Enhanced Bayesian Networks approach to Risk Assessment of Spent Fuel Ponds

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ABSTRACT: A model for the risk assessment of spent nuclear fuel ponds subject to the risk of flooding is proposed. The methodology adopted is based on the enhancement of Bayesian Networks approach with Structural Reliability Methods, in order to overcome the limitations of classic Bayesian Networks (such as the use of only discrete variables in case of exact inference calculations). The computational tool developed for the methodology mentioned is briefly described together with the application to a real-case study. The related results are discussed and compared to those previously obtained by traditional Bayesian Network analysis. Finally, a brief discussion about the advantages and drawbacks of the approach adopted is provided.

1. INTRODUCTION

The attention about issues related to nuclear safety is evidently high, particularly after the Fukushima Daiichi nuclear power plant accident. Whilst most of these concerns are focused on the vulnerability of the reactors themselves, less attention has been paid to the spent fuel ponds which have the potential to be more vulnerable to failures than the reactor containment building. Furthermore, as recognized by the Nuclear Regulatory Commission, even if the likelihood of a zirconium fire due to the exposure of spent fuel is generally very low, the consequences of a similar event would be highly significantCollins and Hubbard (2001). For these reasons the study of the vulnerability of such installations to external events, such as extreme weather conditions, results relevant in view of a more general and accurate risk assessment of nuclear facilities. This kind of analysis implies the use of flexible models able to simulate not only the complexity of the system under study but also different scenarios. For example, assessing the impact of natural hazards on technological installations, the climate change effect on extreme weather hazards cannot be neglected. Furthermore, 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.

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 [Silvia Tolo (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. In light of this, a new methodology (firstly suggested by Straub and Kiureghian (2010)) has been adopted.

2. METHODOLOGY

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

2.1. Bayesian Networks

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. BNs consist of a variable number of nodes, representing the variables of the problem modelled. The nodes are connected to

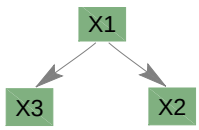

Figure 1: Example of an elementary BN

each other by edges (commonly represented as arrows) expressing informal or causal dependencies. Only nodes among which exists some sort of dependency are linked, whilst those that are not joined refer to variables that are conditionally independent of each other. 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 $X_1, X_2, ..., X_n$ can be expressed as:

$$P(x_1 ... x_n) = \prod_i P(x_i \mid p_i) \tag{1}$$

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

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

A complete overview of Bayesian networks is provided by Pearl and Russell (2000).

2.2. Bayesian Networks Enhanced with system reliability methods

Exact inference algorithms are robust and well established methods for the computation of inference in BNs. These 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 allows to avoid this practise. The resulting strategy is commonly known as Enhanced Bayesian Networks (EBNs). The role of system reliability methods is to reduce the initial EBN (including discrete as well as continuous random variables) to a traditional BN on which is possible to compute exact inference. More in details, each node child of at least one continuous 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). The use of system reliability methods, not only allows to associated to discrete nodes children of continuous conditional probability values (as in traditional BNs) but also erases the dependency of the node from its non-discrete parents. Hence, the links among continuous and discrete nodes can be completely removed, finally allowing the elimination of all continuous nodes. 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:

$$P(D1, D2) = \int_{C_1} p(D_1) p(D_2|D_1, C_1) f(C_1) dC_1 \tag{3}$$

where $p(D_1)$,$p(D_2|D_1, C_1)$ are the probability values associated to the discrete nodes D_1,D_2 whilst $f(C_1)$ is the probability density function associated to the continuous node C_1. Considering the Markov condition, hence the independence of the node D_1

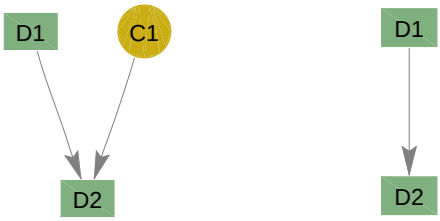

Figure 2: Example of an elementary EBN and its reduced network, where C refers to a continuous whilst D1 and D2 to a discrete node

from the continuous node C_1, the solution of the integral in Eq.4 is reduced to:

$$P(D1|D2) = \int_{C_1} p(D_2|D_1, C_1) f(C_1) dC_1 \qquad (4)$$

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 be than expressed as:

$$P(D1|D2) = \int_{\Omega^{d2}_{D2,d1}} f(C_1) dC_1 \qquad (5)$$

where $\Omega^{d2}_{D2,d1}$ is the domain that defines the event $D2 = d2$ in the space of C_1 given $D1 = d1$. The integral in Eq.5 appears in the form common to structural reliability problems and can be easily solved using structural reliability methods. Please refer to Straub and Kiureghian (2010) for further details.

