Application of dynamic bayesian network in initiating event calculation

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ABSTRACT

The Probabilistic Safety Assessment (PSA) technique uses Initiating Events (IE) probability as the initiator of accident progression in Event Trees (ET). There are various ways to calculate initiating events described in IAEA TECDOC-719 [1]. Most IE calculation method provides static probability, neglects aging, and does not provide information regarding individual influencers on IE probability. Authors developed the technique through a Dynamic Bayesian Network (DBN) that evaluates the probability of initiating event from multiple hazards with aging consideration.

This paper presents a methodology and a structure of a Dynamic Bayesian Network for Loss of Offsite Power (LOOP) IE with such hazards as earthquakes and tsunamis. Earthquake-induced tsunami happed in 2011 in the coast of Japan due to one of the most powerful earthquakes called the Tōhoku earthquake with 9.0 Mw which caused LOOP, and therefore this case could be representative of such structure creation.

1 INTRODUCTION

External Event Probabilistic Safety Assessment (EE-PSA) is a widely used method to evaluate probabilistically the safety of nuclear facilities against the potential impact of external hazards [2]. Typically EE-PSA analyzes only single hazards due to complexity and low probability of multiple hazards. Accident in Fukushima Daiichi caused by Tsunami and Earthquake showed that multiple hazards could pose a danger despite low probability. This accident caused an increase in multiple hazards interest [3]; therefore, many methods and methodologies were proposed to evaluate Core Damage Frequency (CDF) in case of multiple hazards [4]. Contrary to new methods, approaches presented in section 2 use data from similar installations and do not account for the aging of components. These methods do not evaluate the impact of multiple hazards that pose a significant risk; therefore, new methods that can calculate the probability of IE caused by multiple hazards are crucial for nuclear facilities.

Most new methods are usually created to account for up to two hazards; therefore, they cannot predict the probability of IE realistically. The bayesian network allows one to account for as many hazards as needed if probability and correlations are known; therefore, the authors decided to develop a methodology (see Section 3) that will enable to account for multiple hazards, aging in initiating event freaquency calculation. An example of the method is presented in Section 4, and results and conclusions are provided in Sections 5 and 6.

2 INITIATING EVENT ANALYSIS METHODS

Initiating Event analysis is a complicated process for new nuclear facilities due to the identification of Initiating Events and their frequency evaluation. The International Atomic Energy Agency describes this complex process and the most common approaches [1],[5]. For the identification of initiating events, IAEA recommends performing [5]: Deductive analysis; Analytical methods; Review of deterministic analyses and safety analysis report; Comparison with IE developed for PSA Lelvel 1 for similar plants, existing safety standards, and guidelines; Identification based on operating experience from the plant under investigation and similar plants.

The identification process is complicated due to the number of internal and external hazards that pose a danger. The ASAMPSA_E (Advanced Safety Assessment Methodologies: Extended PSA) project highlighted 97 external hazards, some of which can have correlations [6]. Proper identification of hazards and initiating events will eliminate some hazards due to the object's location or low probability of occurrence.

After identification of initiating events, their frequency calculation is performed. The most common frequency calculation approaches are [1] :

- One stage Bayesian methodology that uses generic experience data
- Two-stage Bayesian methodology using both generic and plant-specific data
- Mean frequencies from extensive operating experience data gathered over a long period
- Expert opinion on rare events and similar plants experience
- Failure rates and mission time and failure rate per pipe length;
- Fault Tree analysis for special rare events;
- Special plant attributes and characteristics of the geographic location

Different frequency quantification approaches are used regardless to plant design (new or old). The most common method is similar experience from other plants where PSA practitioners can use frequencies from databases of United States Nuclear Regulatory Commision (U.S. NRC) or other organizations. The LOOP IE frequency calculation methods for new plants are One Stage Bayesian and Special Plant and location attributes [1].

