Probabilistic Failure Analysis of Complex Systems with Case Studies in Nuclear and Hydropower Industries

by

Ahmed El-Awady

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Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner	NAME: **Slobodan P. Simonović** Title: **Professor, Civil and Environmental Engineering, The University of Western Ontario**
Supervisor	NAME: **Kumaraswamy Ponnambalam** Title: **Professor, Systems Design Engineering, University of Waterloo**
Internal Member	NAME: **Keith W. Hipel** Title: **Professor, Systems Design Engineering, University of Waterloo**
Internal Member	NAME: **Shi Cao** Title: **Assistant Professor, Systems Design Engineering, University of Waterloo**
Internal-external Member	NAME: **Bryan Tolson** Title: **Associate Professor, Civil and Environmental Engineering, University of Waterloo**

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

1- Ponnambalam, K.; El-Awady, A.; Mousavi, S. J. & Seifi, A. 2019. "Simulation Supported Bayesian Network for Estimating Failure Probabilities of Dams," in ICOLD 87th annual meeting and symposium, June 2019, Ottawa, Canada. **(Accepted Paper)**

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Abstract

Detailed Monte-Carlo simulation of a complex system is the benchmark method used in probabilistic analysis of engineering systems under multiple uncertain sources of failure modes; such simulations typically involve a large amount of CPU time. This makes the probabilistic failure analysis of complex systems, having a large number of components and highly nonlinear interrelationships, computationally intractable and challenging. The objective of this thesis is to synthesize existing methods to analyze multifactorial failure of complex systems which includes predicting the probability of the systems failure and finding its main causes under different situations/scenarios. Bayesian Networks (BNs) have potentials in probabilistically representing complex systems, which is beneficial to predicting the systems failure probability and diagnosing its causes using limited data, logic inference, expert knowledge or simulation of system operations. Compared to other graphical representation techniques such as Event Tree Analysis (ETA) and Fault Tree Analysis (FTA), BNs can deal with complex networks that have multiple initiating events and different types of variables in one graphical representation with the ability to predict the effects, or diagnose the causes leading to a certain effect. This thesis proposes a multifactor failure analysis of complex systems using a number of BN-based approaches. In order to overcome limitations of traditional BNs in dealing with computationally intensive systems simulation and the systems having cyclic interrelationships (or feedbacks) among components, Simulation Supported Bayesian Networks (SSBNs) and Markov Chain Simulation Supported Bayesian Networks (MCSSBNs) are respectively proposed. In the latter, Markov Chains and BNs are integrated to acquire analysis for systems with cyclic behavior when needed. Both SSBNs and MCSSBNs have the distinction of decomposing a complex system to many sub-systems, which makes the system easier to understand and faster to be simulated. The efficiency of these techniques is demonstrated first through their application to a pilot system of two dam reservoirs, where the results of SSBNs and MCSSBNs are compared with those of the entire system operations simulation. Subsequently, two real-world problems including failure analysis of hydropower dams and nuclear waste systems are studied. For such complex networks, a bag of tools that depend on logically inferred data and expert knowledge and judgement are proposed for efficiently predicting failure probabilities in cases where limited operational and historical data are available. Results demonstrate that using the proposed SSBN method for estimating the failure probability of a two dam reservoir system of different connections/topologies results in probability estimates in the range of 3%, which are close to those coming from detailed simulation for the same system. Increasing the number of states per BN variables in the states' discretization stage makes the SSBN results converge to the simulation results. When Markov chains are integrated with SSBN (i.e. MCSSBN), the results depend on the MCSSBN approach that is used according to the scenarios of interest that need to be included in the BN representation. Evidence of system failure can be used to diagnose the main contributors to the failure (i.e. inflow, reservoir level, or defected gates). This posterior diagnostic capability of the BN is distinctive for the real world case studies presented in this thesis. In Mountain Chute Dam that is operated by Ontario Power Generation, the main contributors to system failure, according to the logically inferred data and expert knowledge, are inadequate discharge capacity of the sluiceway, electromechanical equipment failure, head gates failure, non-safe ice loading, high inflow, high rain/precipitation, sluice gate failure, and high water pressure. While for the Nuclear Waste Management system, the main contributors to system failure according to the known and assumed data are due to high pressures and bentonite failures. In summary, modelling, validating, and developing appropriate modifications of the BN method for applications in complex systems failure analysis is the major contribution of this thesis.

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My precious and dear wife, Reham, you have always been my support in the moments when there was no one to answer my queries. Thank you for your patience, and for taking care of our beloved kids: Basel, Jasmine, and Tarek.

Dedication

To

The inspirational soul of my Grandfather, sorry for not completing this work before you can see it,

TAREK; my supportive DAD,

HANAA; my bright MOM,

REHAM; my lovely WIFE,

My beloved kids; BASEL, JASMINE, and TAREK Jr.,

And my godfather; Prof. MOHSEN…….

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List of Abbreviations

ASCE: American Society of Civil Engineers

BN: Bayesian Network

BNA: Bayesian Network Analysis

BPT: Basic Probability Table

CPT: Conditional Probability Table

CNSC: Canadian Nuclear Safety Commission

DAG: Directed Acyclic Graph

DGR: Deep Geological Repository

DSM: Dam Safety Management

ETA: Event Tree Analysis

FTA: Fault Tree Analysis

FMEA: Failure Modes and Effects Analysis

GHGs: Green House Gases

GSC: Geological Survey of Canada

HCB: Highly Compacted Bentonite

HLW: High Level radioactive Waste

HRT: Head Race Tunnel

IAEA: International Atomic Energy Agency

ICOLD: International Commission on Large Dams

IDF: Inflow Design Flood

IRB: Iron-Reducing Bacteria

LOL: Loss of Life

MA: Markov Analysis

MCS: Monte Carlo Simulation

MCMC: Markov Chain Monte Carlo

MCSSBN: Markov Chain Simulation Supported Bayesian Network

NSDF: Near Surface Disposal Facility

NWM: Nuclear Waste Management

NWMO: Nuclear Waste Management Organization

OPG: Ontario Power Generation

PAR: Population at Risk

PDF: Probability Density Function

PFA: Probabilistic Failure Analysis

PMP: Probable Maximum Precipitation

PRA: Probabilistic Risk Assessment

RH: Relative Humidity

RoR: Run of the River

SSBN: Simulation Supported Bayesian Network

SHPD: Safety of Hydropower Dams

SRB: Sulphate-Reducing Bacteria

TRT: Tail Race Tunnel

TPM: Transition Probability Matrix

UFC: Used Fuel Container

List of Symbols and Units

Unit Symbol	Name	Quantity
Sv	*Sievert*	*Equivalent/ Effective Radiation Dose*
Bq	*Becquerel*	*Radioactivity*
°C	*Degree Celsius*	*Temperature*
°F	*Degree Fahrenheit*	*Temperature*
kg	*Kilogram*	*Mass*
km	*Kilometer*	*Length*
S	*Second*	*Time*
m^3	*cubic meter*	*Volume*
Pa	*Pascal*	*Pressure*
MPa	*Mega Pascal*	*Pressure*
N	*Newton*	*Force*
kW	*Kilo Watt*	*Electric Power*
MW	*Mega Watt*	*Electric Power*
kWh	*Kilo Watt hour*	*Electric Energy*
MVA	*Mega Volt Ampere*	*Apparent Electric Power*

