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RISK ASSESSMENT OF SPENT FUEL PONDS SUBJECT TO THE RISK OF FLOODING

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ABSTRACT

A model for the risk assessment of spent nuclear fuel facilities subject to the risk of flooding is proposed and analysed adopting a novel approach. The methodology and computational tool developed are based on the enhancement of Bayesian Networks with Structural Reliability Methods able to take into consideration both continuous and uncertain but bounded variables. This approach wants to overcome the limitations of classic Bayesian Networks (such as the use of only discrete variables in case of exact inference calculations) and ensures a more faithful representation of the data available. The theoretical background and the computational tool developed for the methodology mentioned are briefly described, together with the application to the real-case study of Sizewell B nuclear power station in East Anglia (UK). The analysis of the model is computed adopting uncertain but bounded parameters and the uncertainty affecting the output is represented through the use of probability bounds. Finally, the results of the analysis are discussed in order to highlight advantages and drawbacks of the new approach.

INTRODUCTION

The occurrence of technological disasters triggered by natural hazards (generally referred as natech events) has progressively nourished the concern of the scientific community and increased the awareness of public opinion about the vulnerability of technological installations and infrastructures to extreme weather conditions. In addition, according to projections, global climate change threatens to intensify both in terms of frequency and severity the occurrence of extreme wind and rain events which, together with sea level rise, increases the likelihood of flooding along shorelines. This growing risk directly affects a large amount of industrial facilities, which have long located along river beds or coastlines to facilitate the transport of materials and to provide easy access to water for industrial processes and waste disposal. At the same time, the growing population density in coastal areas contributes to widening the hazardous areas involving an ever increasing number of communities and technological installations. This trend suggests a parallel growth of the risk of natech events and the need for mitigation measures to enhance the reliability of existing systems and to improve the design standards of new facilities.
A complete evaluation of the risk requires models suitable for long-term decision making support but also for real time risk assessment, in order to lead the decision makers even in case of imminent danger [Cruz et al., 2004]. This study proposes a generic model for the quantification of the risk of exposure of the spent nuclear fuel stored in a fuel pond. The model aims to meet the requirement of flexibility mentioned before. It consists of a simple and intuitive framework which integrates climate change models in order to assess present and future risks of exposure of spent fuel in case of flooding of the storing facility. A previous implementation of the model [Tolo et al. (2014)], based on the use of traditional Bayesian Networks (BNs), highlighted the potential and limitations of such an approach in the field of risk assessment of technological failures triggered by natural hazards. A new methodology has been adopted in this study in order to overcome the limitations previously highlighted.

METHODOLOGY

This section aims to give an overall idea of the theoretical background of the methodology adopted and to briefly describe the computational tool developed for its application.

Bayesian Networks Enhanced with System Reliability Methods

BNs are statistical graphical models which provide the factorization of the joint probability distribution associated with an event of interest exploiting information about the conditional dependencies existing among the variables.

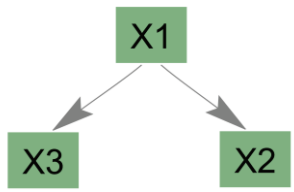

Figure 1. Example of an elementary BN

The nodes, representing the variables of the model, are connected to each other by arrows expressing informal or causal dependencies. Only nodes among which exists some sort of dependency are linked. With regards to the BN introduced in Fig. 1, the node X_1 is called the *parent* of X_2 and X_3, which are also referred to as its *children*. Nodes that have no parents are defined as *roots*. Generally, on the basis of the Bayes' theorem, the joint probability modelled by any BN with nodes $X_1, X_2, \ldots, X_n$ can be expressed as:

$$P(x_1, \ldots, x_3) = \prod_i P(x_i|p_i) \tag{1}$$

where p_i refers to the outcomes assumed by the parents of the node X_i, whose state is represented by x_i. Thus, the joint probability associated with the BN of Figure 1 is:

$$P(x_1, x_2, x_3) = P(x_1)P(x_2|x_1)P(x_3|x_1) \tag{2}$$

Both approximate and exact algorithms are available in literature for the computation of inference in BNs [Pearl and Russel, (2000)]. Generally, exact inference algorithms represent well-established and more robust approach in comparison with approximate inference algorithms which often are computationally inefficient or can have unknown rates of convergence. On the other hand, exact algorithms are restricted to only discrete or Gaussian nodes, often implying the necessity to discretize continuous random variables and hence impoverishing the quality of the information. The integration of the BN approach with system reliability methods, commonly known as Enhanced Bayesian Networks (EBNs), allows avoiding this practice.