Special plant and location attribute is a specific approach developed for LOOP IE frequency calculation. This method establishes connections and relations between the frequency of LOOP and switchyard design, the number of off-site lines connected to the switchyard, and the impact of weather conditions. The first manual describing this approach was NUREG-1032 prepared for the U.S. NRC [7]. Since 1997, U.S. NRC has been publishing reports regarding LOOP events, and the most recent one is from 2021 [8].

3 GENERAL METHOD OF IE CALCULATION WITH DBN

The proposed method can be divided into steps presented in Figure 1. The first step is to choose the initiating event for which frequency calculation is needed. After Initiating event selection, identification of potential hazards that could cause it is performed with their correlations (Step 2 and 3). This step leads to a collection of information regarding failure probabilities and fragility of components (Steps 4 and 5). Based on collected data, a static

Bayesian network is created (Step 6). This bayesian network is updated to a dynamic model (DBN) in Step 8 by adding time dependencies such as the aging of components collected in Step 7. The last step is a DBN model simulation and statistical calculation of IE frequency (Step 9). The following steps are shown in the example from section 4.

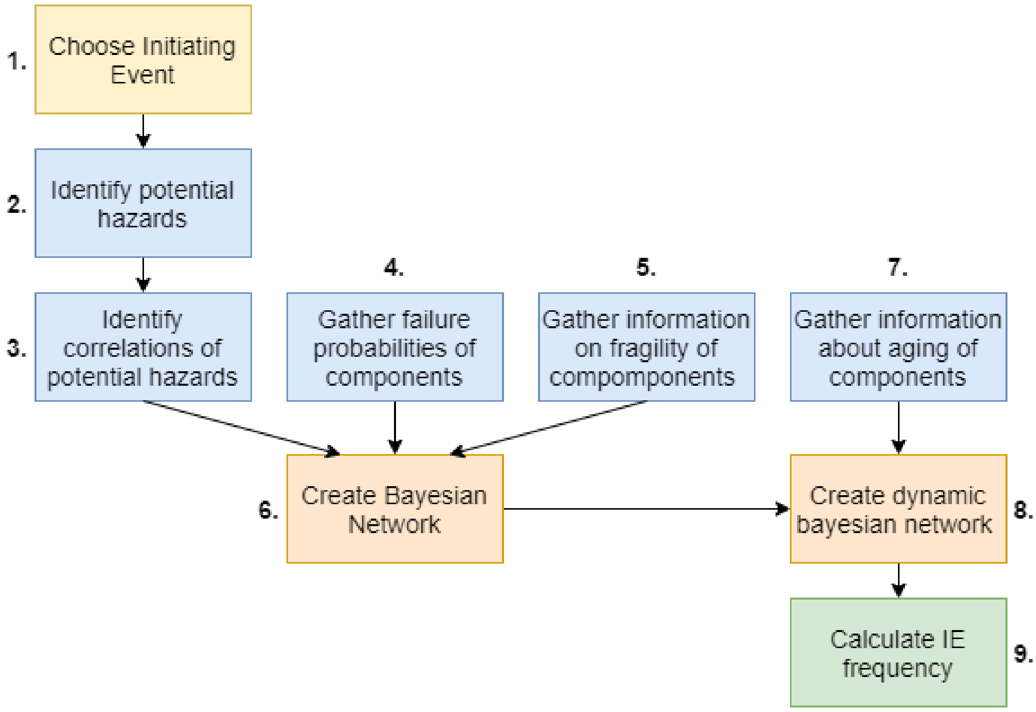


Figure 1: Methodology of DBN creation for IE calculation

4 EXAMPLE OF DYNAMIC BAYESIAN NETWORK IN LOOP IE CALCULATION

Nuclear power plants (NPP) have off-site (power from the grid) and onsite power (power from plant or emergency diesel generators). Electrical power is crucial because safety systems require energy for operation and activation [9].