CHAPTER 1

Introduction, Problem Definition, and Hypothesis

1.1 Introduction

Failure analysis is an important and challenging aspect of the study of complex systems. A system is defined to be consisting of components, sub-systems, inputs and outputs within system boundaries. The inputs provide physical resources and information to the sub-systems, which are interacting among each other to produce some outputs. All interactions are assumed to take place within system boundaries. A complex system can be defined as a system structure that is composed of many components that have complex interactions, [1]. Any failure in performing the required interactions among system components or any failure in getting the expected output/result is considered to be contributing to system failure, [2]. Thus, analysis of a system with its components is a crucial step in determining the difficulties and complexities that the system will experience at any stage. However, in the real world, performance of both inputs and sub-systems is affected by probabilistic uncertainty, and hence a failure may come with an associated probability. Probabilistic uncertainty due to randomness of events or values and limited knowledge are considered main sources of uncertainty in systems introduced in this thesis, [3, 4]. The main goal of this research is to evaluate the probability of failure of complex systems, while finding the failure causes, and hence the analysis is called the probabilistic failure analysis (PFA). For any given system with its inputs and sub-systems, probabilistic failure analysis depends on finding the probability of not getting the required or estimated output of that system. The required output may be the effect that is produced from certain causes (i.e. prediction reasoning), or the determination of the cause responsible for certain results and effects (i.e. diagnostic reasoning). Thus, determining the cause-effect relation is an important first step in the probabilistic failure analysis, which allows for better understanding to enhance the system reliability and take decisions for mitigating the negative effects or better enhancing the causes.

In this research, the concept of probabilistic failure analysis is applied to two main real-world case studies: 1- Nuclear Waste Management (NWM), and 2- Safety of Hydropower Dams (SHPD). The type and complexity level varies in these two case studies; however, both can be analysed as "Complex Systems". For each case study, relevant literature is reviewed to understand the problem, study existing solutions, and determine system factors, parameters, and variables. As a result, the system can be represented graphically. Lastly, probability measures are applied to each system's graphical network to estimate the probability of failure for given scenarios/situations. In this thesis, the graph representation of both systems is conducted using Bayesian Networks (BNs) which allow for representing marginal, conditional, and joint probability measures affecting system components. Representing systems of engineering applications using BNs is affected by multiple factors that affect the probabilistic quantification process. The aim of this thesis is to develop approaches that facilitate the probabilistic quantification of BNs, and hence, facilitate prediction of system failures, as follows:

1- Incorporating simulation of the entire system with the BN representation, given that simulation may be challenging especially for very complex systems that include a huge number of system variables. This approach is named "Simulation Supported Bayesian Network (SSBN)" in this thesis. In this approach, simulation is used as a source of probabilistic information that is used to quantify the basic nodes and conditional relations among system nodes/variables, and
2- Incorporating Markov Chains to the SSBN approach, named "Markov Chain Simulation Supported Bayesian Network (MCSSBN)" in this thesis. This approach is supposed to overcome the limitation of being acyclic in the BN representation of the system. This

allows for cyclic system analysis for different system scenarios/situations, and easy update for the system in case any new data becomes available.

1.2 Problem Definition

Failure analysis of complex engineering systems is challenging for different reasons. Most of the complex systems include multiple factors and variables of different natures (i.e. technical and non-technical). These factors are mostly associated with probabilistic measures which lead to the requirement to represent marginal, joint, and conditional probabilities of the events contributing to any system failure, resulting in probabilistic uncertainty. Current practices use exhaustive simulation models, which may be computationally intensive when dealing with any complex system of a huge number of system components, complex interrelations, and/or nonlinear governing equations. This makes the probabilistic representation for system failure analysis not easy to interpret. Failure analysis of these systems is important in the sense that how likely they will reach a failure state (probability of failure) and what will be the consequences of failure in terms of expected loss or other probabilistic measures quantifying those consequences, e.g. vulnerability, reliability and resilience. Estimating the probability of failure in such systems could be hard because the state of the systems is a vector of multiple stochastic variables having a huge number of possible values in a multidimensional state space. Particularly, when a failure state results from multiple factors, this means that the probability of failure would be a joint probability function of multiple variables and events. Knowing that the relationships between input and output vectors of variables is complex, it would be practically impossible to determine the joint probability function of output vector analytically even if the probability function of input vectors are simply Gaussian and statistically independent, whereas in general the distributions are non-Gaussian and dependent. Hydropower dams and nuclear waste management using deep geological repository systems may be good examples of complex systems that have multiple interrelated factors. Dam systems are complex systems having a huge number of interacting factors and components. The deep geological repository system is also complex in terms of the interactions among system components and the lack of operational data for such future projects. In such systems, exhaustive simulations are challenging while predicting any system failure, and while diagnosing the causes of such failure. Decision makers in charge of such systems need a multifactor representation to overcome the challenges of current practices and to facilitate interpreting the interrelations among system components while predicting the failures or diagnosing the failure causes in terms of probability estimates during different situations/scenarios. Data scarcity is one major factor that makes the risk analysis of such systems challenging. A rational framework to analyze failures and risks of these systems is crucial in both the short terms and the long terms and BN provides the foundation for such framework. It is shown later in this thesis that Bayesian Networks (BNs) have potentials that help solving such problems. Bayesian Network provides a graphical representation of any system using basic probabilities, for system inputs, and conditional (transition) probabilities, for sub-systems and their mutual interactions. There are some advantages and limitations in using BNs. One of the main advantages is that BNs can integrate all types of data (e.g. social, environmental, technical, etc.) because of the probabilistic nature of the BNs, as everything is represented as a probability. Data must also be available to be able to estimate probabilities. This is not feasible for systems which are still under research or will be applied in the future. However, BN analysis allows for integrating subjective probabilistic information and/or simulations, which can be improved with additional data updates, when available. The main limitation is the acyclic behaviour of the BN that doesn't allow for analysis of systems with cyclic behavior that is needed in some applications. When the system is fully represented by BN, the failure probability could be estimated using Bayesian inference. Alternatively, BNs may be used to evaluate the performance of the system components and their interactions to get some information about the failure causes. If the post failure analysis stage is taken into consideration, determination of causes and mitigation or treatment actions should be considered in order to improve the performance and limit the overall system failure that the system may experience in the future. In this research, two case studies are used to develop Probabilistic Failure Analysis (PFA) for complex systems: 1- is for high level radioactive Nuclear Waste Management (NWM), which is still a future project under development, and 2- is to analyse Safety of Hydropower Dams (SHPD), whose risks of failure include failure probability, and consequences of failure. For the purpose of this thesis, we are focussing mainly on the first part (i.e. failure probability) with some extensions to be provided for the second part (i.e. consequences) in the future. The two case studies are totally different in terms of application, but they are both complex systems and can be represented probabilistically, but the main challenge is the data type. In NWM, which is still a blue print, only partial data for this system or its components are available and requires detailed simulations, which are outside of the scope of this thesis. On the other hand, SHPD is a known problem with known technical databases but with a significantly larger number of components than NWM, thus having large data requirements. In this thesis, the BN is used as a multifactor representation for complex systems in order to predict system failures and diagnose failure causes. In case of data scarcity, BN representation may integrate simulation and/or subjective probabilistic information to facilitate the failure analysis. This research presents methodologies utilizing Simulation and Bayesian and Markovian Networks for predicting probabilities of failures of complex systems, using information of system components and their interconnections.

