ of observing r events (e.g. failures) in n trials is independent of the order in which successes and failures occur. The inference problem in this case is to estimate the value of the ϕ parameter of the binomial distribution, which may be uncertain due, for example, to a low number of trials. If ϕ is uncertain, then we can define a probability distribution for ϕ. For simplicity, in this case we adopt also the conjugate pair binomial likelihood / beta prior (another frequent model used in risk assessment applications).

r and n are site-specific observations and the input data required for setting the (binomial) likelihood function. On the other hand, the prior beta distribution is characterised by two parameters (α and β) whose definition might not be intuitive. Therefore, to set the model parameters of the prior distribution, we make use of indirect measures that can be more easily defined by an analyst. In practice, we identify an *average* value as the best prior estimate of the ϕ parameter and a measure of the degree of uncertainty related to that estimate. To define the degree of uncertainty in the *best-estimate* value we use the so-called *equivalent sample size* (or *equivalent number of data*), Λ, with $\Lambda > 0$, as defined in Marzocchi et al (2008) and Selva and Sandri (2013). Λ can be interpreted as the quantity of data that the analyst expects to have at hand in order to modify a prior belief regarding the value of the ϕ parameter. It means that the larger Λ, the more confident the analyst is about the prior state of knowledge. For example, setting $\Lambda = 1$ the analyst is expressing a maximum uncertainty condition, implying that just one singe observation can substantially modify the prior state of knowledge.

It is worth noting here that the definition of θ and Λ needs to be consistent. For example, if a prior belief regarding a given event indicates a prior value of θ in the order of 1×10^{-6}, it means that the analyst is quite confident that the event's probability is very low (in other words, there is low epistemic uncertainty regarding this parameter); in such a case, a high Λ value is required to reflect the low epistemic uncertainty regarding this prior belief (i.e. set-

Table 1 Parameters required for setting a basic event of class *HPP*

Element	Parameter	Description
Prior distribution	$E(\lambda)$, $[0 \geq E(\lambda) \geq 1]$	Prior assumption for the mean value for the rate of event occurrences (lambda)
	$SD(\lambda)$	Standard deviation of the prior mean value
Likelihood function	r, $(r \geq 0)$	Number of events occurred in a time interval Δt
	Δt, $(\Delta t > 0)$	Observation time (in years)

ting, e.g. $\Lambda = 1$ in such a case would be inconsistent with that prior belief). It is difficult to define a *rule of thumb* for setting θ and Λ; indicatively, we can assume that the absolute value of the order of magnitude of θ provides a rough indication about the order of magnitude of the equivalent sample size (or *trials*) required for obtaining such estimation. Therefore, for a consistent definition of Λ we can consider, in general, that *extreme* (high or low) θ values usually imply high confidence (i.e. event is very likely or very unlikely) and therefore a high value of Λ.

Table 2 summarises the data required for defining a binomial basic event. Once the posterior distribution for ϕ, $\pi_1(\phi|E)$, has been calculated (see the section A.2 of Appendix A), samples of ϕ values are drawn from the posterior distribution to define the probability of a binomial BE.

2.3.3 The Weibull model

The Weibull distribution has been identified as one of the most useful distributions for modelling and analysing lifetime data in different areas as engineering, geosciences, biology, and other fields (see, e.g. Garcia-Aristizabal et al 2012). In this approach, the Weibull distribution is used for describing systems with a time-dependent hazard rate in which the probability of an event occurrence is dependent on the time passed from the last event.

The Weibull distribution is characterised by two parameters ($\lambda > 0$ and $k > 0$) and is defined for positive real numbers (e.g. Leemis 2009). The mathematical description of this model is presented in section A.3 of Appendix A. k determines the time-dependent behaviour of the hazard rate: for $k < 1$, the hazard rate decreases with time; for $k = 1$, the hazard rate is constant with time (equivalent to a homogeneous Poisson process), while for $k > 1$, the hazard rate increases with time (i.e. as in an ageing or wearing process). Given the typology of applications in which the MHR model is applied here, the cases of main interest are those for which $k \geq 1$.

In the MHR approach presented in this paper, the Weibull model is used to calculate the conditional probability that an event happens in a time interval $(x, x, +\Delta t)$, given an interval of $x = (\tau - \tau_L)$ years since the occurrence of the previous event, where τ the *current* time of the assessment and τ_L the time form the last event (Eq. 17 in section A.3 of the Appendix A).

The definition of a BE using the Weibull model in the MHR approach presented in this paper requires setting five parameters, as described in Table 3; beyond the values of the two parameters of the distribution (λ, k), the uncertainties in the model parameter values are also required. Likewise, since this model is used for including processes with a time-dependent hazard rate, it is also necessary to set T_o, the time passed since the last event (or, in the case of modelling an element's wearing/ageing, it the time that the element has been operating).

2.3.4 Considering external perturbations through physical reliability models

The *physical reliability models* (PRM) aim to explain the probability (or the rate) of event occurrences (as e.g. hazardous events and/or system failures) as a function of operational physical parameters (e.g. Dasgupta and Pecht 1991; Ebeling 1997; Melchers 1999; Hall and Strutt 2003; Khakzad et al 2012). PRM are often used in reliability analysis for describing degradation and failure processes of both mechanical and electronic components (Carter 1986; Ebeling 1997).

We consider that this typology of modelling approach may be of particular interest for MHR assessments applied to geo-resource development activities because they allow to introduce in the

Table 2 Parameters required for setting a binomial basic event

Element	Parameter	Description
Prior distribution	θ, $[0 \geq \theta \geq 1]$	Prior assumption for the mean value for the event probability (e.g. failure)
	Λ, $(\Lambda > 0)$	Equivalent sample size required for modifying a prior belief
Likelihood function	r, $(r \geq 0)$	Number of events (e.g. failures), out of n trials
	n, $(n \geq 0)$	Number of trials performed

Table 3 Parameters required for setting a basic event of Weibull class

Parameter	Description
λ, $(\lambda > 0)$	Scale parameter (best estimate, determined, e.g. by the max. likelihood method)
$\delta\lambda$, $(\delta\lambda > 0)$	The error (standard deviation) of the scale parameter value
k, $(k \geq 0)$	Shape parameter (best estimate, determined, e.g. by the max. likelihood method)
δk, $(\delta k \geq 0)$	The error (standard deviation) of the shape parameter value
T_o, $(T_o \geq 0)$	Time (in years) passed from last event. In the case of modelling an element's wearing/ageing, it can be considered as the element's operation time

analysis (1) simple cases of expected damage to system's elements caused by generic loads (as, e.g. external hazards as earthquakes, or extreme meteorological events), and (2) to consider operational parameters as covariates in the process of modelling event rate occurrences or probabilities. A number of physical reliability models have been proposed in reliability analysis; for the approach presented in this paper, we are particularly interested in implementing two typologies of PRM: (1) static and (2) dynamic PRM.

Static PRMs - We implement Static PRM as a basic template for assessing damage probabilities of elements exposed to generic loads (e.g. external hazards). This typology of models has been widely used in risk assessments associated with natural hazards, mostly in the field of seismic risk analysis (e.g. EERI Committee on Seismic Risk 1989, among many others).

For a generic conceptual description of the static PRM implemented in this work, we take as reference the random shock-loading model (e.g. Ebeling 1997; Hall and Strutt 2003). This is a simple model in which it is assumed that a variable stress load L is applied, at random times, to an element (e.g. a system's component or infrastructural element) which has a determined capacity to support that load (hereinafter called *strength*). Stresses are, in general, physical or chemical parameters affecting the component's operation. In probabilistic hazard assessment, such stresses are often called *intensity measures* (e.g. Burby 1998). On the other hand, the strength is defined as the highest amount of stress that the component can bear without reaching a determined *damage state* (which can be defined at different degrees of criticality, as for example a failure, a moderate damage, etc).

A distribution function of the intensity measure (stress), associated with reaching a given damage state, is what in the risk assessment practice is usually called as a fragility function (e.g. Kennedy et al 1980). According to this basic model, a given damage state (e.g. failure) occurs when the stress on the component exceeds its strength (e.g. Hall and Strutt 2003). The mathematical description of the implemented model is presented in section B.1 of the Appendix B. Stress and strength can be constant or considered as random variables having known probability distribution functions.

Dynamic PRMs - Dynamic PRMs aim to explain the event occurrence (e.g. the failure of a component) as a multivariate function of operational physical parameters (e.g. Ebeling 1997; Khakzad et al 2012). Operational physical parameters that can be used as covariates may include, among others, temperature, velocity, pressure, vibration amplitude, fluid injection rates, etc. The dynamic PRMs are considered in this approach assuming that it is possible to identify either:

1. A relationship between operational or external parameters of interest and the rate

of occurrence of events stressing the system (i.e. at the *hazard* level); or,

2. A relationship between operational or external parameters and the strength of components of interest (i.e. at the *vulnerability* level).

The mathematical description of the implemented model is presented in section B.2 of the Appendix B. In the first case (i.e. covariates linked to the stress component), we assume that the rate of occurrence of the loading process (hazard) may be modulated as a function of one or more covariates of interest (see Eq. 24 in Appendix B). Such a model is implemented by defining a probability distribution for modelling the rate of the loading process, and the parameters of that distribution are allowed to change as a function of the selected covariates of interest. Examples of hazard-related covariate model implementations of interest for MHR assessments are the covariate approaches for modelling time-dependent extreme events (e.g. Garcia-Aristizabal et al 2015), and the model for assessing induced seismicity rates as a function of the rate at which fluids are injected underground (Garcia-Aristizabal 2018).

In the second case (i.e. covariates linked to the strength component), the covariates are linked to the parameters of the distribution used to model the probability of reaching a determined damage state (e.g. failure) of an element of interest (see Eq. 25 in Appendix B). Examples of models for performing analysis in this case have been presented, for example, by Hall and Strutt (2003) and Khakzad et al (2012).

The implementation of these models into the MHR approach can be done according to the following general procedure (a detailed example of a specific implementation can be found in Garcia-Aristizabal 2018):

1. Identification of informative variables that can be correlated with the rate of occurrence of determined events of interest.
2. Identification of a probability distribution to be used as a basic template for describing the process under analysis.
3. Inference of the parameter values of competing deterministic models relating the parameter(s) of the selected template distribution and the covariate(s) of interest, as well as the definition of an objective procedure for model selection.
4. Testing the performance of the selected model by comparing model forecasts with actual observations.

Once the model has been calibrated and tested, it can be used to calculate the probability of the BE of interest as a function of the values taken by the selected covariates.