LOOP is one of the initiating events commonly analyzed in PSA for nuclear power plants. LOOP is associated with loss of access to an off-site power grid and can lead to an unplanned reactor shutdown, which is performed as a precaution [10]. LOOP can be divided by causes/places of failure such as plant-centered (PC), switchyard-centered (SC), grid-related (GR), and weather-related (WR) [7],[11]. GR LOOP is an event where the initial failure occurred in the transmission grid. SC LOOP is an event induced by equipment failure or human error in the switchyard. PC LOOP is an event where the design and operational characteristics of NPP played a significant role in the cause and duration of the event. WR LOOP is an event caused by weather/external hazards.

During different NPP modes, different LOOP category events were experienced more frequently in U.S. NPPs. The most common LOOP category in the 1997-2018 and 2006-2020 was switchyard-centered LOOP [7],[11]. LOOP events are presented in Table 1.

Weather-related LOOP events in the USA in the years 1997-2018 were: High Winds, Tornado, Salt Spray, Hurricane, Flooding, Ice, Snow and Wind, Snow additionally there were cases of SC LOOP induced by Lightning, Earthquakes.

Table 1: LOOP events in USA [7],[11]

Mode	LOOP category	1997-2018		2006-2020	
		Events	Percent	Events	Percent
Critical Operation	Plant-centered	6	10.53	6	17.14
	Switchyard-centered	19	33.33	12	34.29
	Grid-related	20	35.09	7	20
	Weather-related	12	21.05	10	28.57
	All LOOPs	57	100	35	100
Shutdown Operation	Plant-centered	9	21.95	3	17.65
	Switchyard-centered	17	41.46	8	47.06
	Grid-related	4	9.76	2	11.76
	Weather-related	11	26.83	4	23.53
	All LOOPs	41	100	17	100

4.1 Structure of the ideological Bayesian network for determining initiating events

A static Bayesian network was created at the beginning of the LOOP IE calculation (Figure 1). Static Bayesian network have three types of LOOP failure incorporated: basic (gray color), seismic (yellow), and flooding (blue).

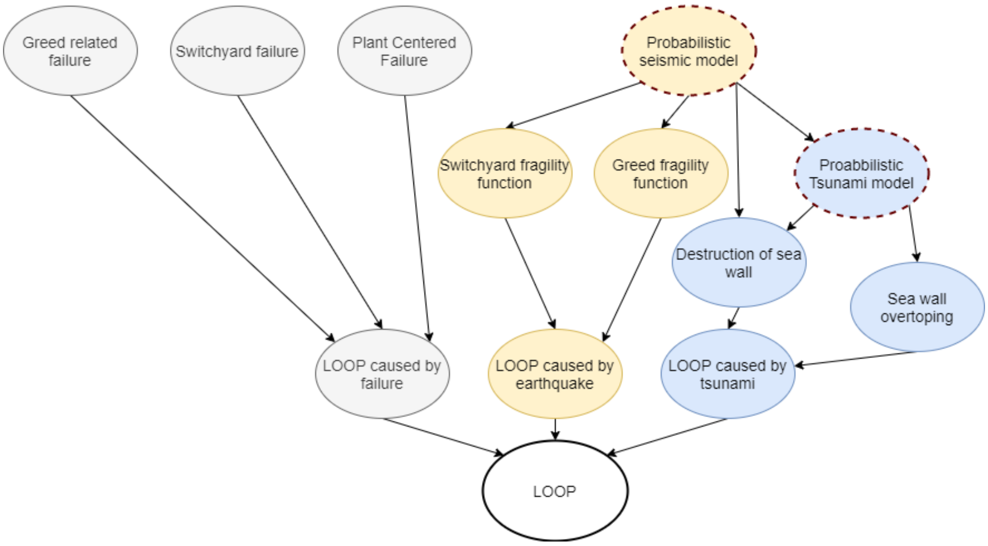
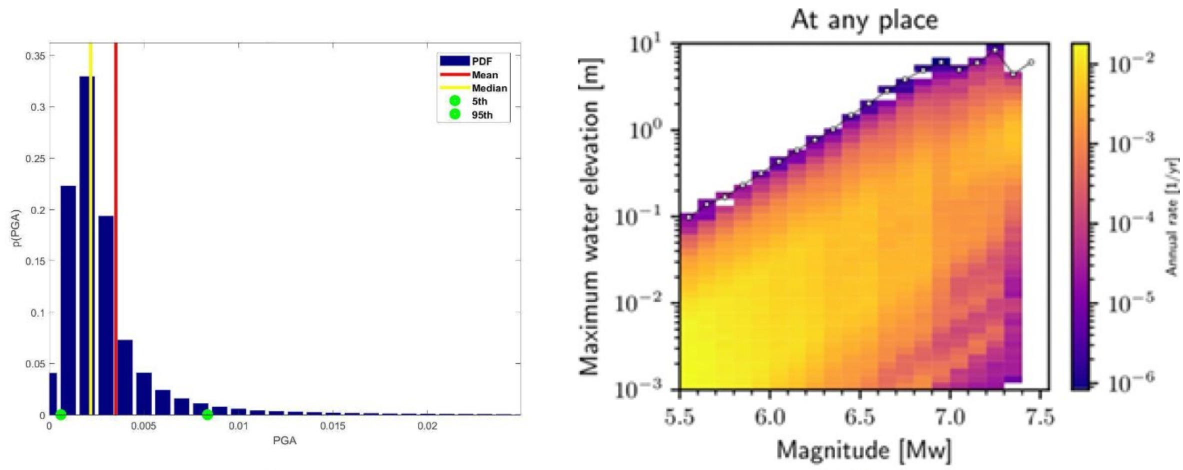