1.3 Hypothesis and Proposed Methodology

In this research, failure is analyzed for two complex systems:

1- NWM (Nuclear Waste Management) using deep geological repository for high level radioactive waste (spent nuclear fuel) management, and
2- SHPD (Safety of Hydro Power Dams), a pilot study of a two dam reservoir system is identified for applying the proposed methodologies. Then, a real-world case study for one of the dams operated by Ontario Power Generation (OPG) is used to apply the proposed methodology, with the restriction of availability of operational data.

Firstly, in **Chapter 2**, the literature explaining both systems and their problems are reviewed. Then, the different factors affecting the system failure in both of them are illustrated. Knowing the different components, factors, parameters, and sub-systems for any system will facilitate the task of constructing a graphical representation for the specified system. As Bayesian Networks (BNs) have shown some advantages in representing any system as a probabilistic graphical network, BNs are used extensively in this research. **Chapter 3** uses the data available for the different components of NWM case study to build the system's BN. Once the graph of the system is constructed, the data available are used to quantify the probabilities of the BN nodes and their interactions (basic and conditional probabilities). Depending on different scenarios, or change in data from location to another (in case of the deep geological repository), or from time to time (for the operation of dams in different seasonal conditions), the probabilities may change resulting in increasing or decreasing the failure probability. Thus, there is a need to compile the BN of such systems to obtain the joint and marginal probabilities related to certain situations or events. To facilitate this task, Hugin Lite software was found to help in the representation of the BN and its compilation [5, 6, 7]. So, the BN is constructed and all the data and scenarios are inserted in order to start the compilation of cause-effect probabilistic analysis, resulting from interrelating system components, and affecting the failure. While the BN representation for failure prediction is dependent on available data in both applications, it is shown that failure prediction is challenging. Probabilistic quantification relies on different sources of data, i.e. expert judgement, logic inference, elicitation, empirical models, and simulation, which result in different levels of inaccuracy in the estimated failure probability, which may be used for decision making. In **Chapter 4**, the approach of incorporating simulation to the BN (SSBN) is introduced and applied to a pilot two reservoir system. The decompositional approach used for simulating complex systems – proposed in this thesis – is introduced as a part of the SSBN method. SSBN is expected to reduce the limitation of exhaustive simulation that may be computationally expensive in some applications. In **Chapter 5**, another approach that uses Markov Chains to be incorporated with simulation and BNs to better quantify the probabilities of the system nodes and their conditional relationships is introduced and applied to the same two reservoir system. Markov Chain Simulation Supported Bayesian Networks (MCSSBNs) are proposed to make the analysis cyclic and more dynamic while introducing different system scenarios/situations, and allow for seamless update of the system with any new available information/data that could affect the prediction process of system failure. As data and mathematical models are not fully available for the real-world case study, as may be expected in most cases today, **Chapter 6** illustrates how the elicitation of expert judgement and logic inference is used for quantifying the BN of Mountain Chute Dam and Generating Station, operated by OPG, to predict its probability of failure. Finally, in **Chapter 7**, conclusions are presented regarding the proposed methodologies and their potentials and limitations in representing complex systems and predicting their failure probabilities. Some recommendations are also suggested. The main focus of the proposed research in this thesis is on the stage of failure prediction. In addition, the work proposed in this research may help in identifying causes of failures by using diagnostic capabilities of BN analysis.

CHAPTER 2

Literature Review

2.1 Introduction

This chapter provides a review of literature for the case studies used in this research. For the first case study-Nuclear Waste Management (NWM) system, different factors that affect the system are discussed. A brief description is also provided for the second case study of this research-Safety of Hydropower Dams (SHPD) system. This chapter also provides an introduction to risk, reliability, and uncertainty. The concept of Bayesian Networks is explained in details. Then a comparison between BNs and other techniques, used for representing systems, is conducted.

2.2 Nuclear Waste Management (NWM)

Disposal is the final stage of the radioactive waste management by which the wastes are isolated from biosphere in the repositories. For the disposal of radioactive solid wastes, multi-barrier approach may be followed. If suitable engineered barriers, backfill materials and the characteristics of the geo-environment of the repository site are properly selected, safety against radionuclide migration will be achieved. Disposal of radioactive solid wastes depends on the nature and type of radionuclide present in the wastes (longevity) and its concentration. Thus, the repository can be near-surface or in deep geological formations. For long lived high level radioactive wastes, deep geological repository (DGR) is the option, for disposal of used nuclear fuel and high-level radioactive waste, which has received world-wide attention and may be the best known method to do that permanently without putting a burden of continued care on future generations. The option of Near Surface Disposal Facilities (NSDF) is preferred for low and intermediate level radioactive wastes with comparatively large volumes, which arise during nuclear power plant operation, and from radionuclide applications in hospitals and research establishments. At NSDF, wastes are normally disposed in a depth around 50 meters (intermediate depth). In NSDF, sub-surface evaluation is carried out systematically by geological and geo-hydrological investigations. Testing of full scale engineered barriers should be conducted for bentonite clay buffers and clay sand as backfill materials in both deep geological repositories and near surface disposal facilities. It is believed that setting up dependency relationships among the geological, hydrological, and ecological aspects will reduce the sources of uncertainty in this area of research [8, 9, 10, 11].

Canada, like many nuclear nations, has been investigating geological disposal of nuclear waste, which is the approach that offers the best passive safety system for permanent disposal, since the early 1970s. The internationally accepted design of a deep geologic repository (DGR) involves the following [12], see Fig.1:

1. At depth of 500 meters below ground surface in a suitable location of dense intact rock, used fuel will be disposed.
2. Nuclear spent fuel will be sealed in a corrosion resistant used fuel container (UFC). This container should withstand anticipated hydrostatic, lithostatic and glaciation loads. The original Canadian UFC, which is dual-walled with an inner iron (or steel) vessel to

provide strength, and a separately fabricated 3 mm-thick copper coated outer shell corrosion barrier, was designed to contain about 48 CANDU fuel bundles.

3. As an additional barrier, compacted bentonite clay will be surrounding the UFC. Compacted bentonite clay swells on contact with moisture. This will tightly seal the system with allowing very little chemical diffusion to occur.

In [10], a full explanation of the definitions and decrees (by Finnish government), regarding the disposal of nuclear waste, is discussed. Spent nuclear fuel (which is considered high level radioactive waste), along with low and intermediate level wastes are accumulated during the operation and decommissioning of nuclear power plants. Spent nuclear fuel is intended to be disposed in deep geological repositories, inside the bedrock, after being encapsulated. Selecting and characterising the disposal site, developing disposal technology, collecting necessary data for long term safety, excavation works, packaging the wastes and transferring the packages to emplacement rooms, and the engineered barriers installation, are required stages in the disposal process. According to Finnish government decrees, disposal facility shall be designed to have the average annual dose to the most exposed individuals of the population not to exceed 0.01 mSv during normal operation of the facility, with maximum of 5 mSv in the event of certain accidents. Also in [10], exact and detailed definitions are given to: Low level waste (activity concentration not more than 1 MBq/kg.), Intermediate level waste (1 MBq/kg –10 GBq/kg), High level waste (>10 GBq/kg), Short-lived waste (less than 100 MBq/kg after 500 years), Long-lived waste (more than 100 MBq/kg after 500 years), disposal facility, disposal site, and barrier (engineered or natural). In [13], some definitions and management actions regarding radioactive wastes are provided. The radioactive properties of radioactive wastes contains the type of radionuclides, the radiation emitted (alpha, beta, gamma), the activity level (number of atomic nuclei disintegrating per unit time, expressed in becquerels), and the radioactive half-life (i.e. time taken by a radioactive sample to lose half of its activity). Short-lived radioactive waste contains radionuclides with a half-life of less than 31 years, while long-lived radioactive waste contains radionuclides with a half-life of over 31 years. See Table1.