2.4 Model for assessing nodes in the event trees: binomial and multinomial distributions

In this section, we focus the attention on the probabilistic tools implemented for modelling nodes in the event tree part of the BT structure. ET nodes are often defined as binary situations characterised by two possible outcomes (e.g. yes/no, works/fails, etc.); in such cases, event probabilities are defined using the binomial model described in the previous section (see also section A.2 in Appendix A). Nevertheless, when constructing an ET for assessing consequences it is often required to set nodes with more than two mutually exclusive events. For example, if the starting event of an ET is the leakage of certain hazardous material (HazMat) on surface water, the subsequent node of the ET can be set to assess the probability that the leaked volume is *large*, *medium*, or *small* (according e.g. to some pre-defined thresholds).

To set event probabilities in such cases, we implement the *multinomial* model, that is a generalisation of the binomial case. It can be set for cases in which there are n possible mutually exclusive and exhaustive events at the ET's node, each event with probability ϕ_i (where, for a given node, $\sum_{i=1}^{n} \phi_i = 1$).

We perform Bayesian inference of the ϕ_i parameters, adopting for simplicity the conjugate pair multinomial likelihood / Dirichlet prior (e.g. Gelman et al 1995). The mathematical definition of the multinomial model can be found in section A.4 of Appendix A).

The parameters required for setting the multinomial model are summarised in Table 4. To set the model parameters of the prior distribution we follow a similar approach as the one used for the binomial model; for the analyst it is usually easier to set an *average* value as the best prior estimate of each parameter (i.e. the probability ϕ_i for the ith event) and to define a degree of confidence on such estimate. Therefore, the parameters of the Dirichlet prior distribution are set adopting an approach analogue to the one presented for the beta distribution (Marzocchi et al 2008), in which it is possible set the prior state of knowledge by defining (1) a vector of *n best estimate* values, θ_i, and (2) an estimate of the uncertainty associated with these prior estimations using the *equivalent sample size*, Λ (which, as defined, is a number representing the quantity of data that the analyst expects to have in order to modify the prior values).

2.5 FT and ET evaluation using Monte Carlo simulations

A BT structure is quantitatively assessed by using the probability data from the BEs of the FT and the nodes of the ET. Large and complex BTs require the aid of analytic- or simulated-based methods for evaluation (e.g. Ferdous et al 2007; Rao et al 2009; Yevkin 2010; Taheriyoun and Moradinejad 2014).

We use Monte Carlo simulations for evaluating the FT and ET components of the risk pathway scenarios structured in a BT approach. The system is structured as follows: first, the FT is solved using Monte Carlo simulations by sampling the probability distributions defined for each BE. In this way, we obtain an empirical distribution for the probability of the critical top event of the FT. Empirical distributions of intermediate events of interest are also provided as an intermediate output.

Second, the empirical distribution obtained for the TE's probability is assigned to the initial node of the related ET, and the outcome of the ET is also assessed using Monte Carlo simulations. The algorithms implemented for solving the FT and ET components of the BT structure are described in Appendix C.

2.6 Integrated assessment modelling

Many of the events of interest for MHR assessments in geo-resource development projects are rare events that, by definition, are characterised by very low occurrence probabilities. Contrary to what usually happens with pure industrial applications, many risk pathways associated with geo-resource development activities involve elements intrinsically related to features of underground geological formations (as, e.g. rock fracture connectivity, fluid flow through porous media, pore pressure perturbations, induced seismicity, etc.) for which direct measurements may be very limited or even unavailable. It is for this reason that we explore alternative sources of information for retrieving useful data for setting a prior state of knowledge for a determined BE, intermediate event or node in the BT structure.

Integrated assessment modelling (IAM) is a tool used for tracking complex problems in which obtaining information from direct observations or measurements is challenging. IAM has been widely used, for example, for the implementation of climate policies that require the best possible understanding the potential impacts of climate change under different anthropogenic emission scenarios (see, e.g. Stanton et al 2009). In the field of geo-resources development, IAM has been used for example to quantify the engineering risk in shale gas development (Soeder et al 2014).

IAM usually tries to link in a single modelling framework the main features of a system under analysis, taking into account the uncertainties in the modelling process. An IAM application to MHR assessment can be implemented to understand how a determined geologic or environmental system, of interest in a given BE (FT) or node (ET), behaves under determined conditions. Furthermore, it may rely on a combination of multiple data sources as numerical modelling or field measurements.

However, physical/stochastic modelling can be a time- and computationally expensive activity, constituting a limit to the implementation of physically based IAM in many practical applications. The use of expert judgement elicitation techniques is an alternative (or complementary) tool that is often used for evaluating rare or poorly understood phenomena.

The elicitation is the process of formally capturing judgement or opinion from a panel of recognised experts regarding a well-defined problem, relying on their combined training and expertise (Meyer and Booker 1991; Cooke 1991). Structured elicitation of expert judgement has been widely used for supporting probabilistic hazard and risk assessment in different contexts, for example for seismic hazard assessment (e.g. Budnitz et al 1998), and volcanic hazards and risk (e.g. Aspinall 2006).

The outcome of IAM, therefore, can be used to set the probability of a determined BE (or ET's node) for which no direct data is avail-

Table 4 Parameters required for setting the multinomial model

Element	Parameter	Description
	n	number of possible mutually exclusive and exhaustive events in a determined node of the ET
Prior distribution	θ_i $(0 \geq \theta_i \geq 1)$	Prior assumption for the mean value for the ith event probability $(i = 1, \ldots, n)$
	Λ $(\Lambda > 0)$	equivalent sample size required for modifying a prior belief
Likelihood function	$y = (y_1, \ldots, y_n)$ $(y_i \geq 0)$	Data vector (y_i); number of *successes* relative to the ith event

able. An example of IAM of interest for MHR assessment applied to the development of geo-resources has been developed in the framework of the European project SHEER (Shale gas exploration and exploitation induced Risks), where IAM has been used to assess a risk pathway scenario in which the connectivity of rock fracture networks connecting two zones of interest is a BE of interest (for details see, Garcia-Aristizabal 2017).

3 Case study implementation and data

A simple synthetic example is implemented to perform, step by step, an illustrative quantitative MHR assessment using the main elements of the proposed methodology. The analysis is focused on the assessment of the possible pollution of an underground reservoir of drinking water during the management of flowback fluids after hydraulically fracturing a geologic formation for unconventional gas development.

Hydraulic fracturing is a method used to stimulate or improve fluid flow from rocks in the subsurface. Once the hydraulic fracturing procedure is completed and pressure is released, the direction of fluid flow reverses. Flowback fluids include (1) the fracturing fluids (water and additives) pumped into the well, (2) any new compounds that may have formed due to reactions between additives, and (3) substances mobilised from the geologic formation due to the fracturing operation (see, e.g. NYSDEC 2011). Hydraulic fracturing waste water can be stored in tanks or pits prior to disposal or recycling; flowback water disposal options usually considered are (a) injection wells, (b) municipal sewage treatment facilities, and (c) industrial treatment plants (NYSDEC 2011).

In this theoretical exercise we consider the following case study: a determined volume of flowback fluids, V_f is stored on-site in N_c containment units (as, e.g. tanks, pits, etc) before being transported to a final disposal located at a travel distance D_t. The objective of the analysis is to assess the risk of polluting an underground aquifer of drinking water. For simplicity, we assume that the groundwater body is extended along the whole area of interest for this analysis (that is, it is extended in the whole area that comprises the well site and the disposal site).

Two scenarios are considered in the analysis: (1) groundwater pollution caused by a spill outside of the site related to a volume of flowback fluid being transported from the well site to a disposal site; (2) groundwater pollution caused by a surface spill within the site related to the failure of a storage unit (e.g. a tank) containing the flowback fluids.

3.1 Groundwater pollution related to a spill of flowback fluid being transported from the well site to a disposal site

The main mechanism identified in this scenario is a truck accident. Figure 3 shows a simple FT for this example, which considers three BEs that are defined as shown in Table 5.

3.1.1 Accident of a truck transporting flowback fluids outside the well site (B01)

This event is implemented using the binomial model. A prior state of knowledge is set by using statistical data from literature, namely (1) the annual number of HazMat truck crashes (N_{cr}) and (2) the total number of HazMat shipments each year (N_{sh}) in a given region. The parameter θ_{B01} of the prior distribution (see

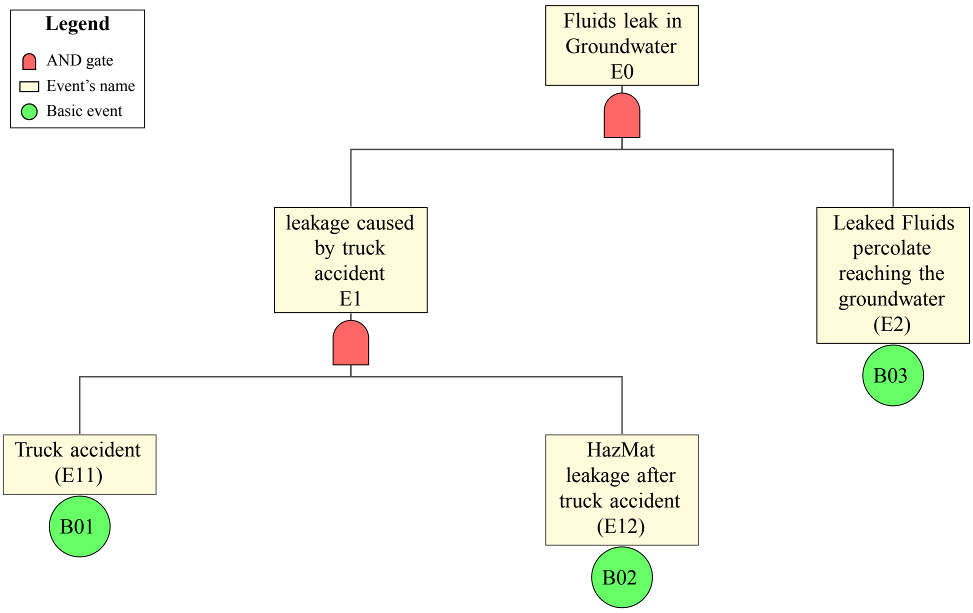

Fig. 3 Fault tree for assessing the probability of HazMat fluids reaching a drinking groundwater layer associated with truck accidents

Table 5 Data used to set the prior and the likelihood distributions of the BEs defined for the scenario associated with truck accidents (binomial models)

Code	Model	Params. prior distribution	Parameters of the Likelihood (description)	
B01	Binomial	$\theta_{B01} = 1.6 \times 10^{-5}$	$r_{B01} = 0$	(Number of HazMat truck crashes each year, in the project)
		$\Lambda_{B01} \geq 1 \times 10^3$	$n_{B01} = 30$	(Total number of HazMat shipments each year, in the project)
B02	Binomial	$\theta_{B02} = 3.6 \times 10^{-1}$	$r_{B02} = 0$	(Number of HazMat leaks after accident)
		$\Lambda_{B02} \sim 5$	$n_{B02} = r_{B01}$	(Number of HazMat transport accidents)
B03	Binomial	$\theta_{B03} = 1.5 \times 10^{-3}$	$r_{B03} = 0$	(Number of times that leaked fluids reach groundwater, in the project)
		$\Lambda_{B03} \geq 1 \times 10^2$	$n_{B03} = r_{B02}$	(Total number of HazMat leaks)

section A.2 in the Appendix A) is calculated as:

$$\theta_{B01} = \frac{N_{cr}}{N_{sh}} \tag{1}$$

The prior state of knowledge in this example is set by using U.S. HazMat truck shipments and accidents data from the Department of Transportation (Craft 2004); using this data set, we set $N_{cr} = 5,200$ crashes/yr and $N_{sh} = 3.3\times10^8$ HazMat shipments/yr. The resulting parameters to set the prior distribution for this BE are summarised in Table 5; note that we assume a certain level of confidence in the average value for the prior probability of truck accidents, and therefore the equivalent sample size, Λ_{B01}, has been set to be at least 1×10^3.