2.3. *Computational tools*

The EBN methodology briefly outlined in the previous section has been implemented in the general purpose software OpenCossan [Patelli et al. (2012)] in an object oriented fashion. The computational tool developed provides the graphical and numerical implementation of models as well as the reduction of EBNs to traditional BNs. Two main options are provided to the user for this procedure: the first relies on the use of First Order Reliability Method, providing a less computational expensive analysis at cost of poorer accuracy, the second is based on the use of Monte Carlo methods. The computation of inference in the network it is possible thanks to the interaction of the tool with the Bayes Toolbox for Matlab [Murphy et al. (2001)].

3. 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.

3.1. *Natural-technological interaction section*

The upper part of the network (Fig.4) aims to model the direct effects of natural events on the nuclear facility and its surroundings. Three main mechanisms of external flooding are considered: coastal, river and surface water flooding. This

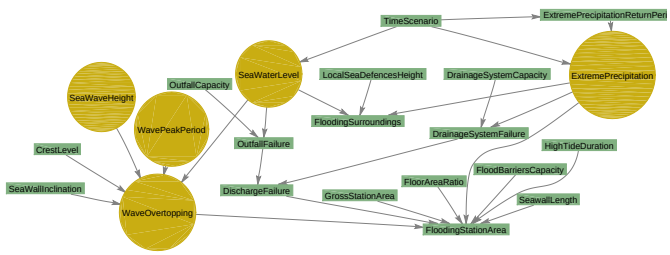

Figure 4: Section of the network modelling the direct effects of natural events

section involves nodes either related to weather conditions (*ExtremePrecipitation*, *SeaWaterLevel*, *SeaWavePeriod*, *SeaWaveHeight*) or representing failures directly triggered by the natural event (*DrainageSystem*, *FloodingSurroundings*, *Outfall*, *WaveOvertopping*). The first category is generally represented by continuous nodes, which better describe the aleatory nature of such events. Coastal flooding is considered in terms of both sea wave overtopping of coastal defences and tidal flooding. The first case involves the modelling of the mechanism of discharge of sea water inside the station perimeter due to the action of sea waves overcoming the station protections (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 in the model by the edge joining the node *ExtremePrecipitation* and *FloodingSurroundings*.