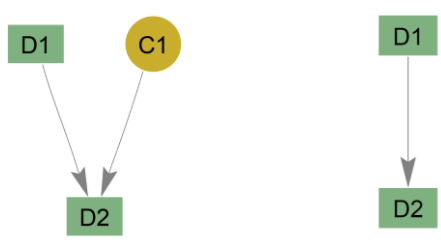

Figure 2 Example of an elementary EBN (left) and its reduced network (right), where C refers to a continuous whilst D1 and D2 to a discrete node

The role of system reliability methods is to reduce the initial EBN (including non-discrete variables) to a traditional BN on which it is possible to compute exact inference. In more detail, each node child of at least one continuous node has to be defined as domains in the outcome space of its parents (deterministic nodes) or by a PMF that is parametrized by the parent nodes (random nodes). Through system reliability analysis is then possible to associate discrete children of continuous nodes with conditional probability values (as in traditional BNs) and to erase the dependency of the node from its non-discrete parents. Thus, the links among continuous and discrete nodes are progressively removed, allowing the elimination of all continuous nodes from the initial network.
In light of Eq.1, the joint probability associated to the reduced network in Fig.2 can be computed solving the integral in Eq.3:

$$P(D_1|D_2) = \int_{C_1} p(D_1)P(D_2|D_1, C_1)f(C_1)dC_1 \tag{3}$$

where $p(D_1)$ and $p(D_2|D_1,C_1)$ are the probability values associated to the discrete nodes D_1, D_2 whilst $f(C_1)$ is the probability density function associated with the continuous node C_1. Considering the Markov condition, hence the independence of the node D_1 from the continuous node C_1, the solution of the integral in Eq.4 is reduced to:

$$P(D_1|D_2) = \int_{C_1} p(D_2)P(D_1|C_1)f(C_1)dC_1 \tag{4}$$

In light of the initial hypothesis, the state of the node D_2 can be expressed as domain in the outcome space of the nodes C_1 and D_2. The integral can then be expressed as:

$$P(D_1|D_2) = \int_{C_1} f(C_1)dC_1 \tag{5}$$

where $\Omega_{D_2,d_2}^{d_2}$ is the domain that defines the event $D_2=d_2$ in the space of C_1 given $D_1=d_1$. The integral in Eq.5 appears in the form common to structural reliability problems and can be easily solved using structural reliability methods.

Computational Tools

The EBN methodology, firstly suggested by [Straub and Kiureghian (2010)], has been implemented in the general purpose software OpenCossan [Patelli et al. (2012)] in an object oriented fashion and extended to include interval variables. The computational tool developed provides the graphical and numerical implementation of models as well as the reduction of EBNs to traditional BNs through the use of structural reliability methods. Several options are provided for this procedure: in the case of only probabilistic and discrete variables being involved it is possible to use traditional or advanced Monte Carlo methods (such as Line Sampling) as well as the well-known First Order Reliability method (FORM). In the case of uncertain but bounded variables being involved (i.e. intervals), two methods are available: the first consists in a generalization of the FORM method [Luo et al. (2009)] relying on the use of convex models; the second in an Advanced Line Sampling method [De Angelis et al., (2015)] which provides quantification of the uncertainty affecting the output. The computation of inference in the network it is possible thanks to the interaction of the tool with the Bayes Toolbox for Matlab [Murphy (2001)].

MODEL

The overall aim of the model is to evaluate the risk of exposure of the spent fuel stored in a spent fuel pond of a nuclear facility in light of the impact of a flooding (Fig.3). For the sake of clarity, the description of the model proposed below is organized in three sections, according to the aim of as many different subsets of the network.