To set the likelihood function, we use site-specific data; in this case, we assume that in the test case example there have been 30 truck shipments transporting HazMat fluids without any incident (see Table 5). It is worth noting here how the conditions of the site-specific operations update the prior state of knowledge; in this way, the BE probabilities are updated as local data, related to the real operations in the project under analysis, are collected.

3.1.2 HazMat leakage caused by truck accident (B02)

To set the prior information for this BE, implemented using the binomial model, we use again data from the U.S. HazMat truck shipments (Craft 2004), where it can be found that about 36% of accidents of HazMat transporting trucks in the US produce a spill of HazMat fluids. Therefore, we set $\theta_{B02} = 3.6 \times 10^{-1}$ and assume a relatively low degree of confidence in this value by setting $\Lambda_{B02} \sim 5$ (Table 5).

To set the likelihood function we assume, as site-specific data, that zero leak events after truck accidents have occurred during the operations in this project, since no truck accidents have been reported (see Table 5).

3.1.3 Leaked fluids percolate reaching groundwater (B03)

This is an example of a BE in which the prior information can be set by using a specific IAM in which both the permeability characteristics of sedimentary sequence (between the surface and the aquifer) and the response capacity of the operator to mitigate the effects of a spill, are used to assess the probability that a certain volume of HazMat, leaked in the surface, reaches the groundwater level. The implementation of a model for assessing fluid flow in a porous media is out of the scope of this paper; for the sake of the example presented in this paper the parameter values for the prior probability associated with this BE are arbitrarily assumed and presented in Table 5.

Regarding the likelihood function, the data for this case study indicates that no leaks occurred during the operations; therefore the likelihood function is set by defining a zero number of leaks reaching groundwater out of zero HazMat leaks during operations (Table 5).

3.2 Groundwater pollution caused by a surface spill related to the failure of a storage unit containing flowback fluids

In this section we develop the FT for the scenario in which the groundwater pollution is caused by an on-site HazMat leak after the failure of a containment unit. Fig. 4 shows a simple FT for this example, which considers three BEs defined as shown in Table 6. It is assumed also that an isolation (impermeable) membrane has been installed in the site to protect groundwater from on-site surface spills.

3.2.1 HazMat leakage caused by storage failure (B04)

The HazMat storage failure basic event (B04) is set by assuming that flowback fluids are stored in tanks whose failure rates are modelled using a homogeneous Poisson process. It is worth noting that in a MHR analysis this event can be further developed to consider the failure rates associated to the occurrence of specific events as for example the material fatigue, extreme winds, or earthquake ground motions (see, e.g. B04x in Fig. 4).

For the scope of the example presented in this paper, we set a single basic event (B04) aggregating all the failures, regardless of the cause. To set the prior distribution for this BE, we use tank failure rates data published by Gould and Glossop (2000). To calculate the probability of HazMat storage failure, we consider that a number N_c of storage containers contain flowback fluids in the site.

According to the failure rates reported by Gould and Glossop (2000), the rate of a catastrophic failure is $\lambda_f = 4.0 \times 10^{-6}$ per vessel/year. Therefore, for N_c containers operating on-site, each of which can fail independently, $E_1(\lambda)$ can be set as:

$$E_1(\lambda) = N_c \lambda_f \qquad (2)$$

The defined values are reported in Table 6 (the N_c value is defined in Table 7). To set the likelihood function, we assume that no fluid-container failures have been recorded in the analysed case (i.e. $r_{B04} = 0$) in the observation period ($t_{B04} =$ 1 year).

3.2.2 Failure of the isolation membrane (B05)

Regarding the basic event B05, the failure of the isolation membrane is also modelled as a homogeneous Poisson process. To our knowledge, no data regarding the failure rates of a plastic membrane installed for site isolation in this kind of applications is available in literature; therefore, for the sake of the example presented in this paper, the prior distribution is set by assuming arbitrarily a generic failure rate value as shown in Table 6. To set the likelihood function, it is assumed that no membrane failures have been detected during the

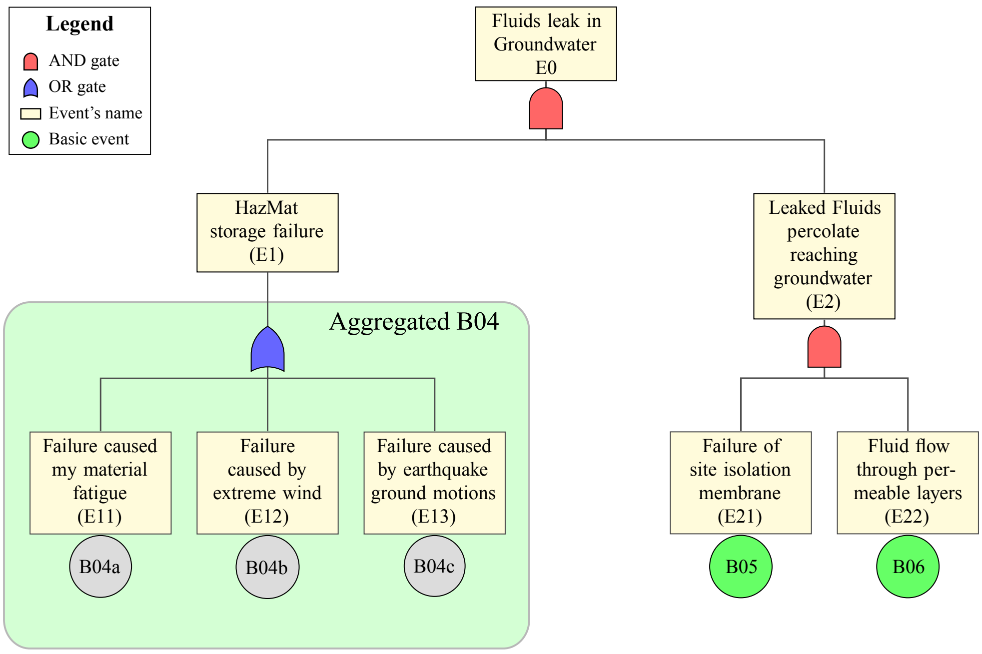

Fig. 4 Fault tree for assessing the probability of HazMat fluids reaching a drinking groundwater layer associated with the failure of a storage unit containing flowback fluids

Table 6 Data used to set the prior and the likelihood distributions of the BEs defined for the scenario associated with truck accidents (Poisson and binomial models)

Code	Model	Params. prior distribution	Parameters of the Likelihood (description)	
B04	Poisson	$E_{B04}(\lambda) = 8.0 \times 10^{-6}$	$r_{B04} = 0$	(Number of failures in t_{B04} years)
		$SD_{B04}(\lambda) = 8.0 \times 10^{-6}$	$t_{B04} = 1$	(Years of operation)
B05	Poisson	$E_{B05}(\lambda) = 1.0 \times 10^{-4}$	$r_{B05} = 0$	(Number of membrane isolation failures in t_{B05} years)
		$SD_{B05}(\lambda) = 1.0 \times 10^{-4}$	$t_{B05} = 1$	(Years of operation)
B06	Binomial	$\theta_{B06} = 1.5 \times 10^{-3}$	$r_{B06} = 0$	(Number of times that leaked fluids reach groundwater in the project)
		$\Lambda_{B06} \geq 1 \times 10^{2}$	$n_{B06} = r_{B04}$	(Total number of HazMat leaks)

time of project operations (that is, $r_{B05} = 0$ and $t_{B05} = 1$ year, see Table 6).

3.2.3 Leaked fluids percolate reaching groundwater (B06)

The B06 basic event is a similar case as the one in B03 and is implemented using the binomial model; also in this case, the prior information can be set using IAM to assess the probability that fluids from a surface spill can flow through a porous media and reach the groundwater level. As stated before, the definition of such IAM is out of the scope of this paper, and therefore, for the sake of this example, this value is arbitrarily assumed (see Table 6). Regarding the likelihood function, the data for this case study indicates that no failure leaks have occurred during the operations; therefore, the likelihood function is set by defining a zero number of leaks reaching groundwater ($r_{B06} = 0$) out of zero HazMat leaks caused by tank storage failures during operations (i.e. $n_{B06} = r_{B04} = 0$, see Table 6).

3.3 Setting the ET for assessing consequences

In the previous sections we defined the FTs required for calculating the probability of leak events impacting a groundwater layer. In this

Table 7 Description of parameters required for assessing the expected impact associated with HazMat leaks in groundwater

Parameter	Description	Value used in the presented example	Source
V_f	Total volume of HazMat available on-site (in m^3/well)	[0.9 to 3.0] $\times 10^4$	(NYSDEC 2011; Ingraffea et al 2014);
P_{as_i}	Fraction of fluids spilled in a crash of a given level of severity	*Small*: from 0 to 5% *Medium*: from 5 to 30% *Large*: >30%	(Assumed)
$Pr(v_{a_i}\|\text{a.leak})$	Conditioned on the occurrence of a transport accident leak, the probability of leaking a given volume of HazMat (v_{a_i}, in three categories representing a small, medium, and large spill)	*Small*: 0.6 *Medium*: 0.25 *Large*: 0.15	(Assumed)
P_{fs_i}	Fraction of fluids spilled in from a storage system given the severity of the failure	*Small*: from 0 to 10% *Medium*: from 10 to 30% *Large*: >30%	(Assumed)
$Pr(v_{f_i}\|\text{f.leak})$	Probability of leaking a given volume of HazMat (v_{f_i}, in three categories representing a small, medium, and large spill) caused by a failure in a storage element (correspondingly small, medium, large failure)	*Small*: 0.85 *Medium*: 0.10 *Large*: 0.05	(Assumed)
P_{perc}	Fraction of fluids spilled by a containment failure that percolate through surface layers.	20%	(Assumed)
N_{trips}	Number of shipments transporting HazMat out of the site	30	(Given data)
N_c	Number of storage units available on-site	20	(Given data)

section, we set a simple ET for consequence assessment. Given that flowback fluids are spilled in a primary risk receptor (because a transport accident or a tank failure), the question to be answered by the ET analysis in this case is, which is the expected impact on the primary risk receptor of interest?