Radionuclide	**Half-life**
Cobalt-60	5.2 years
Tritium	12.2 years
Strontium-90	28.1 years
Caesium-137	30 years
Americium-241	432 years
Radium-226	1,600 years
Carbon-14	5,730 years
Plutonium-239	24,110 years
Neptunium-237	2,140,000 years
Iodine-129	15,700,000 years
Uranium-238	4,470,000,000 years

Table 1: Different types of radionuclide with their half-lives [13]

The following engineered barriers should be considered in planning the waste disposal [10]:

1- The waste matrix;
2- The waste package;
3- The buffer surrounding the waste packages;
4- The backfilling of emplacement rooms; and
5- The closing structures of the disposal facility.

The bedrock of the disposal site is considered to be a natural barrier that lends support to safety functions, but, there are also some factors that indicate the unsuitability of a disposal site [10]:

1- Proximity to natural resources;
2- High rock stresses;
3- High seismic or tectonic activity; and
4- Adverse groundwater characteristics,

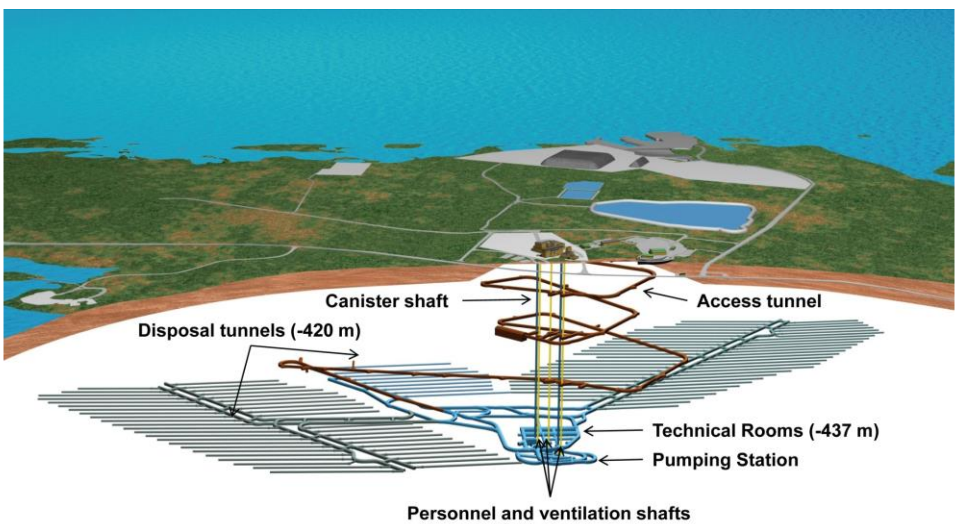
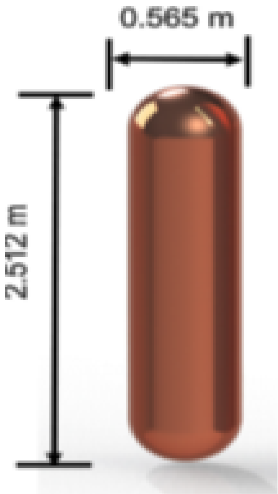


Fig.1: Final Disposal Facility for spent nuclear fuel (High Level Waste HLW) [14]

In Canada, Nuclear Safety and Control Act (2000) created the Canadian Nuclear Safety Commission (CNSC), Canada's single nuclear regulator to regulate all nuclear-related facilities and activities, from cradle to grave. CNSC, which is an independent commission, makes continuous updates for its regulations regarding nuclear activities including regulations of safe spent fuel and radioactive waste management. Nuclear Fuel Waste Act (2002), which established a framework for national long-term management solution respecting Canada's spent fuel, created the Nuclear Waste Management Organization (NWMO) as a not-for-profit corporation funded by waste producers. In the Government of Canada Radioactive Waste Policy Framework (1996), both the federal government and waste producers and owners have responsibilities towards the radioactive waste problem, [15]. Full details for nuclear waste management program in Canada are provided in [16], with understanding the fact that high level radioactive waste can stay in the wet storage (in pools) for 7-10 years, and in dry storage for up to 70 years before being disposed into deep geological repository (DGR). International Atomic Energy Agency (IAEA) provides all the safety standards, in the disposal of radioactive waste, for protecting people and the environment. Emplacing radioactive waste in a facility or location with no intention to retrieve the waste is called “disposal” of radioactive waste. The lack of intention to retrieve wastes doesn’t mean that retrieval is not possible. This is different than the term “storage”, which means the retention of the radioactive waste with having retrieval intention. Both, disposal and storage, aim at containing the waste and isolating it from accessible biosphere. Thus, waste storage is considered a temporary stage followed by future actions of conditioning, packaging, and final disposal [17].

Figures 2, 3, and 4 give a representation for the problem under study. The used fuel bundle (Fig.2) is placed in the container shown in Fig. 3. The container should contain an assembly of 48 fuel bundles. These bundles generate both radioactive heat and mass that can be transferred to the surrounding and needs to be shielded. For that reason, the used fuel container is made of steel, with an outer corrosion barrier of copper. Then, the container is placed in a buffer box made of bentonite clay as another barrier. Many buffer boxes are placed in placement room (Fig.4) in the repository, which is 500 meters deep, and separated by backfill material as an additional barrier. Then the whole placement room is filled with gap fill material to fill the gap with the rocks of the placement room.

Fig.2: ACR-1000 FUEL Bundle (~ 20 kg) [16]



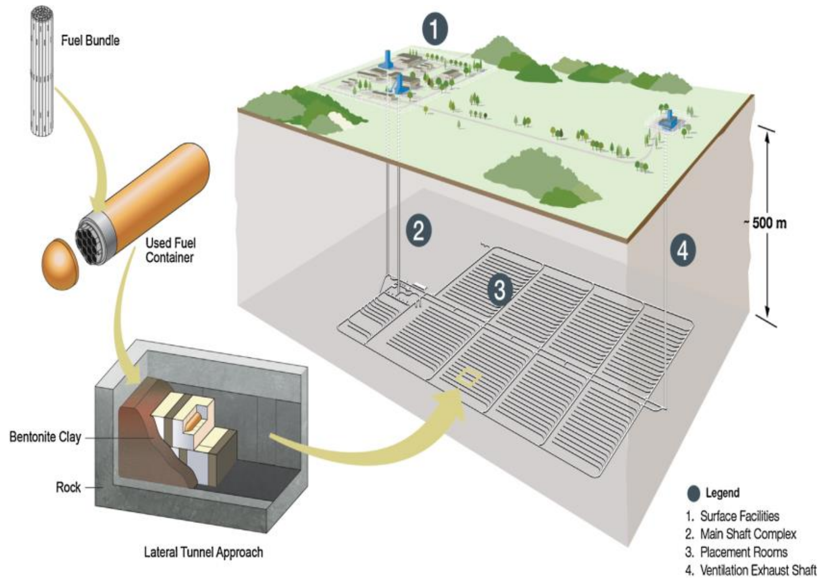


Fig.3: The conceptual container design for the disposal of Canadian high level nuclear waste [12]