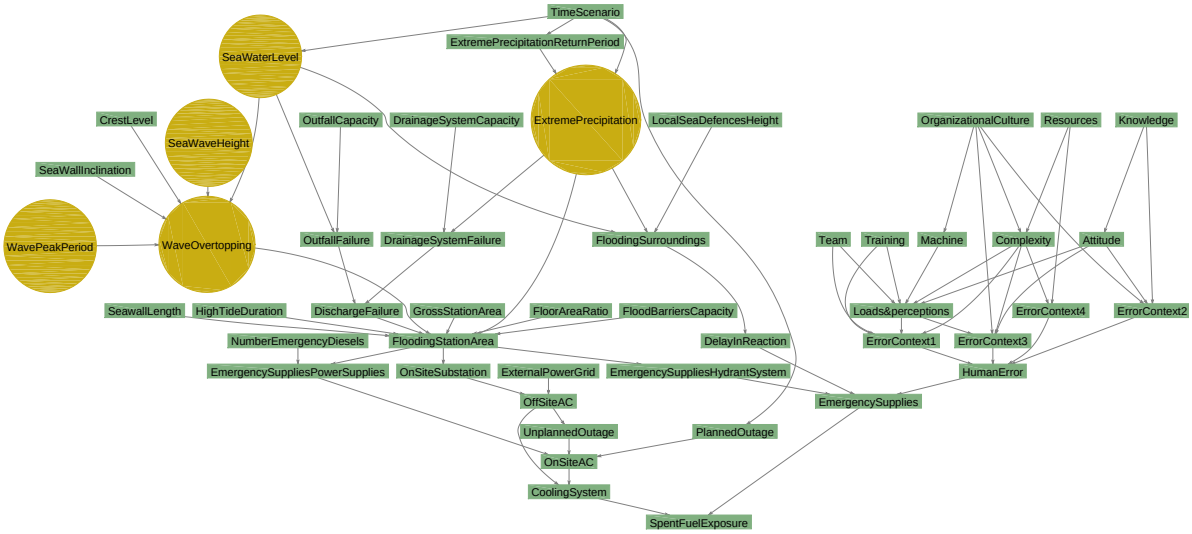

Figure 3: Overview of the BN model proposed for the risk assessment of spent nuclear fuel ponds subject to the risk of flooding

Surface water flooding involves the events of failure of the drainage system (*DrainageSystem*) due to exceptionally heavy rainfall (*ExtremePrecipitation*) and the unavailability of the *Outfall* due to extreme sea level. The overall combination of these flooding dynamics can lead to accumulation of water within the perimeter of the facility, event represented by the node *FloodingStationArea*. The node *TimeScenario* allows to run analysis with regards to a particular time interval of choice. Introducing evidence in the node, hence selecting the time scenario of interest, it is possible to take into account the influence of climate change on natural events.

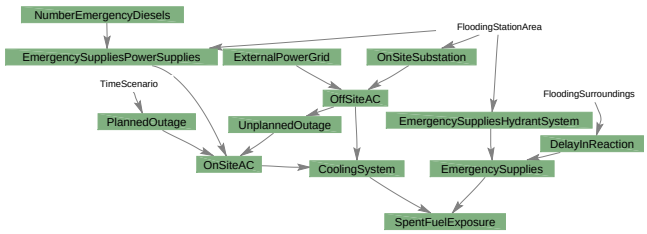

Figure 5: Section of the network modelling internal failures

3.2. Internal failure section

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, either generated on site (*OnSiteAC*) or 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. If both the outage and the failure of emergency diesels occur, no power generation is available on site. 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 pond in the case of unavailability of the cooling system. It can be caused by lack of supplies (loss of reservoirs *Reservoirs* or *EmergencyHydrantSystem*) or by delay of actions from the outside (*DelayInReaction*, e.g. the intervention of fire tenders) or the occurrence of *HumanError* which nullify or prevent the action.

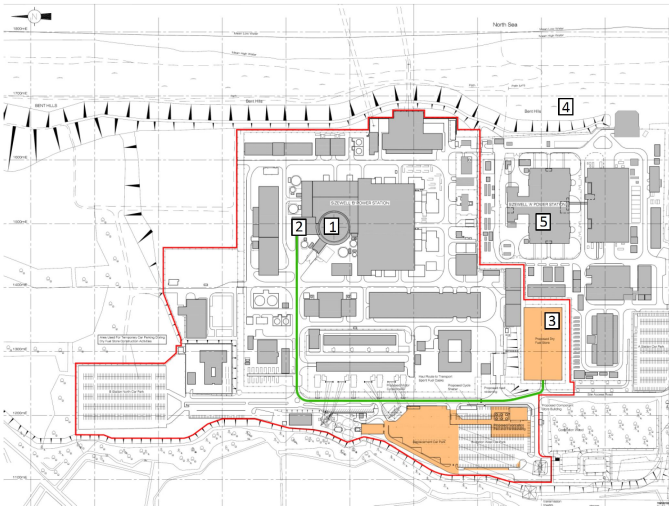

Figure 6: Layout of the nuclear site with Sizewell B reactor building(1), fuel building(2) and dry fuel cask(3). On the East of the site are located the so called Bent Hills(4), on the west the Sizewell A Power Station(5). Figure available from EDF (2014)

3.3. Human Error section

The BN model proposed by Groth and Mosleh (2011) to quantify the probability of human errors in case of significant incident at a nuclear power plant has been integrated in the overall framework. This part of the network is linked to the rest of the model through the causal dependency between the nodes *HumanError* and *EmergencySupplies*.