In this example we assess the consequences on the primary risk receptor in terms of expected volume of HazMat fluids leaked on the groundwater reservoir. To perform this assessment we construct a simple event tree with the following two nodes: (1) the initial event, corresponding with the TEs of the FTs previously described (i.e. a spill event probability); and (2) a node assessing the probability distribution of the leaked volume (represented here by three general categories as *small*, *medium*, and *large* events). The characteristics of these size categories are defined in Table 7). Note that further nodes could be added to assess the consequences on a final risk receptor.

Fig. 5 shows a general template of the ET implemented in this exercise. Evaluating the ET we calculate the probability of each path of interest. Furthermore, for the MHR results it is necessary to calculate the expected consequences associated with each path of the ET (which in this case corresponds with the expected leaked volume, see section 4.2 for details).

Probabilities at node 2 of the ET are encoded using the multinomial distribution (see section A.4 in Appendix A), considering the probabilities associated with determined threshold leak volumes [that is, $Pr(v_{a_i}|\text{a.leak})$ in the truck accident scenario and $Pr(v_{f_i}|\text{f.leak})$ in the storage failure scenario], as well as assuming a determined level of epistemic uncertainty (see section A.4 in Appendix A). The assumed values are presented in Table 7. Note that, in both cases:

$$\sum_i Pr(v_{x_i}|\text{x.leak}) = 1$$

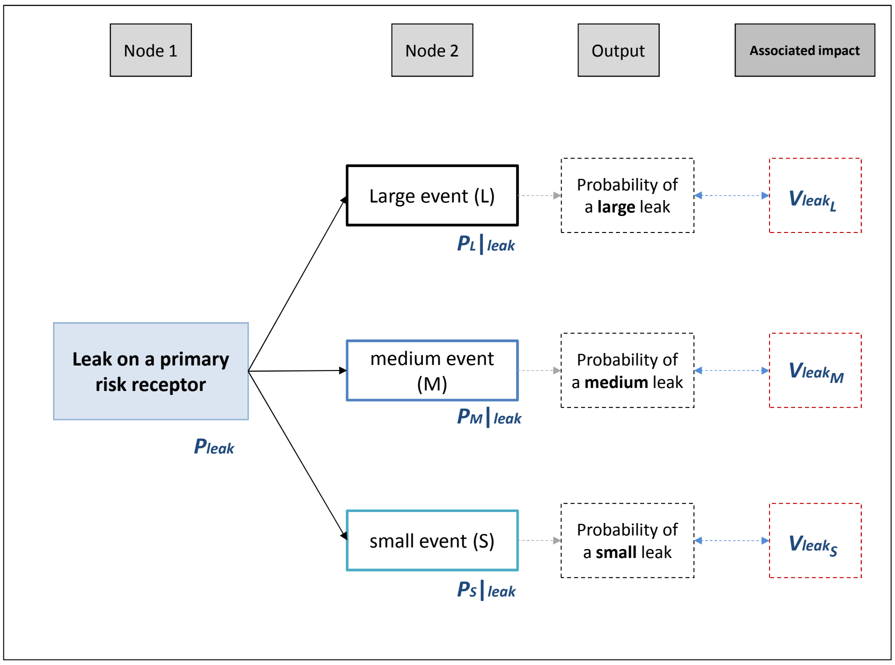

Fig. 5 Basic template of the event tree defined for assessing impacts on primary risk receptors defined in this work: node 1 corresponds with the top event of the related FT; node 2 is related with the leak size distribution. On the other hand, the associated impact corresponds with the expected leaked volume associated with each path of the ET.

4 Results

4.1 Evaluation of the fault trees

After defining the BE models and the related input data (see section 3 for details), each BE is fully characterised by a distribution defined over the BE probability parameter. N_s probability values are then sampled from each BE distribution ($N_s = 1000$ in this example), and each set of BE probability samples are used to analyse the FT using Monte Carlo simulations (see section C.1 in Appendix C for details). The outcome of the FT analysis is a set of N_s samples of the TE probability, which are used to define an empirical distribution for the probability of the top event.

Regarding the scenarios analysed in this study, Fig. 6 shows a histogram of the TE probabilities calculated for the FT shown in Fig. 3 (i.e. groundwater pollution due to a spill after a truck accident), whereas Fig. 7 shows the histogram of the probabilities calculated for the TE of the FT shown in Fig. 4. It is worth mentioning that the variability of the solutions (TE probabilities) obtained using this approach reflects the uncertainties associated with the BEs.

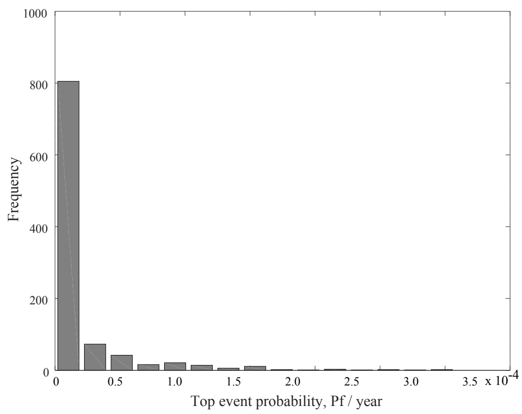

Fig. 6 Histogram of the top event probabilities obtained by analysing the FT shown in Fig. 3 for the case of groundwater pollution associated with the event *flowback-fluid transport accident*

From these results it is also possible to calculate summary statistics for the TE probabilities, which for the two FTs analysed in this study are presented in Table 8. The median

Table 8 Summary statistics for the top event probability of the two FTs analysed in this example

Scenario	Top event (TE)	TE probability Median	5th percentile	95th percentile
Transport accident	Groundwater pollution related to a spill of flowback fluid being transported from the well site to a disposal site	9.5×10^{-7}	6.4×10^{-8}	9.4×10^{-5}
Storage failure	Groundwater pollution caused by a surface spill related to a the failure of a storage unit containing flowback fluids	7.8×10^{-6}	3.9×10^{-6}	9.8×10^{-6}

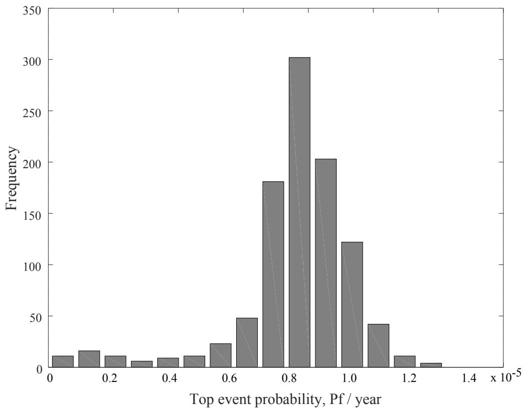

Fig. 7 Histogram of the top event probabilities obtained by analysing the FT shown in Fig. 4 for the case of groundwater pollution associated with failure of storage unit filled with a flowback fluids

value is used as the best estimate of the TE probability, and the 5th and 95th percentiles represent uncertainty bounds.

4.2 Evaluation of the event trees and consequence assessment

In this section, we present the results obtained from evaluating the ETs linked, in a BT structure, with the respective FTs implemented for the two scenarios analysed in this case study. The probability of each path of the ET is obtained using Monte Carlo simulations as described in section C.2 of the Appendix C. Combining the path probabilities and the related expected consequences (in terms of expected leaked volume), it is possible to summarise the results of the full MHR analysis using risk matrices.

The assessment of the expected consequence of the truck accidents pathway (expressed in m^3/HazMat-transporting truck crash) can be calculated considering (1) the total volume of HazMat being transported (V_f); (2) the fraction of fluids spilled in an accident of a given severity level (P_{as_i}); and (3) the number of shipments required for transporting a given volume V_f of HazMat (N_{trips}).

We calculate the expected HazMat leaked volume from a transport accident of severity i as:

$$V_{\text{leak}_i}^{\text{transp}} = \left[\frac{V_f}{N_{trips}}\right] [P_{as_i}] [P_{perc}] \tag{3}$$

where i is referred to a given level of leak severity (small, medium, and large), N_{trips} is the number of HazMat shipments from the site, and P_{perc} the fraction of fluids spilled in a crash that percolate through surface layers.

On the other hand, to evaluate the consequences associated with spills from fluid storage failures, it is necessary to calculate the expected leaked volume associated with different levels of incident severity (small, medium, large). We calculate the expected HazMat volume leaked in groundwater from a storage failure of severity j as:

$$V_{\text{leak}_j}^{\text{storage}} = [V_{\text{cont}}] \left[P_{fs_j}\right] [P_{perc}] \tag{4}$$

where V_{cont} is the average volume of HazMat fluids stored per container located on-site; P_{fs_j} is the fraction of fluid leaked from a storage element given a failure of severity j (small, medium, large); P_{perc} is the fraction of leaked fluids that reach the groundwater, and depends on specific properties of shallow layers of the porous media, as well as on the capacity of the operator to mitigate the effects of the spill (e.g. the clean-up time). The average volume of HazMat fluids stored per container can be calculated as $V_{\text{cont}} = V_f/N_c$. The values used to set all the parameters in this example are summarised in Table 7.