Figure 2: Static Bayesian Network for LOOP IE

The case under consideration presented in Figure 2 resembles the Fukushima Daiichi like accident caused by the earthquake and subsequent tsunami. In contrast to the accident mentioned above, the developed Bayesian network takes into account not only the overtopping through the sea wall but also the destruction of the wall due to the earthquake.

A probabilistic seismic model node in the Bayesian network performs presampling of the peak ground acceleration (PGA) based on the empirical distribution presented in Figure 3 (a). Sampled PGA is used in fragility functions of switchyard and greed. The probabilistic Tsunami model was developed based on an empirical distribution (Figure 3 (b)) that randomizes the height of the tsunami based on the randomly selected peak ground acceleration that is transformed to magnitude is calculated in the seismic model. If the sampled tsunami height is higher than the sea wall height, the tsunami may cause a loss of power due to the tsunami. Otherwise, the wall may fail due to an earthquake, and a tsunami of lower height may result in a loss of off-site power caused by a tsunami.



(a) (b)

Figure 3: (a) PGA probability histogram used in the probabilistic seismic model for the first year, (b) Annual probability as a function of magnitude and maximum water lift for a selected location [12]

The parameters of the switchgear and grid fragility functions used in the model were obtained from the Electric Power Research Institute (EPRI) document "Seismic probabilistic Risk Assessment Implementation Guide" [2], and probabilities of switchyard, grid, plant-centered failures were taken from the U.S. NRC database [13].

4.2 Aging of NPP components

The mission time of components/elements of a nuclear facility can significantly affect its reliability. Literature sources describe this impact as the aging/degradation of reinforced concrete structures (containment, tsunami walls, etc.). Corrosion processes occur here, for example, due to chlorine compounds, which can significantly affect the fragility functions.

Ghosh and Padgett [14] presented a time-variant quadratic model for fragility parameters (Equation 1) of concrete structures with model coefficients.

$$P[DS|PGA](t) = \Phi\left(\frac{\ln(PGA)-\ln\left(p_{1\_m}t^2+p_{2\_m}t+p_{3\_m}\right)}{p_{1\_\zeta}t^2+p_{2\_\zeta}t+p_{3\_\zeta}}\right) \quad (1)$$

Where: DS - damage state, PGA - peak ground acceleration in g (1g = 9.81 m / s2), p1_, p2_, p3_ - model coefficients, the subscripts of the coefficients indicate the median m or dispersion ζ.