Figure 3 Overview of the BN model proposed for the risk assessment of spent nuclear fuel facility subject to the risk of flooding

Natural-technological interaction section

The upper part of the network (Fig.4) models the direct effects of natural events on the nuclear facility and its surroundings. This section involves nodes either related to weather conditions (*ExtremePrecipitation*, *SeaWaterLevel*, *SeaWavePeriod*, *SeaWaveHeight*) or representing failures directly triggered by the natural event (*DrainageSystemFailure*, *FloodingSurroundings*, *OutfallFailure*, *WaveOvertoppingOccurrence*). The first category is generally represented by continuous nodes, which better describe the aleatory nature of such events, whilst parameters involved in the computation of the failure events (i.e. *CrestLevel*, *SeaWallInclination*, *LocalDefenceHeight*, *DrainageSystemCapacity*, *OutfallCapacity*, *GrossStationArea*, *FloorAreaRatio*, *FloodBarriersCapacity*, *HighTideDuration* and *SeawallLength*) are considered uncertain but bounded (in orange in Fig. 3 and 4).
Three main mechanisms of external flooding are taken into consideration: coastal, river and surface water flooding. Coastal flooding concerns both sea wave overtopping of coastal defences and tidal flooding.

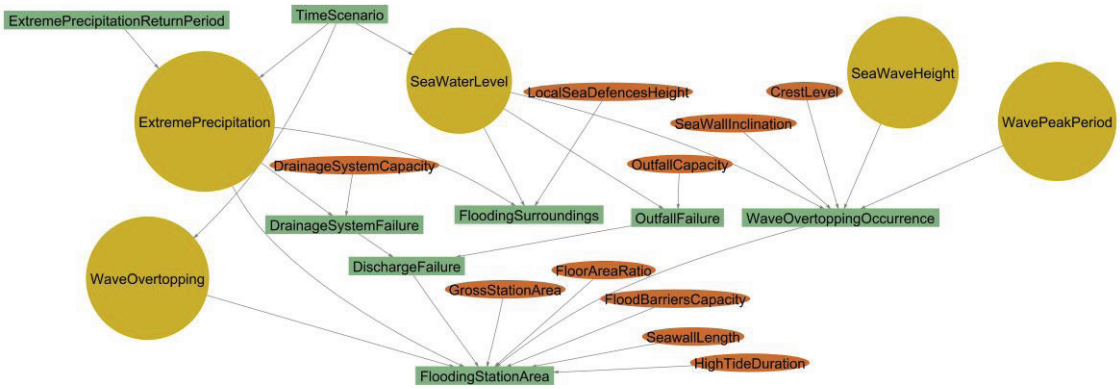

Figure 4 Section of the network modelling the direct effects of natural events

The first implies modelling the mechanism of discharge of sea water within the station perimeter due to the action of sea waves (involving *ExtremeSeaWaterLevel*, *SeaWaveHeight* and *SeaWavePeriod*) [Hedges et al. (1998)]. Tidal flooding is assumed to affect only the surrounding area (*FloodingSurroundings*). Also the river flooding mechanism can affect the surroundings and it is mainly represented by the interaction between *ExtremePrecipitation* and *FloodingSurroundings*. Surface water flooding presupposes the failure of the drainage system (*DrainageSystem*) due to exceptionally heavy rainfall or the unavailability of the *Outfall* due to extreme sea level. According to the projections available [Met Office (2013)], the extreme precipitation event is represented by two nodes: one discrete (*ExtremePrecipitationReturnPeriod*) and one continuous (*ExtremePrecipitation*), associated with the probability distribution of the return period values. The overall combination of the flooding dynamics mentioned may potentially lead to the accumulation of water within the facility, event represented by the node *FloodingStationArea*. Finally, the node *TimeScenario* allows selecting a particular time interval of reference (thus the influence of climate change on natural events).