Finally, the full BT structures defined for the scenarios analysed in this case study can be assessed combining the path probabilities and the expected consequences. The results of

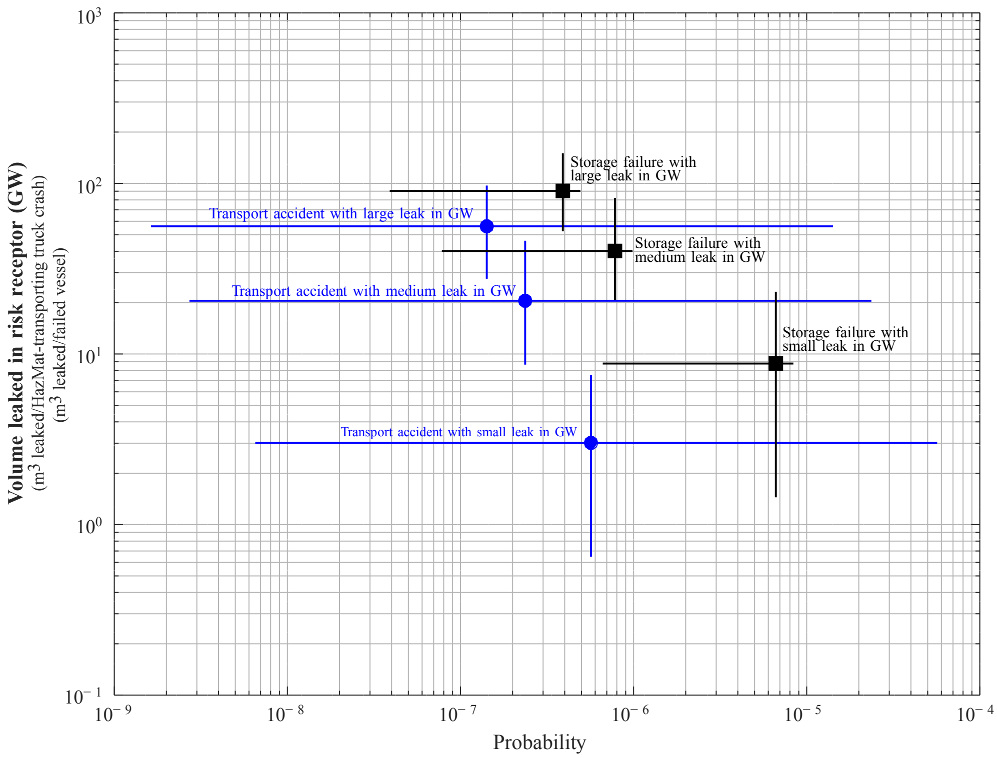

Fig. 8 Risk matrix summarising the MHR analysis for the two risk pathway scenarios considered in the worked example. Each point in this plot represents the median of the distribution of probability and consequences obtained for each ET path. Error bars are defined considering the 5th and the 95th percentiles of the solutions.

the MHR analysis for this case study are summarised in the risk matrix shown in Fig. 8. In this way, different risk pathway scenarios can be compared quantitatively; the bars in Fig. 8 indicate the uncertainties in the results and are defined considering the 5th and the 95th percentiles of the solutions. Considering the solutions obtained for this synthetic example, larger uncertainties are obtained in the risk estimates for the scenario involving transport accidents respect to the uncertainties in the risk estimates associated with storage failures.

4.3 Software tool development: MERGER

The functionalities of the methodology described in this paper for quantitative MHR assessments using a BT structure have been implemented in an open source computational tool denominated *Simulator for Multi-hazard risk assessment in ExploRation/exploitation of GEoResources* (MERGER). Furthermore, in the framework of the European project EPOS-IP (European Plate Observing System, Implementation Phase), a web-based tool that integrates all the functionalities of MERGER is at the moment under implementation as an online application running in the environment of the IS-EPOS platform (`https://tcs.ah-epos.eu/`).

The IS-EPOS Platform, which constitutes the *Anthropogenic Hazards thematic core service* (TCS-AH) of EPOS-IP, is a web portal created to facilitate analyses of anthropogenic seismicity, related hazards, and for assessing potential environmental impacts of geo-resources development. This platform provides a collection of data sets of time-correlated geophysical, technological and other relevant geo-data organised in so-called *Episodes*, which relate anthropogenic seismicity to its industrial cause. Apart from the data, the IS-EPOS Platform provides also a set of ready software applications to analyse this data, as well as a user workspace where the analyses can be performed and saved. The MERGER system is integrated as one of such applications and is available to all the users of the IS-EPOS Platform affiliated with the EPOS-IP project. Apart from making it available to a broader range of users, another added value of this integration is that MERGER could be combined with other analytic tools present in the platform (as IAM tools). A detailed description of the MERGER application implemented in EPOS is presented in Appendix D.

5 Discussion and concluding remarks

In this paper, we present an integrated approach and a computational tool (MERGER) for performing MHR assessments using a bow-tie analysis approach. The implemented approach is a highly specialised and transparent modelling tool tailored for analysing risk scenarios associated with the development of geo-resources. We integrate a number of probabilistic tools that can be used to model a number of processes of interest for assessing environmental risks associated with anthropogenic hazards.

The probabilistic model for MHR assessment presented here relies on three fundamental concepts: (1) a logical structure that follows a bow-tie approach, (2) a Bayesian implementation for handling probabilistic information, (3) propagation of modelling uncertainties, and (4) the possibility of using data derived form IAMs and expert judgement elicitation for analysing complex processes for which direct data is unavailable.

The proposed approach has been implemented in a software tool called MERGER, which is being implemented as a web-based service in the IS-EPOS platform. The core system includes the algorithms for quantitatively analysing FTs and ETs, the functions for defining the BEs, and a user-friendly graphical interface to simplify the inputting of the data and the analysis.

The added value of the presented approach is that a number of useful modelling tools are available and harmoniously integrated in the same system, some of which are particularly relevant for analysing both natural and anthropogenic hazards; moreover, using the proposed methodology, a wide range of data can be meaningfully integrated in quantitative multi-hazard risk analyses. Finally, the web-based implementation provides a valuable service in which computational power constraints are released for the end user.

The modular structure of the implemented system opens the way for enhancing a dynamic community-based development of the system. The main challenge in the near future is to make the system grow by integrating specialised IAM tools. This activity requires the input from a number of specialised disciplines; for this reason, our vision is to propose the MERGER system as a meeting point in which different research communities can find a supporting environment where to implement highly specialised models as IAM tools.

The general framework provided by the EPOS-IP project is of paramount importance to pursue this ambitious objective. In fact, the EPOS-IP project provides the infrastructure and the sustainability for implementing, testing and operating the system as a web-based service; furthermore, it also provides the exposure to scientific communities potentially interested in integrating scientific models as IAM tools, making them available for specialised MHR assessments.

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Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

A Basic probabilistic models for setting BE in fault trees and nodes in event trees

A.1 Events characterised by the homogeneous Poisson process

The inference problem in this case is to estimate the rate of event occurrence (λ) per time unit. A constant failure rate implies that failures are generated by a Poisson process; therefore, the likelihood function for this evidence can be set using the Poisson distribution:

$$p\{r \text{ failures in } [0,t] | \lambda\} = \frac{(\lambda t)^r}{r!} e^{-\lambda t} \tag{5}$$

A prior distribution for λ can be developed from other generic data (as, e.g. data from similar cases or components, or from expert opinion elicitation). Because of the simplicity in calculations, we adopt a conjugate prior for the λ parameter, which in this case is the Gamma distribution:

$$\pi_0(\lambda) = \frac{\beta^{\alpha} \lambda^{\alpha-1}}{\Gamma(\alpha)} e^{-\beta\lambda} \tag{6}$$

where α and β are the parameters characterising this distribution. Usually, the prior state of knowledge can be defined using the actual analyst's knowledge of a *mean* value, $E(\lambda)$, as a best value, and a standard deviation, $\mathrm{SD}(\lambda)$, as an uncertainty range. In such a case, the α and β parameters of the Gamma prior distribution can be set by solving:

$$\begin{cases} E(\lambda) &= \frac{\alpha}{\beta} \\ \mathrm{SD}(\lambda) &= \frac{\sqrt{\alpha}}{\beta} \end{cases} \tag{7}$$

The Posterior distribution, $\pi(\lambda)$, for the Poisson-Gamma conjugate pair is the Gamma distribution:

$$\pi_1(\lambda|E) = \frac{\beta'^{\alpha'} \lambda^{\alpha'-1}}{\Gamma(\alpha')} e^{-\beta'\lambda} \tag{8}$$

where

$$\alpha' = \alpha + r \quad \text{and} \quad \beta' = \beta + t \tag{9}$$

Once the posterior distribution $\pi_1(\lambda|E)$ has been obtained, λ samples are drawn from that posterior distribution and used to calculate the probability of at least one event occurring in a determined period of time Δt of interest:

$$Pr(r > 0, \Delta t) = 1 - e^{-(\lambda \Delta t)} \tag{10}$$

A.2 Events characterised by the binomial model

The binomial distribution can be used to model processes whose evidence is given by a number of *event occurrences* out of a number of *trials*. Using this model, the likelihood function is the conditional probability of observing r events (e.g. failures, successes, etc.) in n trials, given ϕ (i.e. the probability of the event's occurrence):

$$p\{r \text{ failures in } n \text{ trials} | \phi\} = \frac{n!}{r!(n-r)!} \phi^r (1-\phi)^{n-r} \tag{11}$$

The conjugate Prior for the binomial distribution is the beta distribution, which has the form:

$$\pi_0(\phi) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \phi^{\alpha-1} (1-\phi)^{\beta-1} \tag{12}$$

where α and β are the parameters characterising the beta distribution. To set the model parameters of the prior distribution, the analyst usually can have an *average* value as the best estimate of the ϕ parameter and an interval representing a (prior) uncertainty regarding ϕ. To set the α and β parameters of the beta prior distribution we adopt a simple model in which the analyst set (a) the prior state of knowledge by defining a *mean* value as the best estimate of the parameter, and (b) to set an uncertainty order of magnitude, the analyst defines the so-called *equivalent sample size*, Λ, ($\Lambda > 0$), which is a number representing the quantity of data that the analyst expects to have in order to modify his prior beliefs regarding the parameter (Marzocchi et al 2008). It means that the larger Λ, the more confident the analyst is about his prior state of knowledge. For example, setting $\Lambda = 1$ the analyst is expressing a maximum uncertainty condition, implying that just one single observation can substantially modify the prior state of knowledge.

Once these two parameters have been defined, the parameters of the beta prior distribution can be set using the following equations (Marzocchi et al 2008):

$$\alpha = \theta(\Lambda + 1) \quad \text{and} \quad \beta = \Lambda + 1 - \alpha \tag{13}$$

The posterior distribution, $\pi_1(\phi)$, for the binomial-beta conjugate pair is the beta distribution:

$$\pi_1(\phi|E) = \frac{\Gamma(\alpha'+\beta')}{\Gamma(\alpha')\Gamma(\beta')} \phi^{\alpha'-1} (1-\phi)^{\beta'-1} \tag{14}$$

where

$$\alpha' = \alpha + r \quad \text{and} \quad \beta' = \beta + n - t \tag{15}$$

A.3 Events characterised by the Weibull model

The Weibull distribution, with parameters $\lambda > 0$ and $k > 0$ is defined for positive real numbers with Probability density function (e.g. Leemis 2009):

$$f(t) = \frac{k}{\lambda} \left(\frac{t}{\lambda}\right)^{k-1}, \qquad \text{for } t \geq 0 \tag{16}$$

where $k > 0$ and $\lambda > 0$ are the shape and scale parameters, respectively. k determines the time-dependent behaviour of the hazard rate (with $k < 1$, h decreases with time; with $k = 1$, h is constant with time, and for $k > 1$, h increases with time (i.e. as in an ageing or wearing process). Regarding the methods for determining the model parameter values, the maximum likelihood is the method most widely used (e.g. Leemis 2009).