Fig.4: Schematic representation of the proposed Canadian Deep Geological Repository (DGR) [12]

Failure in nuclear systems is related to the emissions of radioactive nuclides, or possible accidental releases of radioactivity, like the ones described in ref [18]. From the nuclear aspect, risk can be defined to be an exceeding expectation of the magnitude of undesirable radioactive releases (i.e. the product of probability of an accident/failure, and the consequence of this accident). In probabilistic risk assessments, uncertainty measures arise due to both, lack of the knowledge and stochastic features of system components. So, complex uncertainty propagation may result in future potential risks. In the next sections, Bayesian Network is shown to be a concept for reasoning complex uncertain problems, where network means a graphical model [9, 18]. In [19] and [20], different and effective waste management policies are investigated with giving detailed explanation of the radioactive waste management process. An overview is given in [21] of the nuclear data required to make a correct prediction of the source of radioactive wastes, and the radiation doses in the different activities of: manufacturing, production, handling, transport, recycling, transmuting, and storing of radioactive, or fissionable, materials.

2.3 Factors Affecting the NWM System Failure

The operation of NWM Deep Geological Repository system is to keep the used nuclear fuel away from interacting with the surrounding environment by encapsulating the fuel bundles in used fuel containers. The system is considered to fail when the used fuel container fails to prevent any interaction between the nuclear bundles and the surrounding environment. In this section, the different factors that affect the NWM system operation and failure are explained in details.

2.3.1 Temperature Effect (Geothermal Gradient)

Variation of surface air temperature, with the seasons and regional variations according to local weather conditions, is a known fact. Thus, ventilation of current temperature in underground openings may affect temperature variation [22]. In [23], the surface average temperatures in the Canadian cities all over the year are demonstrated, with giving the maximum and minimum annual temperatures based on weather data collected from 1981 to 2010. The numbers allow comparing the average daily high and low temperatures for the 33 largest Canadian cities. Temperature is known to increase with depth in the Earth influenced by the heat generated at depth and transferred through rocks and sediment layers. This is called terrestrial heat flow which is described by the following equation [24]:

$$\boldsymbol{Qz} = \frac{\Delta \boldsymbol{T}}{\boldsymbol{\lambda}\, \Delta \mathbf{D}} \qquad \text{Eqn. 2.1}$$

Where:
Qz = Heat flow per unit area in the vertical direction,
λ = Thermal conductivity, and
ΔT/ΔD = Geothermal gradient (difference in temperature / difference in depth).

Because of some data constraints in both heat flow and thermal conductivity, the principal basis for calculating geothermal gradients depends on bottom-hole temperatures measured in boreholes [24]:

$$Geothermal\ Greadient\ = \frac{Formation\ Temperature - Mean\ Annual\ Surface\ Temperature}{Formation\ Depth}$$

In Canada, geothermal favourability ranking, in areas with geothermal gradient data, is given in [25]. It can be concluded that geothermal gradient falls in the range between 30 – 55 (°C / km). In [26], Government of Canada (Environment Canada) provides Historical Climate Data for different Canadian Provinces by which monthly data reports for Canadian provinces and cities can be easily gotten. While [27] provides geothermal maps of Canada at different depths in different locations within the Canadian geological regions. Globally, the average geothermal gradient ranges between 25 – 29°C / km depth, with actual value of more than 55 °C / km depth in some regions. According to the above mentioned information, the surface temperature will affect the final temperature at the deep geological repository according to the average geothermal gradient. Accordingly, and because the average seasonal surface temperature data is available, in this research, the year is divided into three seasons: Winter (W), Spring Summer (SS), and Fall (F). Each season is assumed to have average weather conditions within its period. The maximum geothermal gradient that will be used in this study will be the 29°C / km depth (assuming that the repository will not be built in any of the regions that have extreme temperature and geothermal conditions). However, for the post-closure processes in the repository, the surface temperature is not showing significant effect or significant change in the temperature of the repository from season to season. The reason behind that is because the radioactive decay coming from the used fuel will be much higher than the change in the surface temperature. The radioactive heat decay will be the most dominant temperature changing factor after closure of the repository. According to NWMO, there are studies for five locations (three crystalline rocks, and two sedimentary rocks) where the repository is supposed to be placed in one of them. The location that will be selected should have an average surface temperature of 5°C, with 16°C/km geothermal gradient; in order to have about 12°C temperature at the repository (500 m depth) resulted from the surface temperature. From another side, the maximum temperature at the surface of the used fuel container should be at maximum of 100°C at any time during the radioactive decay. This means that the radioactive decay may be responsible for more than 80°C of the temperature in the repository, or at least at the surface of used fuel container.

2.3.2 Pressure Effect (Geostatic and Lithostatic Gradient)

Pressure increases with depth in the earth due to the increasing mass of the rock overburden. The geostatic pressure at a given depth is the vertical pressure due to the weight of a column of rock and the fluids contained in the rock above that depth. Lithostatic pressure is the vertical pressure due to the weight of the rock only. Computing the pressure as a function of depth in a homogeneous crust is a straightforward calculation:

$$\mathbf{P} = \frac{\boldsymbol{\rho}\,\mathbf{V}\,\mathbf{g}}{\mathbf{A}} = \boldsymbol{\rho}\,\mathbf{g}\,\mathbf{H} \qquad \text{Eqn. 2.2}$$

Where:
A (m^2): surface area of the repository
ρ (Mass (M) /Volume (V) = kg/m^3): the density of rocks (in case of lithostatic pressure), or the summation of rock and water densities (in case of geostatic pressure), and M (kg) is the rock mass (in case of lithostatic pressure), or the summation of rock and water masses (in case of geostatic pressure),
V (m^3): volume of the repository = A (surface area) * H (depth),
g (9.81 m/s^2): gravitational acceleration, and
P (N/m^2 = Pascal Pa): Lithostatic Pressure (in case of just rocks), or Geostatic Pressure (in case of both rocks and fluids).

Higher rock densities will yield higher pressure gradients. The geostatic gradient changes with depth as the density increases. This is called crustal geostatic gradient. In that order, to calculate the pressure in the deep geological repository, it is important to know the densities of all the rock types all over the country. According to [28], Canada can be divided into six geological regions: The Canadian Shield, Interior Platform (Canadian Interior Plains including Hudson Bay Low Lands), Appalachian Orogen (East), Eastern Continental Margin (St. Lawrence Low Lands), Innuitian Orogen (North Arctic Lands), and Cordilleran Orogen (Western Sedimentary Basin). Each geological region has specific characteristics and different mineral resources (see Fig.5 and Table 2).