Internal failure section

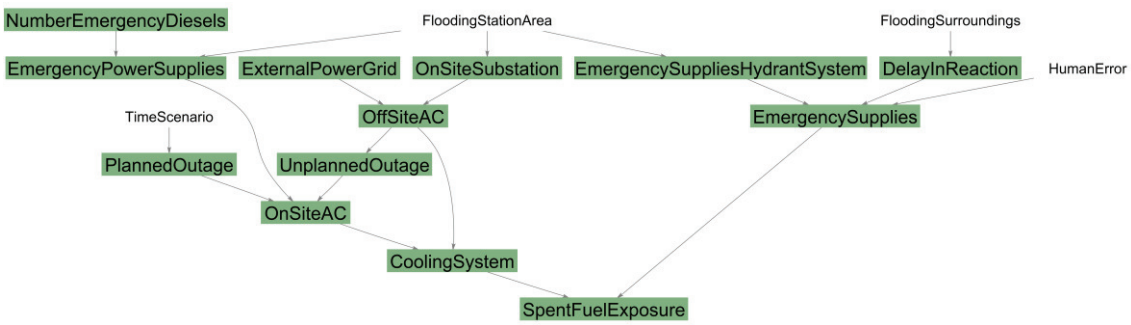

Figure 5 Section of the network modelling internal failures

According to the BN model proposed, the event of exposure of the spent nuclear fuel is bound by the availability of either cooling systems or emergency supplies. If both these subsystems are out of order, the event *SpentFuelExposure* is assumed to occur (Fig.5)**.** The cooling system is expected to fail if no electric power, both generated on-site (*OnSiteAC*) and supplied to the station from the external grid (*OffSiteAC*), is available. The failure of on-site generation can be attributed to power station outages, planned (e.g. due to refuelling or decommissioning) or unplanned (loss of grid or unplanned reactor shut-down); the failure of emergency power supplies (*EmergencyPowerSupplies*), such as emergency diesels, is also a precursor event of station blackout. Moreover, the decommissioning of the station is taken into account through the node *Closure*. If both the outage and the failure of emergency diesels occur, no power generation is available on site. On the other hand, the loss of power from the external network can occur in the case of failure of the power grid as well as on-site electric substations and connections (*OnSiteSubstation*). The node *EmergencySupplies* refers to the lack of effective actions on the facility in the case of unavailability of the cooling system. This kind of intervention involves both technological and human aspects: the first is considered in terms of lack of supplies, such as in the case of loss of reservoirs (*Reservoirs*) or hydrants (*EmergencyHydrantSystem*); the second involves the delay of actions from the outside (*DelayInReaction*), e.g. the intervention of fire tenders, and the occurrence of human errors (*HumanError*) which nullify or prevent the action. This section of the network is connected to the overall model through four nodes: FloodingSurroundings, *FloodingStationArea*, *TimeScenario* and *HumanError*. The first two belong to the upper part of the network previously discussed and affect the system in similar ways: flooding nearby the station has the potential to affect roads of access and then to make the rescue from the outside impossible; likewise, the accumulation of water inside the facility can affect a wide range of subsystems, such as emergency supplies or electric transformers. Also the node *TimeScenario* belongs to the first section

described but, as mentioned before, it does not represent an event: the links it shares with other nodes have no causal meaning.

Human Error section

The BN model proposed by Groth and Mosleh (2011) to quantify the probability of human errors in the case of significant incident at a nuclear power plant has been integrated in the overall framework. The approach suggested in the study integrates Performance Influencing Factors (PIFs), largely used in literature to predict human behaviour and cognitive processes, and their interdependencies in a BN framework. The nodes *Resources*, *OrganizationalCulture*, *Knowledge*, *Team*, *Training*, *Complexity*, *Machine*, *Attitude*, *LoadsAndPerceptions* refer to as many groups of PIFs, while the four *ErrorContext* nodes aim to capture the interrelation among different factors and correlations among nodes not linked by direct causal relationships. Each of these four nodes acts as a precursor of the event *HumanError*, to which all of them contribute with different weights. For further details regarding the approach please refer to the original article. This part of the network is linked to the rest of the model through causal dependency between the nodes *HumanError* and *EmergencySupplies*, as argued in the former section. An accurate approach should take into account other aspects, such as the consequences of flooding on the availability of suitable tools (*Resources*) or the effect of downsizing (in case of decommissioning) on the team of work (*Team*). However data limitations preclude at the moment this kind of development of the model. Further study in this direction is strongly advisable but beyond the purpose of this work.