A U.S. NRC report describes the aging behavior of nuclear power plant components [15]. Most of the studies in the U.S. NRC report focused on the effects of aging of mechanical and electrical components playing an active role in mitigating accidents. The doctoral dissertation of Rajan S. [16] summarizes the impact of aging on the sensitivity functions of electrical components, pipes, and pipe systems. According to this summary, electrical components are replaced every ten years, and the maximum deterioration is expected at 20%, which gives an annual average of 2 % deterioration of the sensitivity function of electrical components per year.

4.3 Dynamic Bayesian network for determining initiating events probability

Due to the aging of the components described in section 4.2, the static Bayesian network presented in section 4.1 has been modified to obtain a dynamic network. According to the definition of a dynamic Bayesian network (DBN), it is a network that connects variables in consecutive time steps. In dynamic Bayesian networks, at any moment of time T, the value of a variable can be calculated based on internal parameters called regressors and the immediately preceding value of a given variable [17]. Generally speaking, DBN is a Bayesian network that considers time dependencies or other dependencies on additional variable technical parameters of the installation. The practical realization of the DBN implementation consists of time discretization; therefore, the state of the installation depends on the previous time step. The network dynamics in the developed model is ensured by considering the changes in the probability of component failure caused by aging processes during the installation operation. Due to the 40-year life cycle of nuclear installations, the dynamic model uses 40 time periods, each of which is one year. A diagram of the dynamic Bayesian network structure is shown in Figure 4.