For a history-dependent point process, the conditional probability that an event happens in a time interval $(x, x, +\Delta t)$, given an interval of $x = (\tau - \tau_L)$ years since the occurrence of the previous event (with τ the *current* time of the assessment, and τ_L

the time form the last event) can be calculated as follows (see, e.g. Garcia-Aristizabal et al 2012):

$$Pr(x, x+\Delta t) = \frac{\int_x^{x+\Delta t} f(s)ds}{1-F(x)} \quad (17)$$

where $f(x)$ is the probability density function (Weibull in this case) and $F(x)$ is the cumulative distribution.

A.4 Multinomial model for assessing nodes in the event trees

We perform Bayesian inference of the ϕ_i parameters of the Multinomial distribution. The conditional probability for a multivariate random variable $\phi_i = \{\phi_1, \phi_2, \ldots, \phi_i,\}$ reads (e.g. Gelman et al 1995):

$$p(y|\phi_i) = \binom{\sum_{j=1}^{i} y_j}{y_1 \cdots y_i} (\phi_1)^{y_1} \cdots (\phi_i)^{y_i} \quad (18)$$

where $y = (y_1, \ldots, y_i)$ is the data vector, and the elements y_i are the number of successes (occurrence) relative to the event i with probability ϕ_i. The sum $\sum_{j=1}^{i} y_j$ represents the total number of data. i is therefore the number of possible mutually exclusive and exhaustive events in a given node. $L(y|\phi_i)$ is the marginal distribution of ϕ_i. Note that the case $i = 2$ is equivalent to the binomial distribution.

The conjugate Prior for the Multinomial distribution is the Dirichlet distribution (e.g. Gelman et al 1995), which for a generic multivariate random variable ϕ_i reads:

$$\pi_0(\phi_i) = \frac{\Gamma(\alpha_1 + \cdots + \alpha_i)}{\Gamma(\alpha_1) \cdots \Gamma(\alpha_i)} [\phi_1]^{\alpha_1 - 1} \cdots [\phi_i]^{\alpha_i - 1} \quad (19)$$

where $\Gamma()$ is the Gamma function, $\alpha_i > 0$, $\phi_i > 0$, and $\sum_{j=1}^{i} \phi_j = 1$, with i the number of possible mutually exclusive and exhaustive events. Since the random variable is a probability, the Dirichlet distribution is particularly suitable, being unimodal and with domain $[0, 1]$ in each variate.

To set the model parameters of the prior distribution we follow a similar approach as the one used for the binomial model. To set the parameters of the Dirichlet prior distribution we adopt the same approach presented for the beta distribution (Marzocchi et al 2008) in which the analyst set the prior state of knowledge by defining (1) a *mean* value, θ_i, as the best estimate of the θ parameters, and (2) an uncertainty order of magnitude, using the so-called *equivalent sample size*, $\Lambda, \Lambda > 0$. As stated before, Λ is a number representing the quantity of data that the analyst expects to have in order to modify the prior beliefs regarding the parameter. Once θ and Λ have been set, the parameters of the Dirichlet distribution can be set solving the following set of equations (Marzocchi et al 2008):

$$\begin{cases} \theta_i = \frac{\alpha_i}{\sum_{j=1}^{i} \alpha_j} \\ \Lambda \quad = \left[\sum_{j=1}^{i} \alpha_j\right] - i + 1 \end{cases} \quad (20)$$

The posterior distribution distribution, $\pi_1(\theta|E)$, for the Multinomial-Dirichlet conjugate pair is the Dirichlet distribution:

$$\pi_i(\phi_i|E) = \frac{\Gamma(\alpha'_1 + \cdots + \alpha'_i)}{\Gamma(\alpha'_1) \cdots \Gamma(\alpha'_i)} [\phi_1]^{\alpha'_1 - 1} \cdots [\phi_i]^{\alpha'_i - 1} \quad (21)$$

where:

$$\alpha'_i = \alpha_i + y_i \quad (22)$$

B Considering external perturbations through physical reliability models (PRM)

B.1 Static PRM

We use Static PRM as a basic template for assessing the failure probabilities of elements exposed to (mainly) external hazards. To provide a generic description we take as reference the Random Shock-Loading model (e.g. Ebeling 1997; Hall and Strutt 2003). It is assumed that a variable stress load L is applied, at random times, to an element (e.g. a mechanical component or infrastructural element) of given strength. Stresses are often considered as physical or chemical parameters affecting the component's operation. Strength is defined as the highest amount of stress that the component can bear. According to the definition of stress and strength, a failure occurs when the stress on the component exceeds its strength (Ebeling 1997; Hall and Strutt 2003). Both stress and strength can be constant or considered as random variables having probability distribution functions. For example, the failure probability of component Q having a constant strength k, and being under random load, L, can be defined as the probability of Y being greater than k (see, e.g. Ebeling 1997; Hall and Strutt 2003; Khakzad et al 2012):

$$\Pr(L > k) = \int_k^{\infty} f_L(l)dl \quad (23)$$

where $f_L(l)$ is the probability density function of the stress L (see, e.g. Khakzad et al 2012). It is also possible to assume an uncertainty in the strength limit k; in such a case, the limit strength is therefore characterised by a probability density function $f_S(k|l)$. Such a function can be understood in similar way as the fragility functions developed for seismic risk analyses. On the other hand, stress variables in this case are equivalent to the intensity measure (IM) usually used for hazard assessment in probabilistic frameworks [see, for example, hazard assessments associated with seismic occurrences (e.g. Cornell 1968), tsunami waves (Davies et al 2018), extreme meteorological events (e.g. Garcia-Aristizabal et al 2015), etc.]. Therefore, the stress function can be basically defined using the output of probabilistic hazard assessments.

B.2 Dynamic PRM

Dynamic PRMs aim to explain the event occurrence (e.g. the failure of a component) as a multivariate function of operational physical parameters (e.g. Ebeling 1997; Khakzad et al 2012). The dynamic PRMs in the MHR approach are implemented considering two special cases assuming that it is possible to identify a relationship between (1) operational parameters of interest and the rate of occurrence of events stressing the system (i.e. *hazard*); (2) operational parameters of interest and the strength of components of interest.

B.2.1 Covariates linked to the stress component

In this case, the covariate model for assessing the probability of having a determined damage state (D_n, as, e.g. a failure) can be written as:

$$Pr(D_n) = \int g(D_n|l) f_L(l|\mu_i(\theta))dl \tag{24}$$

where $f_L(l|\mu_i(\theta))$ is the probability distribution of the loads stressing the system, whose parameters are a function of the covariates; θ is the vector of covariates, μ_i is the ith parameter of the probabilistic model $f_L()$ that depends on the defined covariates θ; $g(D_n|l)$ is the probability distribution associated with the occurrence of the damage state D_n given the stress l (intensity measure). In this case, therefore, we assume that the rate of occurrence of the loading process (hazard) is changing as a function of a covariate of interest. An example of the implementation of such a covariate model can be consulted in Garcia-Aristizabal (2018).

B.2.2 Covariates linked to the strength component

In this case the covariates are associated with the distribution that characterises the probability of having a given damage state (e.g. failure) of a given element of interest. It is defined as (e.g. Khakzad et al 2012; Hall and Strutt 2003):

$$Pr(D_n) = \int g(D_n|l,\theta) f_L(l)dl \tag{25}$$

where $g(D_n|l,\theta)$ is the probability distribution associated with having the damage state D_n given the stress l (intensity measure) and the covariates θ.

C Algorithms implemented for solving FTs and ETs

C.1 FT analysis

Analytic methods for evaluating a FT usually express the whole tree in terms of a set of minimal cut sets (a cut set is a set of components that can together cause the system to fail; see, e.g. Lee et al 1985; Carrasco and Sune 1999; Ferdous et al 2007; Ruijters and Stoelinga 2015). The analysis of complex FTs with large number of minimal cut sets can be performed using a Monte Carlo approach (e.g. Rao et al 2009; Taheriyoun and Moradinejad 2014; Ruijters and Stoelinga 2015). Monte Carlo methods constitute a class of algorithms based on repeated random sampling of input parameters to compute a required output. The algorithm implemented in MERGER for evaluating FTs is based on a general template often used by Monte-Carlo based methods for solving FT structures, as the one presented, e.g. in Han and Lim (2012).

The algorithm for the FT analysis consists of randomly determining the state of each BE and calculating the state of the TE using the FT logic. The state of the TE of a FT can be expressed as a function of BEs as (Han and Lim 2012; Taheriyoun and Moradinejad 2014):

$$T = f(BE_i) = f(BE_1, BE_2, \ldots, BE_n) \tag{26}$$

where T is a TE of a FT, $f()$ represents the FT logical equations, and BE_i is the vector of the FT's BEs. The state of all BEs and their occurrence probabilities are represented as:

$$S_T = (S_1, S_2, \ldots, S_n) \tag{27}$$

where S_i is the state of the ith BE, whose state in a given trial iteration can be *false* (0) or *true* (1) (Han and Lim 2012). The probability that $S_i = true$ corresponds with the probability of the ith BE, p_i.

The probability of T is stochastically determined by sampling the state of the BEs based on their occurrence probabilities and propagating their states to determine the state of the TE. In practice, inserting the state vector S_T into Eq. 26 at each trial iteration allows us to find the state of the TE. By repeating this process a sufficient number of times (n_t trials), the probability of the TE can be asymptotically obtained by the fraction m/n_t, where m is the number of top event's *true* states found out of n_t trials (Han and Lim 2012).

In our approach, the p_i of the BEs are not simple probability values; rather, we define probability distributions defined over each BE's probability value. In this way, the modelling uncertainties associated with the BE's definition are taken into account in the analysis. Therefore, in our approach the Monte Carlo algorithm previously described is iterated N_s times; in each iteration the p_i is sampled from the distributions defined for each BE_i, obtaining in this way N_s realisations of the TE probability, P_T.

The following algorithm, based on the one presented in Han and Lim (2012), summarises the two key functions implemented in the MERGER system for analysing the FTs.