Case-study: Sizewell B Nuclear Power Station

Sizewell B power plant is built on a plateau at 6.4m Above Ordnance Datum (AOD) on the coast of East Anglia in the county of Suffolk. It shares a site of 97 Hectares with Sizewell A station (no longer operating) which lies on the southern side. The area to the east of the station consists of a series of sand dunes which gradually slope down to the sea shore covering a width of approximately 100m. These ridges, commonly known as the Bent Hills, have been remodelled in order to provide a 10m high sea defence embankment along the east boundary of the site. The land surrounding the station to the north and west is swampy and subject to the risk of flooding. Nevertheless, thanks to the major elevation of the nuclear island respect to the surroundings, floods in this area are not expected to represent a direct hazard to the station. The site access road is located at an elevation of 3.5m AOD.
Built between 1988 and 1995, the power plant includes two main turbine generators and a single reactor based on a Westinghouse standard four loop pressurised water design. The initial design was modified, mainly in terms of capacity and redundancy of safety system, in order to fulfil UK requirements. The on-site electric substation is connected to the external grid at three separate 400kV points (two at Bramford, one at Norwich and one at Pelham) and provides connection with the external network for the import and export of power. Adjacent to the reactor building, the fuel building accommodates the pond where both new and used fuel is stored [Fullalove (1995)] under water. The pool consists of a stainless steel lined reinforced cavity where the fuel assemblies are located at a depth of water adequate to guarantee the coverage of the fuel for 24h in case of total loss of the cooling system. The latter consists of a primary ultimate heat-sink (seawater) and a reserve ultimate heat-sink (air-cooling system) which ensure the thermal exchange required for the pumped flow. The availability of AC power on-site binds the working order of the cooling system in the fuel facilities. These, as all the building of the nuclear island, are provided with fire doors that can act as flood barriers up to a water depth of 1m [EDF (2012)].

Input and Data Sources

Three different time scenarios have been considered: one related to the actualised risk and two to future hazards, evaluated using frequency and severity forecasts for extreme events projected in 2055 and 2099. In the first two the plant is assumed to be fully functional whilst the last scenario involves the presence of

spent fuel stored and the production of electric power on-site limited to the only emergency diesels due to the closure of the facility. To represent the hazards related to future scenarios, projections have been adopted for the sea water level (Fig.6) [Met Office (2013)] and extreme precipitations values [Francis and Sanderson (2011)], which have been represented as continuous random variables.

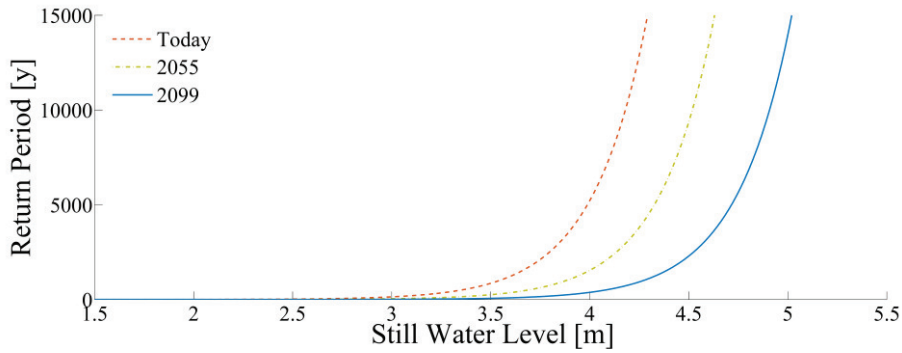

Figure 6 Return period curves for extreme sea water level

All the predictions related to climate change and adopted in the case study refer to the medium emissions scenario A1b1 according to IPCC classification [Nakicenovic and Swart (2000)]. Probabilistic models have been implemented for *SeaWaveHeight* and *WavePeriod* fitting historical data [CEFAS (2013)] adopting the least squares approach (see Table I and Fig.8).