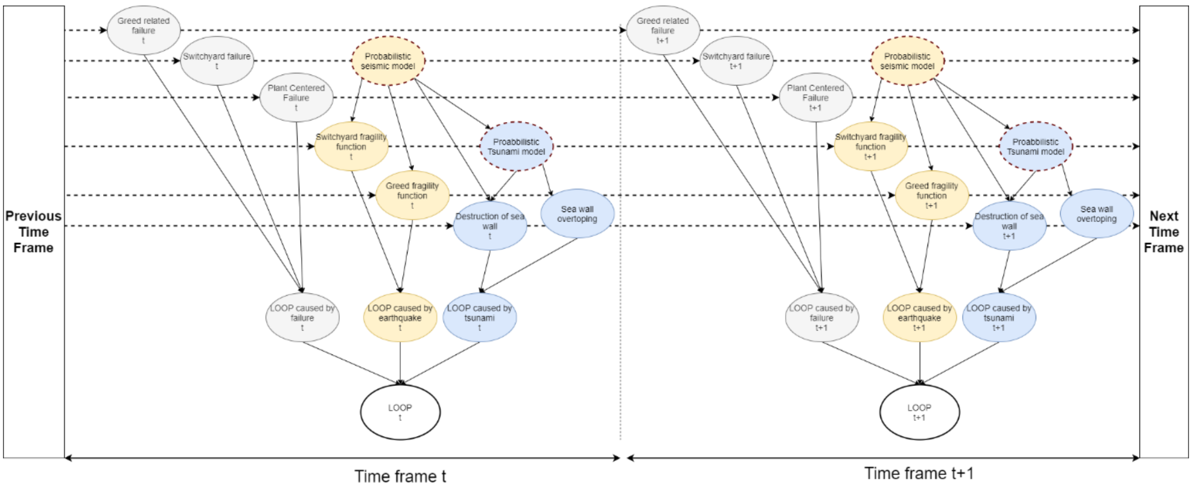


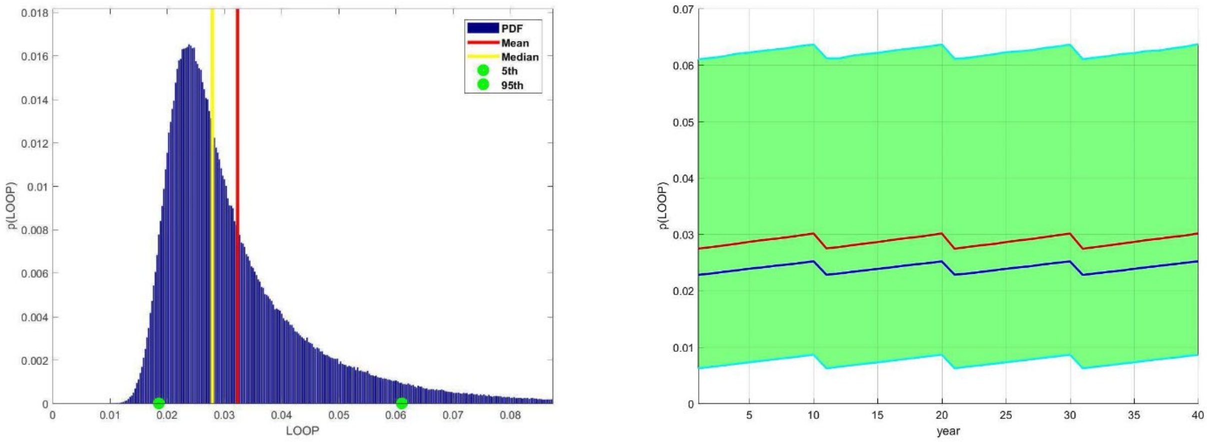
Figure 4: Structure of a dynamic Bayesian network for determining the probability of LOOP

The DBN allows the calculation of LOOP probability more closely to reality by considering the aging processes that occur in all components (reinforced concrete structures, electrical components). In addition, it allows the calculation of the probability at a selected time point in the installation's lifetime.

5 RESULTS AND DISCUSSION

DBN allows the evaluation of different LOOP IE parts and total LOOP IE frequency. One of the main DBN advantages is modularity, which allows to account for as many potential hazards as necessary and to implement any correlations. To show the credibility of the example, a DBN comparison to U.S. NRC LOOP probability [13] was performed. The comparison is shown in Figure 5, and the results are presented in Table 2.

For the basic case (NRC data), the calculated frequency for the LOOP IE is shown in Figure 5 (a), mean and median values are red and yellow vertical lines, respectively. Figure 5 (b) presents frequency from DBN in the function of time where the mean value is red, the median value is the blue line, and values between 5th and 95th are located in the green zone.



(a) (b)

Figure 5: (a) LOOP frequency for basic case, (b) LOOP frequency from DBN in the function of time; mean and median are red and blue lines; values between 5th and 95th are represented by green zone

Table 2: Calculated LOOP probabilities

Model	Time Frame Value	5th val.	Median	Mean	95th val.
DBN	Min	6.24E-03	2.28E-02	2.74E-02	6.10E-02
	Max	8.65E-03	2.52E-02	3.01E-02	6.37E-02
NRC		1.86E-02	2.79E-02	3.23E-02	6.11E-02

This figure shows that the LOOP median probability obtained from DBN differs from the referential model by about 10-18% (depending on the year). The most extensive variation of result is observed in 5% val. that can be up to 3 times lower than NRC. This difference is due to the number of external hazards taken into account (two in DBN, ten in NRC) and the complete improvement of failure probability after replacement/conservation. Future work on the example model by adding additional hazards and more accurate aging influence should provide as realistic results as possible.

6 CONCLUSIONS

The methodology for implementing DBN in IE calculation was presented and illustrated using a simple example of LOOP IE calculation with aging and external weather-related hazards such as earthquake and tsunami. The example shows the model's viability if additional hazards would be accounted. External Hazards can pose a considerable threat to nuclear facilities. Still, because of the low probability of external hazards in the considered example case, its influence is only a fraction of the overall failure probability, the influence of aging had a more significant influence.

The example case and model assumption can be further updated to reflect more external hazards such as High Winds, Tornado, Salt Spray, Hurricane, Ice, Snow and Wind, Snow Lightnings. This update of DBN that accounts for every potential external (weather-related) hazard and implements improvement coefficient after maintenance for better incorporation of aging effects [18] would lead to more realistic results.

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