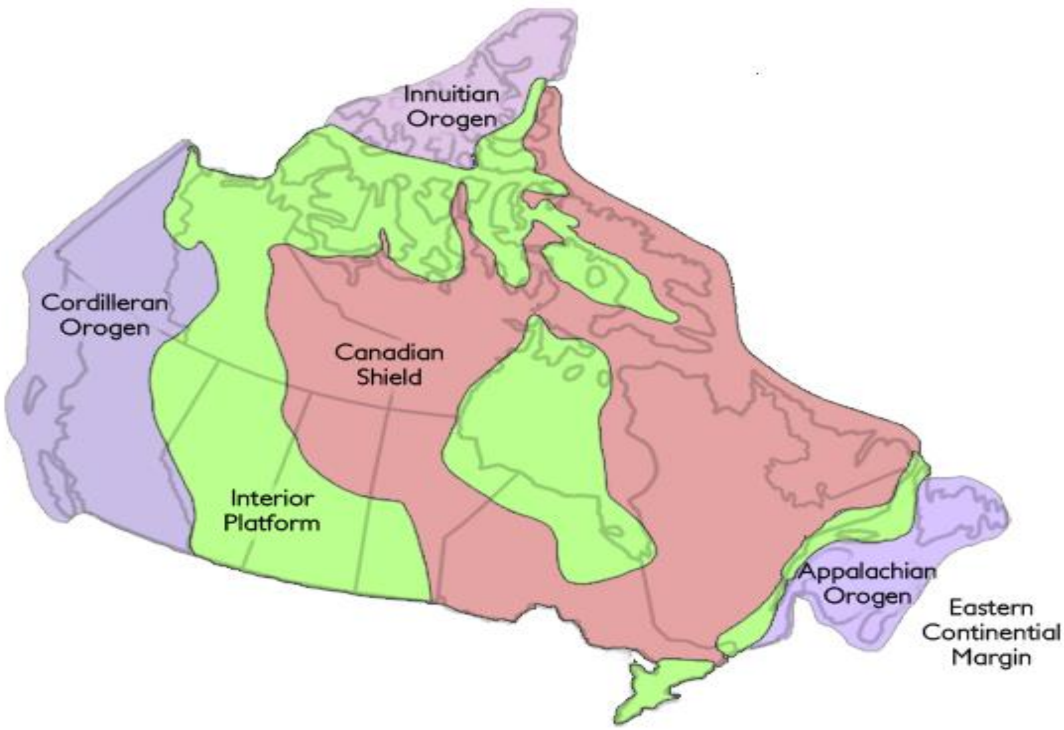


Fig.5: Geological Regions of Canada [28]

Geological Region	Percentage of Canada's Area
The Canadian Shield	~50%
Interior Platform (Canadian Interior Plains including Hudson Bay Low Lands)	~22.5%
Appalachian Orogen (East)	~3.6%
Eastern Continental Margin (St. Lawrence Low Lands)	~1.8%
Innuitian Orogen (North Arctic Lands)	~5.4%
Cordilleran Orogen (Western Sedimentary Basin)	~16%

Table 2: Geological Regions in Canada

So, if the decision is not taken yet about the location of the repository, it will be impossible to calculate the maximum effect that comes from the pressure factor. Thus, this led to considering something else. The Earth crust contains both continental and oceanic parts. The oceanic crust counts for the seas, oceans, rivers, and lakes, while the continental crust accounts for the rest. In Canada (9,984,000 km^2), the continental crust counts for 92% of the Canadian Land, while the oceanic counts for about 8%. The average density of continental crust is known to range between 2500-3000 kg/m^3 (2.5-3 g/cm^3) according to the rock type. While the oceanic crust average density ranges between 3-3.3 g/cm^3 [29]. Accordingly, more realistic data can be estimated about the maximum pressure that could be faced in case of building the repository beneath rocks or under (or near) oceans and seas. Moreover, if there is ice accumulation at the location where the repository is built, ice pressure should be taken into account (ice loading). Another factor, that will affect the pressure in the repository, is the bentonite swelling pressure. The used fuel container will be emplaced in a Highly Compacted Bentonite (HCB) buffer box. If the bentonite is hydrated or gets wet at any time, it will swell to seal the buffer box and prevents any diffusion, form inside to the outside or vice versa, from taking place. The swelling pressure of the bentonite should be taken into consideration for calculating pressure on both the used fuel container, and the walls of the emplacement room. In the five location that are being tested by NWMO, the total of geostatic pressure and the bentonite swelling pressure should count for 15 MPa, while the ice loading will count for at most 30 MPa. That is 45 MPa in total maximum pressure in the repository.

2.3.3 Relative Humidity and Water Saturation

Relative humidity is the ratio of vapor pressure (mixing ratio) to the saturation vapor pressure (saturation mixing ratio). Given by another definition, Relative Humidity is the ratio of the actual amount of water vapor in a given volume of air to the amount which could be present if the air was saturated at the same temperature. It is expressed as a percentage (percentage of saturation humidity), and reaches 100% when the air is saturated with respect to water (the case of ice).

$$\boldsymbol{Relative\ Humidity = \frac{Actual\ Vapor\ Density}{Saturation\ Vapor\ Density} \times 100\%} \qquad \text{Eqn. 2.3}$$

At a given vapor pressure (or mixing ratio), relative humidity with respect to ice is higher than that with respect to water. For unsaturated air, relative humidity is inversely proportional to the temperature. Since warm air will hold more moisture than cold air, the percentage of relative humidity must change with changes in air temperature. In that order, relative humidity doubles with each 20 degree (Fahrenheit) decrease, or halves with each 20 degree increase in temperature. Generally, as temperature goes up, relative humidity goes down and vice versa. Ref [23] also demonstrates the average relative humidity in the Canadian cities all over the year, and gives the morning and afternoon annual relative humidity averages based on weather data collected from 1981 to 2010. The numbers allow comparing the average daily high and low relative humidity for the 33 largest Canadian cities. It is obvious that the relative humidity average never exceeds 95% at the surface, with having most of the big cities below the 88%.

Relative humidity measures the actual amount of moisture in the air as a percentage of the maximum amount of moisture the air can hold (saturation). Accordingly, at the repository, while the temperature increases with going down in depth, the relative humidity should decrease. In the post-closure conditions, the changes in surface temperature will not have significant effect on the repository temperature, so, changes in surface relative humidity will not have significant effect on the repository conditions as well. From the humidity saturation point of view, the dominant factor in the post-closure case will not be the relative humidity, but rather, it will be the water saturation in the repository. Having wet, humid, or hydrated contents of the repository will affect the swelling conditions of the bentonite clay used to cover the used fuel containers, and may be considered a water diffusion in the repository. Water diffusion may be taking place because of the surrounding environment at the repository location, and may lead to corrosion factors for the used fuel container. One example for the water diffusion and water saturation is the groundwater in case it is present at any stage in the repository post-closure life time. The salinity level of the groundwater may affect the bacterial activity, and the corrosion factors of the used fuel containers. In summary, the water diffusion, which leads to swelling pressure, will affect the bentonite clay surrounding the containers (according to its density or compaction factors), and is affecting the bacterial activity levels around the containers. If bacterial activity is present in the repository, this leads to increasing sulphide levels, which is considered the main corrodent for the used fuel containers. Thus, proximity to hydrological resources is another measure that should be taken into consideration, means, how far the repository is from hydrological resources?