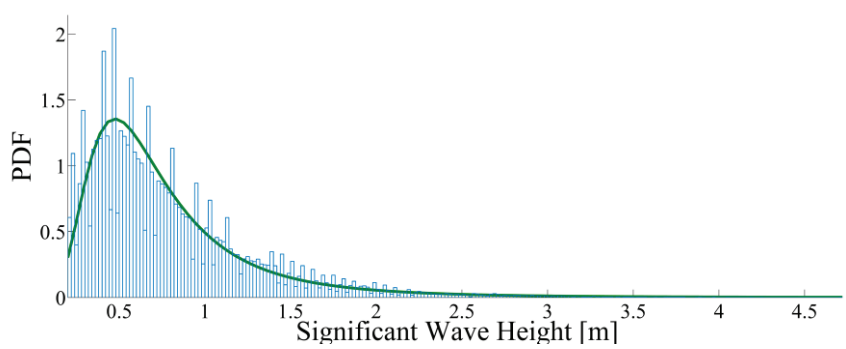

Figure 7 Generalized extreme value model of the wave significant height probability distribution

Table 1 Generalized extreme value distributions computed with maximum likelihood estimation

Parameter	WaveHeight	WavePeriod
Shape Parameter	0.26803	0.00513
Scale Parameter	0.28039	1.45702
Location Parameter	0.53985	4.62444

A linear correlation factor of -0.29 between the two variables, represented by the continuous line in Fig.9, has been considered. In the implementation of the model all the waves have been assumed normally incident to the seawall and no integration with off-shore near-shore wave transformation models has been considered. This hypothesis and the resulting strongly conservative approach make the contribution of climate change totally negligible. Hence, the effect of climate change on wave condition nodes has been neglected. Finally, Table 2 shows the values adopted for the uncertain parameters.

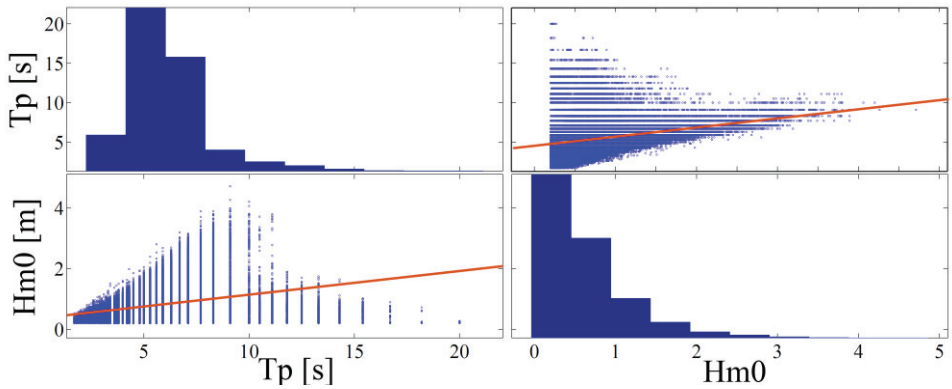

Figure 8 Analysis of the correlation between significant wave height (Hm0) and peak period (Tp)

Table 2 Values for the uncertain but bounded variables in input

Parameter	Central Value	Lower Bound	Upper Bound
OutfallCapacity [m]	5	4.9	5.1
CrestLevel [m]	10	9.8	10.2
SeaWallInclination [rad]	5.1E-02	4.9E-02	5.2E-02
SeawallLength [m]	350	348	352
GrossStationArea [m^2]	133492	132492	134492
LocalDefenceHeight [m]	4	3.9	4.1
DrainageSystemCapacity [mm/d]	300	290	310
FloorAreaRatio	0.7266	0.7138	0.7397
FloodBarriersCapacity [m]	1.15	1.10	1.20
HighTideDuration [h]	3	2.5	3.5

Dissimilarly from the upper part of the network, the nodes involved in the remaining sections of the model are all discrete. The input associated with such nodes have been deduced either from previous studies or, more generally, from data available in literature (see Table 3).