(i) Function to evaluate Top Event Probability, $[P_T]$:

- Set N_s: number of iterations;
- Set n_t: number of trials (within each iteration);
- for the number of iterations N_s do (j):
  - set $m = 0$ (number of TE *true* states);
  - Sample p_i from the BE_i distribution (for all the BE defined);
  - for the number of trials n_t do (k):
    - Randomly determine the state of each BE:
      * sample a random number $r_{i,k}$: $0 \leq r_{i,k} \leq 1$
      * if $r_{i,k} \leq p_i$: then $S_{i,k} = true$
      * else: then $S_{i,k} = false$

- Calculate the jth state of the top event (S_{T_j}):
  $* \ S_{T_k} = \mathbf{GetTopEvState}[f(S_{:,k})]$
  $*$ if $S_{T_k} = true$, then: $m = m + 1$
  - Evaluate the jth TE probability:
    - $P_{T_j} = \frac{m}{n_t}$ (see also Eq. 29 for optimisation)

- Return $[P_T]$ samples (N_s realisations of P_T)

(ii) Function to get the state of top event
This function, $\mathbf{GetTopEvState}[f(S)]$, uses the state S_i of each BE and the logic (gates) defined in the fault tree to determine the jth state of the TE. A FT may contain a large number of intermediate gates to handle the relationships among BEs. To determine the state of the TE, the state of the intermediate gates should be determined. For example, the state of the kth gate, G_k, can be calculated based on the states of its inputs:

- if the states of all inputs for an OR gate are *False*, G_k becomes *False*; otherwise it becomes *True*.
- If the states of all inputs for an AND gate are *True*, G_k becomes *True*; otherwise it becomes *False*.
- In MERGER, the fault tree equations are evaluated from bottom to top according to these rules, Assessing:
  - first, the state of intermediate gates whose inputs are all BEs;
  - the state of intermediate gates in which at least one input is an intermediate event (i.e. from the output of another gate);
  - the higher level whose output is the state of the TE.

At each iteration, an approximated value of the TE failure probability (P_{T_j}) is calculated as the ratio of the number of *failures* obtained for the TE to the total number of trials: $P_{T_j} \approx m/n_t$. The accuracy of this calculation can be assessed by considering the standard error ϵ_j of this proportion, which for a large number of trials can be defined as $\epsilon_j = \sqrt{P_T(1-P_{T_j})/n_t}$. Solving this equation for the number of trials n_t, and assuming that the TE probability is small ($P_T << 1$), it is possible to determine the expected number of trials for a defined standard error (e.g. Yevkin 2010):

$$n_t = \frac{P_T}{\epsilon^2} \tag{28}$$

The required number of trials in a given iteration considerably increases as the (desired) standard error decreases. As a reference, Table 9 summarises the required number of trials for different values of P_T and different reference values for the standard error ϵ as a percentage of P_T. For example, for a P_T of the order of 1×10^{-2}, the number of trials required for having a standard error of $\sim 1\%$ of that P_T is $\sim n_t = 1 \times 10^6$, while for a standard error of $\sim 10\%$ of P_T, n_t must be in the order of 1×10^4. In the MERGER system, the n_t is dynamically set in order to ensure a predetermined accuracy level.

It is worth noting that this algorithm performs an estimate of P_{T_j} using all the sampled BE states; however, when the BE probabilities are low, a high number of trials results in all the BE set to *false*; consequently, in such cases the FT will be uselessly evaluated with no TE failures as the outcome. To avoid unnecessary FT evaluations (and therefore to save computational time), an optimisation is implemented so that the FT is evaluated only for trials in which at least one occurring primary event is simulated (see, e.g. Kumamoto et al 1980; Han and Lim 2012; Taheriyoun and Moradinejad 2014). It means that we can exactly calculate the probability γ of having at least one BE defined as *true* in a set of trials, so that P_{T_j} can be calculated as:

$$P_{T_j} = \gamma \frac{m}{n_t} \tag{29}$$

The Monte Carlo simulation approach for analysing FTs has advantages and disadvantages respect to analytic methods. Among the main advantages we consider that (1) the Monte Carlo method can be easily applied to relatively large FTs, and (2) it allows us to easily set different models for defining BE probabilities, providing adequate flexibility for better describing the different processes involved in the applications of interest. Conversely, among the main disadvantages we can consider that (1) the numerical values obtained by Monte Carlo simulations are approximated solutions whose accuracy strongly depends on the number of trials (n_t) performed; when very low probabilities are involved, the number of trials may enormously increase, making the assessments very expensive from a computational perspective; (2) the failure modes generated by Monte Carlo simulations might not be complete, and therefore it is not guaranteed that the cut sets that can be identified are minimal.

C.2 ET consequence analysis

The Monte Carlo procedure for the analysis of the ET is based on sampling the distributions used to set each node of the ET, as follows:

1. The initiating event (first node), which coincides with the TE of the FT, is sampled by constructing the empirical distribution function using the N_s values of P_T generated by the algorithm used for evaluating the FT.
2. Nodes with two exhaustive and mutually exclusive branches are defined using the binomial model. Given the Bayesian implementation using conjugate pairs (beta prior / binomial likelihood), the events are randomly sampled form the beta posterior distribution.
3. Nodes characterised by more than two exhaustive and mutually exclusive branches are defined using the multinomial model. Given the Bayesian implementation using conjugate pairs (Dirichlet prior / multinomial likelihood), the events in this case are randomly sampled form a Dirichlet posterior distribution.

To calculate the probability of each path of the ET, N_{et} samples (usually about 1000 samples) are drawn from each distribution (i.e. the ones defined at each node), and the empirical distribution characterising the probability of each path is calculated by using each set of node samples at a time. In this way we obtain N_{et} samples of the probability of each ET's

Table 9 Estimated number of trials for different values of P_T and different reference values for the standard error of P_T

Top event probability (P_T)	Estimated number of trials, $\mathbf{n_t}$, for a given ϵ value [$\epsilon = 1\%P_T$]	[$\epsilon = 5\%P_T$]	[$\epsilon = 10\%P_T$]
1×10^{-2}	1×10^{6}	4×10^{4}	1×10^{4}
1×10^{-4}	1×10^{8}	4×10^{6}	1×10^{6}
1×10^{-6}	1×10^{10}	4×10^{8}	1×10^{8}

path, obtaining a numerical approximation of its distribution. Therefore, we propagate both the aleatory and the epistemic uncertainties defined at all nodes. Finally, summary statistics are also provided as output (the median as *best estimate* of the path probability and two percentiles representing uncertainty ranges).

D Overview of the MERGER system in EPOS

In this section, we briefly describe how to use the application according to its current state of development; nevertheless, the reader is invited to read the user manual available in the platform for more detailed and up-to-date instructions.

In the IS-EPOS Platform, MERGER is available to be used from the *Applications* menu (Fig. 9). To use any application from the platform it has to be first added to the user's workspace (using the *Add to workspace* button; see the quick start guide IS-EPOS 2018).

Once the MERGER application is available in the *Workspace*, the user can open the application, which at this point is ready to be used. The first step of an assessment is to provide the input data required for quantitative analyses, which in the most general definition can be structured as: (a) the definition of the TE of interest; (b) *input/analysis of the Fault Tree*, and (c) *input/analysis of the Event Tree*. At the moment of preparation of this paper, only the FT component of the BT structure of MERGER has been integrated in the IS-EPOS platform. For this reason here we focus on the description of the interface for the construction and analysis of the FT component. It is worth noting that a more detailed description regarding the construction and analyses of the full BT structure will be available in the user manual to be released with the application in the platform.

Fig. 10 shows the interface for inputting data for the FT analysis. In this case, three main inputs are required, namely:

1. general information, as the following:
   - Run ID: identification of the application run (used for naming output files);
   - Time-dependent calculations: option to control if it is required to perform the time-dependent calculations;
   - Number of iterations: number of samples to be drawn from the distributions defined for the BEs. This will also be the number of times that the full FT evaluation will be iterated, so it strongly influences the computer time.
   - Mission time: it is the *mission time* for time-dependent calculations (that is, the time window for the time-dependent probability calculations);
   - Time slices: time points where to write results in time-dependent analysis. To speed up calculations, a low number of time slices should be used
2. Definition of basic event's models, where the user may create all the BEs, by typology, that will be required for constructing the FT. In practice, the user can create any number of BEs for each available class (namely homogeneous Poisson process, on-demand failure, Weibull, static and dynamic physical reliability models). To define a BE of a determined class it is required to provide all the input data (see, e.g. Tables 1 to 4 in the methodology section). Figure 11 shows an example of the interface for adding a BE of class homogeneous Poisson process.
3. Definition of fault tree equations; the FT is constructed from BEs (of all the types listed above) or intermediate events (i_n in Fig. 10, where n is a subsequent number automatically created each time that an intermediate event is defined), joined by logical operators. Intermediate events are created either from BEs or from other in intermediate events. The end point of the tree is the critical TE (*te* in Fig. 10), which is constructed in the same way as intermediate events, but marked with a property of being the top-most event (which indicates that the higher level of the tree has been reached).

After specifying the FT inputs and running the application (the button *Run*), the MERGER software is executed on distributed computing resources. The computation itself may take some time, depending on the complexity of the fault tree and on the number of iterations supplied as one of the input parameters. After the computation is finished, the results of the application are saved to the user's *Workspace* and is available to be displayed (see, e.g. Fig. 12) or downloaded. The application run is asynchronous; therefore, the results will be saved even if the user is not logged-in to the IS-EPOS Platform. This is a very important feature, especially when analysing large, complex problems, because in the case of computationally expensive analyses, the user can launch calculations, log-off of the system, and retrieve the results after some time by logging-in again into the platform.