Proximity to hydrological resources means that the probability of having water diffusion from outside the repository to its inside may take place because of the underground water resources (that is generated from sea, ocean, or precipitation infiltration). Groundwater flows through aquifers, which are geological formations made up of granular or fractured material from which a sufficient quantity of water can be extracted to serve as a water supply. According to [30], the first sub-question that should be asked in this case is “What current knowledge gaps limit our ability to evaluate the quantity of the resource, its locations and the uncertainties associated with these evaluations?”. Accurate estimates of the volume of groundwater in Canada were impossible to be identified. The Geological Survey of Canada (GSC) stated that, according to [30], “the amount of groundwater stored in Canadian aquifers and their sustainable yield and role in ecosystem functioning are virtually unknown”. In another meaning, the groundwater consumption in Canada is known, but the actual volume is unknown. Because of that, the proximity to hydrological resources will be determined from being located in or near to the regions having oceanic crust (which is about 8% of Canada). As a result, if the repository is located in a continental crust region, it may be assumed to be far away from underground hydrological resources. However, for the locations that are being tested by NWMO, precautions will be taken to locate the repository in an area that is known for low groundwater amounts, or to be far away from the groundwater aquifers. If the repository is chosen to be in a groundwater existing location, it should be of low salinity levels and low concentration of potentially corrosive agents.

2.3.4 Bacterial (Microbial) activity

The sulfide content and salinity level of the bedrock, in which the repository will be located, represent a crucial factor. Sulfides and salinity are influencing the corrosion process of metals contained in the repository (spent fuel waste metal containers). Salinity level is different for every rock type, and may exist because of the water diffusion coming from groundwater, which have different salinity levels depending on the aquifers. Bacterial (or microbial) activity is affected by salinity, as with the salinity increases, the bacterial activity decreases, and vice versa. If bacteria are active, this will result in sulphide content, and sulphide is considered a corrodent to metals. Thus, in the bedrock, in which the repository will be located, the existence of microbial or bacterial activity affects the corrosion level of the metal containers. Moreover, if the salinity increases, the tendency of metals to corrode also increases. So, care should be taken when deciding which rock type and bedrock in which the repository will be built, as choosing a saline rock type will decrease the bacterial activity in the repository, but will increase the salinity level in the repository, and then, increases the metal tendency to corrode, and vice versa. Moreover, regular measures and field data should be available in order to realize the amount of activity of the microbes and bacteria, as the microorganisms' life transform from phase to phase over time. In that order, the locations, which are being tested by NWMO, should be chosen to have low salinity levels and low concentration of potentially corrosive agents. And in order to achieve that, locations of low salinity levels will be chosen, along with limiting the bacterial activity with maintaining high pressure values in the repository in order to prevent the bacteria from being active, and thus, not producing sulphides. For that reason, the compacted bentonite clay used to surround the container should have high dry density, in order to reduce the bacterial activity in the dry phase. While in the wet case, when having humidity, water diffusion, or water saturation, the swelling pressure of the bentonite, of high dry density, will do the job of preventing the bacteria from being active, and limit the existence of free water (bacterial growth increases in free water). This will lower the sulphide contents in the repository, and thus, reducing the tendency of metal corrosion of the used fuel containers.

2.3.5 Corrosion and Welding Corrosion of the Used Fuel Containers (UFCs)

Corrosion of the containers, in which the spent fuel assemblies (which assemble the fuel bundles) are emplaced, is an important factor that may affect the diffusion analysis in case the failure happens. According to [12] and [31], at a depth of about 500 m in bedrock, where the spent fuel will be deposited in the repository, the waste canister provides safety during handling and emplacement of the waste in the repository. It also ensures complete isolation of the waste for a desired period of time (minimum of 500-1000 years) during which most of the important fission products will decay, and the heat generation (by radioactive decay) of the waste is most important. This temperature rise will result in a low humidity environment in the vicinity of the container (lowering expectation of corrosion). After emplacing the canister in the emplacement room, the room will be sealed with bentonite clay mixture. The dimensions and waste load of each canister, which is double walled with thickness that acts as a radiation shield, have been chosen such that the temperature on the outer surface of the canister never exceeds 100° C. The external pressure in the repository may reach the value of 15 MPa resulting from a 5 MPa hydrostatic pressure and maximum of 10 MPa bentonite swelling pressure. In [31], corrosion is discussed deeply: corrosion by oxygen (aerobic corrosion), corrosion by sulfides (anaerobic corrosion), and other types of corrosion and how they may affect the canister and its welding over time. The sulphides, which act as the main corrodents, can be supplied from the buffer mass/backfill in deposition holes and tunnels as well as from the groundwater. In addition to these sources, it can also be produced from sulphates through microbial activity. In order to face all these types of corrosion, copper was chosen to be the coating material of the canister, and presented as a reference canister material, because of its thermodynamic stability in pure water. In the Canadian repository, corrosion conditions will be taken initially to be aggressive and extreme until reaching a benign state [12]. Another aspect to be determined, what if the container is emplaced in the repository with a through-coating defect (in the copper coating or welding)? Obviously, this situation can be avoided by proper inspection of the container prior to emplacement, but failure to detect defects will be considered [12]. So, this arouses the need to know the factors influencing the corrosion of weldments, which may be one or more of the following [32]: weldment design, fabrication technique, welding practice, welding sequence, moisture contamination, organic or inorganic chemical species, oxide film and scale, weld slag and spatter, incomplete weld penetration or fusion, porosity, cracks (crevices), high residual stresses, improper choice of filler metal, or final surface finish. This means that if the welding technology has any of the above problems, there may be some weak points present in the weld, which will definitely be followed by a failure in the canister. Fig.6 shows the UFC coating.

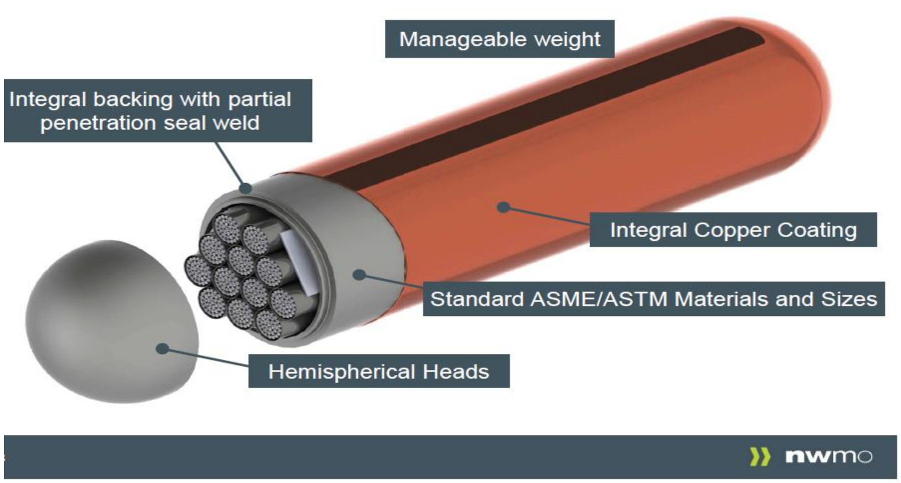


Fig.6: Spent fuel container and its coating [33]