Table 3 References for the model input

Event	Reference
Power Grid Failure	Nack (2005)
Hydrant System Failure	I.A.E.A. (1989).
On-site Substation Failure	Nack (2005)
Planned Outage	EDF (2013)
Unplanned Outage	EDF (2013)
Power Supplies Failure	NRC (2007)
Human Error (section)	Groth and Mosleh (2011)

Results

The analysis has been carried out adopting the Advanced Line Sampling method. According to the results shown in Table 4, the overall risk of exposure of the spent fuel grows along with the three scenarios considered. This trend can be explained with the analogous growth of the probability of on-site flooding which, as foreseeable on the basis of the climate change projections, results significantly affected by the

expected intensification of extreme weather events in time. In spite of this, in none of the time periods considered the probability of fuel exposure assumes values above an order of magnitude of 10^{-11}.

Table 4 Quantification of risks of several events computed

Event	Scenario 1 (Today)	Scenario 2 (2055)	Scenario 3 (2099)
On-site Flooding	[0 1.11E-16]	[0 1.06E-10]	[0 4.86E-10]
Cooling System	[1.74E-11 3.43E-11]	[1.74E-11 1.24E-10]	[1.74E-11 5.04E-10]
Spent Fuel Exposure	[1.64E-17 4.86E-17]	[5.83E-17 7.58E-13]	[4.57E-16 2.37E-11]
Flooding in Surroundings	[3.86E-05 1.14E-04]	[1.37E-04 4.97E-04]	[1.08E-03 2.95E-03]

Also the probability of failure of the cooling system follows the same trend, remaining below a value of 10^{-10}. On the contrary, the marginal probability associated with the occurrence of flooding event in the surrounding area reaches significant values, with a maximum of 2.95E-03 for the 2099 scenario.

Table 5 Risk of Spent Fuel Exposure

What if...?	Scenario 1 (Today)	Scenario 2 (2055)	Scenario 3 (2099)
Cooling S. Failed	[9.40E-07 2.79E-06]	[3.34E-06 6.12E-03]	[2.62E-05 4.68E-02]
Drainage S. Failed	[6.84E-17 2.17E-16]	[3.40E-16 8.26E-10]	[2.50E-15 2.57E-08]
Surroundings Flooded	[4.25E-13 4.25E-13]	[4.25E-13 2.09E-09]	[4.25E-13 8.54E-09]
Human Error	[6.73E-16 2.00E-15]	[2.39E-15 7.67E-13]	[1.88E-14 2.36E-11]
Human Error & Surroundings Flooded	[1.74E-11 2.31E-10]	[1.74E-11 2.11E-09]	[1.74E-11 8.56E-09]

Moreover, several *what-if* scenarios have been analysed in order to estimate the risk of exposure conditional to the failure of different subsystems. As shown in Table 5, the occurrence of human error alone does not affect strongly the final risk of accident. On the contrary, the cooling system failure significantly raises the probability of spent fuel exposure, which in this case grows up over an order of magnitude of 10^{-5} in both 2055 and 2099 scenarios. Finally, flooding in the surrounding area contributes to the overall growth of the risk of exposure of the spent fuel, even if not affecting directly the facility.

CONCLUSIONS

A model for the assessment of the risk of exposure of spent nuclear fuel has been proposed. The methodology adopted is based on the enhancement of BNs using structural reliability methods and it has been implemented in the general purpose software OpenCossan. The computational tool obtained allows taking into consideration continuous and uncertain but bounded variables not renouncing to the advantages and robustness of exact inference algorithms, at the cost of a higher, but still acceptable, computational cost. The network proposed has been applied to a real-world case study, in which aleatory and epistemic uncertainty have been represented through the use of probabilistic models and intervals. The results have been briefly discussed, in order to highlight the potential of the model and tool developed.

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