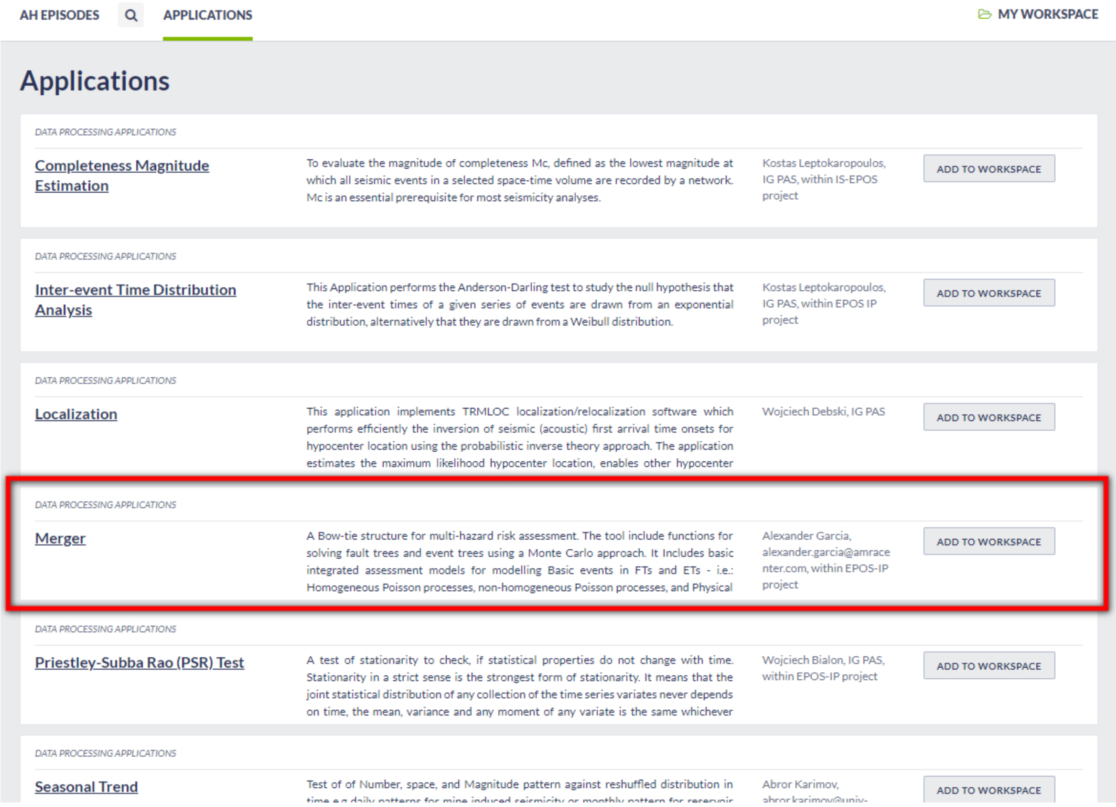

Fig. 9 View of the Applications list within the IS-EPOS Platform

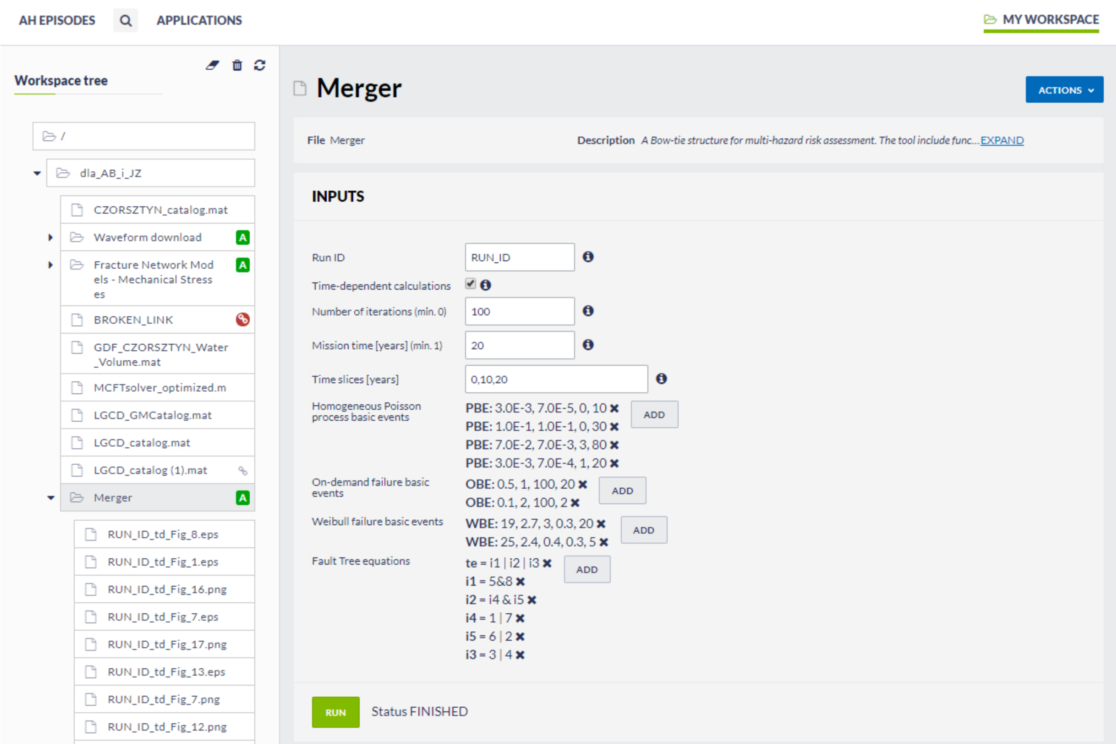

Fig. 10 View of the Fault tree input/analysis of MERGER (MERGER-FT) within IS-EPOS Platform workspace

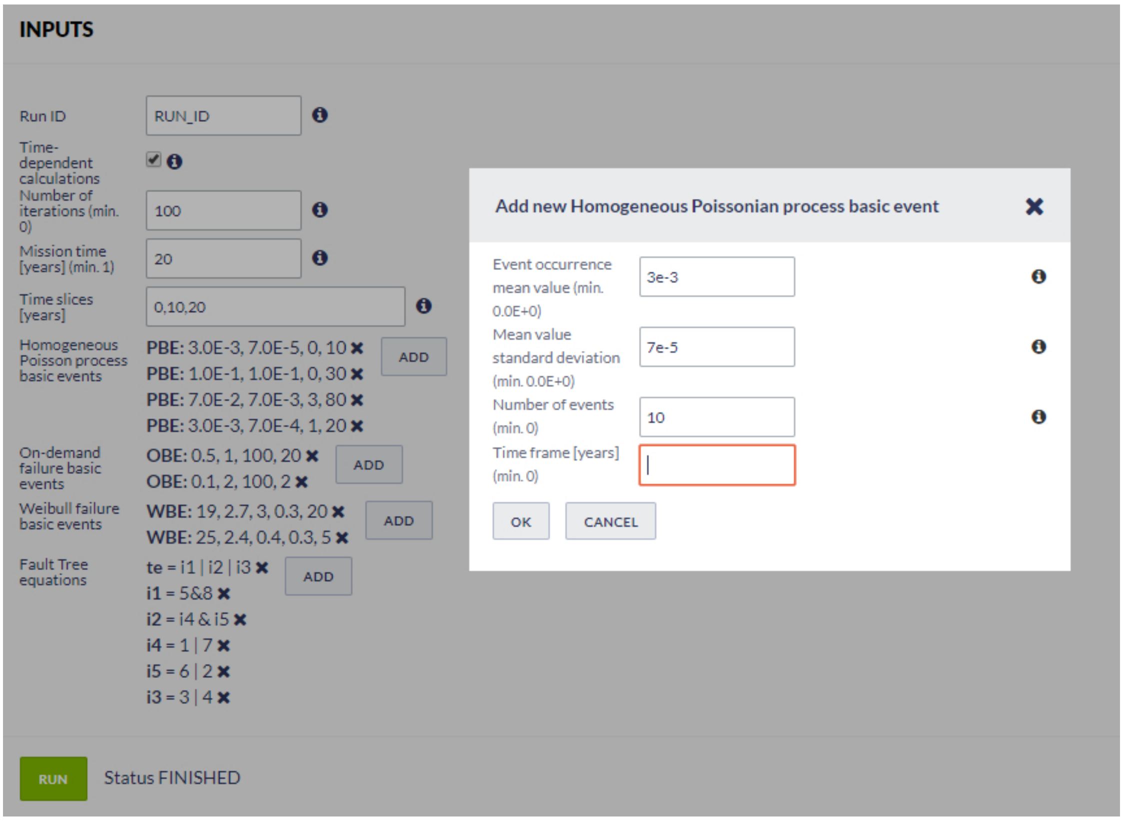

Fig. 11 Detailed view of MERGER-FT application: Homogeneous Poisson process basic events input within IS-EPOS Platform workspace

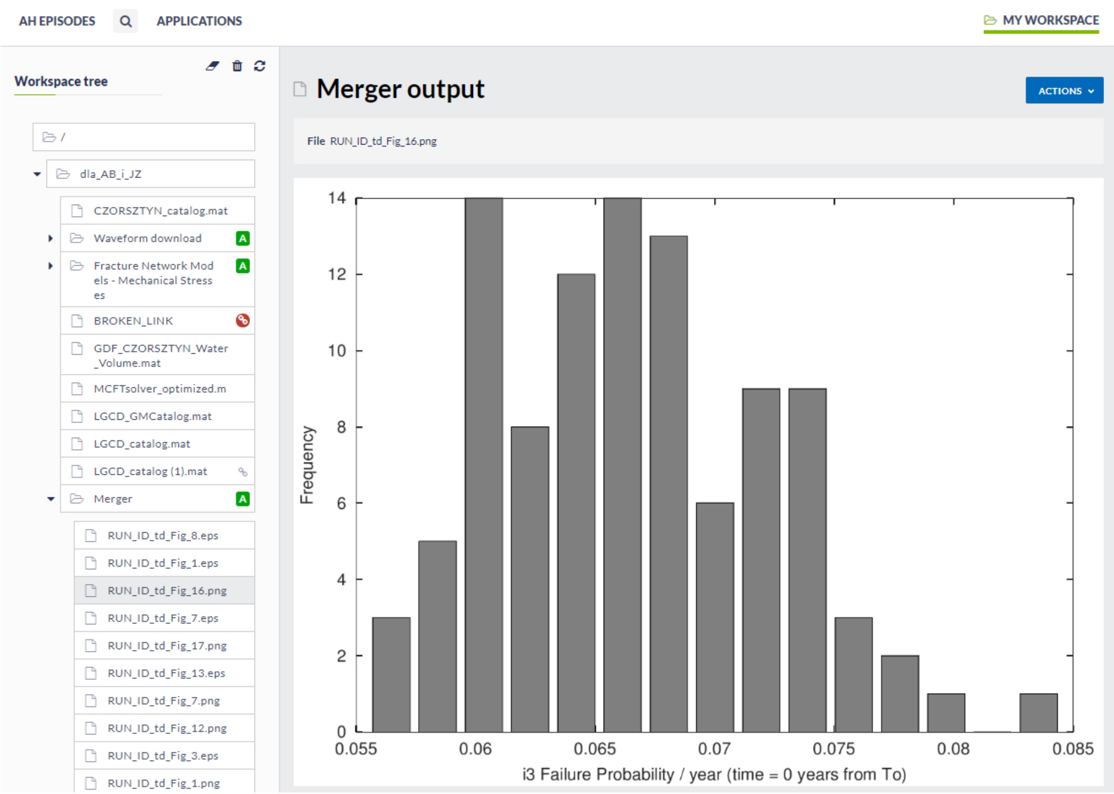

Fig. 12 View of one of the FT-MERGER outputs within IS-EPOS Platform workspace. One of the outputs is displayed directly in the workspace, others are visible as files in the workspace tree on the left

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