3.4. Case study

The nuclear power plant of Sizewell B (Fig.6) in East Anglia, UK, operated by EDF Energy, has been selected as real-world case study for the application of the BN model proposed.

According to the flood maps provided by the Environment Agency [Environment Agency (2013)], the surrounding area is subject to risk of flooding. Moreover, EDF's strategic target is to extend the operational life of the installation postponing the decomissioning date from 2035 to 2055 [Houlton (2013)]: it is then of particular interest to evaluate the impact of climate change on the risks to which the facility is subject. Unlike British Magnox and AGR stations [(Office for Civil Nuclear Security and Industry)] the management strategy adopted for Sizewell B revolves long term on site storage under water: the current rate of accumulation and current safety restrictions suggest that full capacity of the on site pond will be reached by 2015. 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 slope down to the sea shore covering a width of about 100m. These ridges provide a 10m high sea defence embankment along the east boundary of the site. The site access road is located at an elevation of 3.5m AOD. 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 fuel assemblies are located in the pool 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 availability of AC power on-site binds the working order of the cooling system in the fuel facilities. 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)].

3.4.1. Input and Data Sources

A wide range of data sources has been adopted for the application of the model to the Sizewell case study. Three different time scenarios has 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 (see Table I).

Table 1: Characterization of the time scenarios adopted in the study

	Year of reference	Station state
Scenario 1	2013	Operational
Scenario 2	2055	Operational
Scenario 3	2099	Closed

In order to represent the hazards related to future scenarios, projections have been adopted for the

sea water level [Office (2013)] and extreme precipitations [Francis (2011)] values, which have been represented as continuous random variables. The return period for the sea water level are shown in Fig.7. All the predictions related to climate change and adopted in the case study refer to a medium emissions scenario *SRES A1B* according to IPCC classification. Also the wave characteristics (*Sea-*

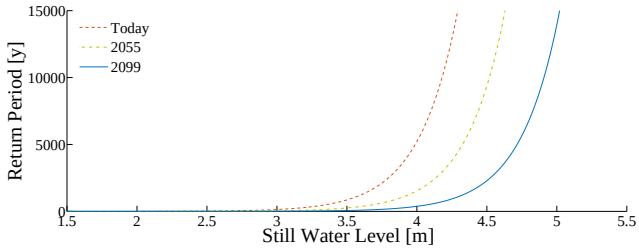

Figure 7: Return period curves for extreme sea water level

WaveHeight and *WavePeriod*) are represented by continuous nodes. The probabilistic models have been implemented fitting historical data [CEFAS (2013)] to generalized extreme value distributions (see Table II and Fig.8) adopting the least squares approach. A linear correlation factor of -0.29 between the two variables, represented by the continuous line in Fig.9, has been considered. In

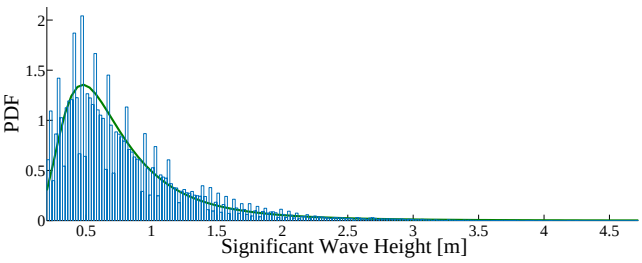

Figure 8: Generalized extreme value model of the wave significant height probability distribution

Table 2: Parameters of generalized extreme value distributions computed with maximum likelihood estimation

Parameter	*WaveHeight*	*WavePeriod*
Shape Parameter	0.268026	0.00512954
Scale Parameter	0.280391	1.45702
Location Parameter	0.539845	4.62444

the implementation of the overtopping model all the waves have been considered normally incident to the seawall and no integration with off-shore near-shore wave transformation models has been considered. This simplificative 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.

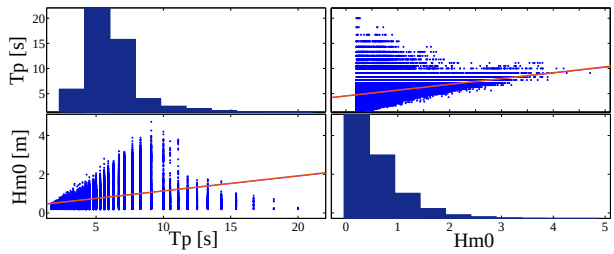

Figure 9: Analysis of the correlation between significant wave height(Hm0) and peak period(Tp)

Table 3: References for the model input

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

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. Table III shows the references related to nodes for which probability values have been collected or derived from the available literature. The state of the remaining events involved in the bottom part of the network is considered to be directly inferable from the outcomes of their precursor nodes, according to Section 3.2.

3.4.2. Results

The analysis of the model has required the evaluation of 156 system reliability problems. The over-

all risk of exposure of the spent fuel grows along with the three scenarios considered. This trend can be mainly 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, as shown in Table 4, in none of the time periods considered the probability of fuel exposure assumes significant values, remaining below an order of magnitude of 10^{-10}. On the contrary, the probability of flooding events in the area surrounding the station, reaches not negligible values in particular with reference to the 2099 scenario. It must be pointed out that this estimates could be strongly affected by the conservative approach resulting from the hypothesis discussed in section 3.4.1.

Table 4: Quantification of risks of several events

Event	Scenario1 (Today)	Scenario2 (2055)	Scenario3 (2099)
On-site Flooding	0	1.11E-16	1.10E-10
Cooling System	1.74E-11	1.74E-11	1.27E-10
Spent Fuel Exposure	2.61E-17	1.09E-16	3.32E-12
Flood Surroundings	6.14E-05	2.57E-04	1.80E-03

Several what-if scenarios have been analysed in order to estimate the risk of exposure conditional to failure of different subsystems. As shown in Table 5, the failure of the drainage system and the occurrence of human error alone slightly increase the final risk of accident. On the contrary, the the failure of the cooling system significantly rises the probability of spent fuel exposure which, in this case, grows up to an order of magnitude of 10^{-2} in the 2099 scenario. Finally, BNs allow also to easily take into consideration the combination of simultaneous occurrence of more failures events, such as shown in Table 5 for the failure of drainage system and the lack of reaction of operators. In this case, the combination of the two accident scenarios contributes to the overall growth of the risk of spent fuel exposure more than what previously seen for the two separate events.

Table 5: Risk of Spent Fuel Exposure

What if...?	Scenario1 (Today)	Scenario2 (2055)	Scenario3 (2099)
Cooling S. Failed	1.50E-06	6.27E-06	2.61E-02
Drainage S. Failed	1.26E-16	6.15E-16	3.36E-09
Surroundings Flooded	4.25E-13	4.25E-13	1.84E-09
Human Error	1.07E-15	4.48E-15	3.35E-12
Human Error & Drainage S. Failed	1.74E-11	1.74E-11	1.86E-09

4. 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 to take into consideration continuous random variables not renouncing to the advantages and robustness of exact inference algorithms, at the cost of a higher, but still acceptable, computational cost. Hence, the main advantage is the capability of adequately represent aleatory uncertainty through the use of probabilistic models. This is a crucial aspect for risk analysis involving natural events and more generally climate modelling variables.

On the other hand, the tool proposed lacks the capability of representing likewise epistemic uncertainty. Indeed, often lack of data prevents the implementation of suitable probabilistic models: in this case, the adoption of intervals can be a more accurate choice for the representation of the information available. Furthermore, as pointed out in section 3.4.2, the current implementation does not allow to estimate the uncertainty affecting the output.

These limitations can be overcome fully exploiting the flexibility of the methodology adopted, as well as the relative computation tool. Reliability methods able to take into consideration a wider range of variable representations (e.g. intervals or other models of imprecise probabilities theory) can be adopted for the reduction of Enhanced Bayesian Networks including, hence, not only continuous and discrete variables. Future research will be ded-

icated to the integration of these methods with the traditional BN framework and the implementation of models for validation purpose.

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