2.3.6 Bentonite Clay (Buffer Boxes, Gap Fills, and Back Fills)

Canada, China, Belgium, France, Germany, Japan, Sweden, and many other countries have considered deep geological repository for high-level radioactive waste (HLW). In present design concepts, compacted bentonite-based materials are supposed to be used as sealing/buffer materials in the emplacement rooms of the deep geological repository of the high level radioactive wastes (nuclear spent fuel) due to their low permeability, high swelling capacity, and high radionuclide retardation capacity [34]. It is also supposed to use bentonite clay as a back fill material in the repository. A fundamental property of bentonite is that when it absorbs water, it expands. However, not all bentonites have the same absorption capacity. According to [35], thermal treatment of bentonite (up to 400°C) drastically reduces its swelling behavior. In [36], bentonite clay is evaluated as an alternative sealing material in oil and gas wells. As compared to cement, which has the tendency to shrink, bentonite shows superior sealing ability during hydration (as it swells and expands). Along with that, it has lower permeability, than cement, during hydration, with the ability to reshape itself and heal any cracks which may occur during subsurface movements. In [37], swelling test (swelling pressure test) and hydraulic conductivity test are performed for bentonite clay under the same conditions of deep geological repository. This work was conducted because the bentonite clay showed high swelling capacity, and good durability under disposal environment, so that the penetration of groundwater from the host environment can be minimized. After closing the emplacement rooms, under hydration conditions, bentonite will swell to fill the gaps among the bentonite bricks (i.e. buffer boxes), between the canister and the buffer box, between buffer box and the host rock, and fills the fractures in the host rock due to excavation. After that, the subsequent swelling is restrained by the host rock and swelling pressure is developed (this pressure must be lower than certain limits). Fig.7, Fig.8, and Fig.9 show the bentonite buffer box and the placement room. Thus, proper understanding of the behaviour of compacted bentonite-based materials during hydration is vital for determining short and long term performance of the deep geological repository, [34].

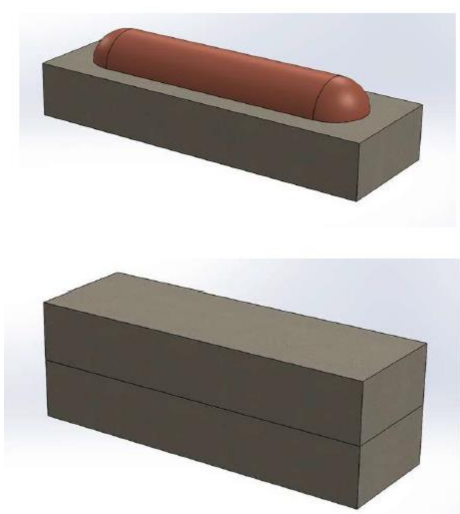


Fig.7: Bentonite Buffer box [33]

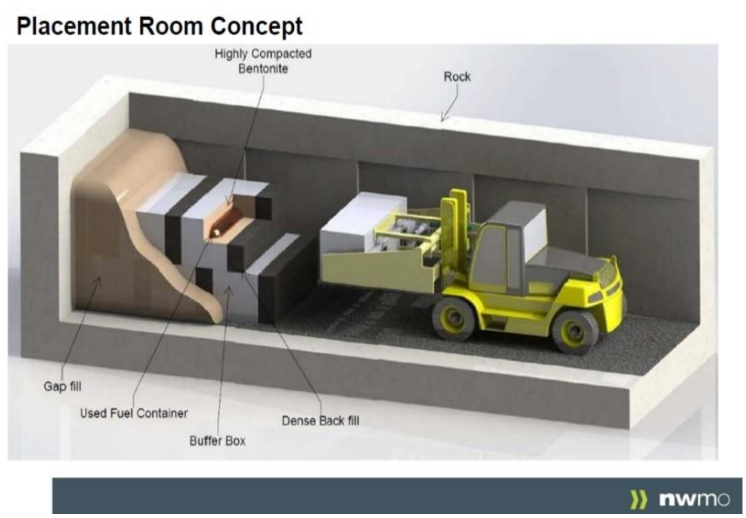


Fig.8: Placement Room Concept [33]

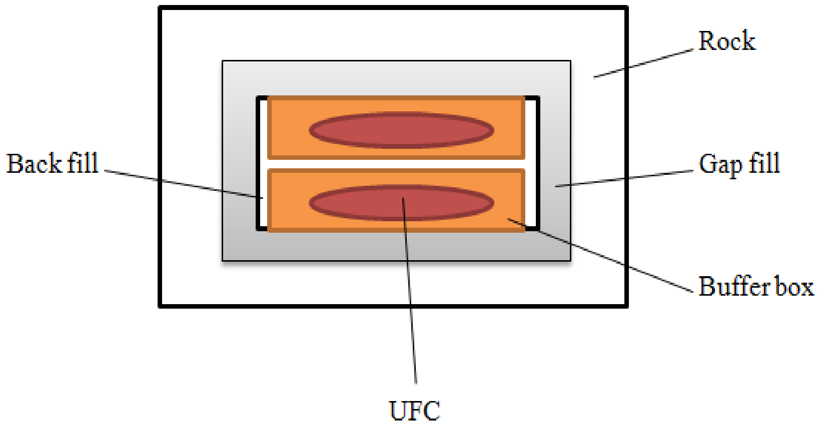


Fig.9: Placement Room (side view)

2.4 Safety of Hydropower Dams (SHPD)

Dams are of different types and techniques of operation. In this research, many types of dams can be considered for the application of the proposed failure prediction approaches that are explained in the next chapters. However, embankment dams, which include both earthen and rockfill dams, are the main type that is reviewed in this section.
In [38], a procedure for incorporating the risk of catastrophic failure in project evaluation is presented. The evaluation of risk depends mainly on estimating the probability of failure. So, the main challenge is how to determine the probability of failure of dams or dam systems. The different factors affecting the failure of dams are briefly explained in the next section.

2.4.1 Factors Affecting the SHPD System Failure

Dams are complex engineering structures that incorporate huge number of interacting system components. Failure in dam systems depends on failure in performing the required interactions among system components, and/or failure to achieve at least one of the required system outputs/results. In this section, the different factors, related to the SHPD system operation and failure, are reviewed.

2.4.1.1 Hydrological Factors

Dams are used for controlling and/or storing water for different purposes, which mean that water is the main factor affecting dams' operation. The hydrological factors are mainly the inflow to the dam, the water storage, and the outflow from the dam. The water inflow to any dam is affected by upstream events, i.e. precipitation, flood, or connection to any upstream dams. Depending on the inflow rate to the dam, water is stored in the dam reservoir and/or released to the downstream of the dam by water management techniques (i.e. gates). If the water inflow results in exceeding the maximum capacity that the reservoir can hold, there is a requirement to spill, and the extra amounts of water should be released using spillway gates. In hydropower dams, water is also released from the hydropower turbines after generating electric power using the head difference between upstream and downstream water levels. Failure in dam reservoir operations is considered a failure of the dam system.

2.4.1.2 Structural and Design Factors

Dams are of different types like embankment dams, arch dams, gravity dams, saddle dams, buttress dams, coffer dams, and diversion dams, amongst other types. In every type, there are different designs and different operating conditions. The type of the dam, its design, and the structural aspects play an important role in dam failure. This section presents a review of some literature on structural and design aspects that affect the failure of dams, especially embankment dams, as they are the most widely used dams in the world involved in the most historical dam failure events, including breaching.

For dam failures, the input breaching characteristics, which are dependent on breach formation mechanisms, are presented in references [39] and [40].
In general, amounts of data reported for dam failures are minimum, which limits the assessment studies (qualitative and quantitative) for dam breaches and failures. One type of the important data is the embankment dam characteristics, which includes size and shape of the embankment, cohesion of embankment material, embankment zoning (zones' type, size, and number), and foundation geology [39, 41]. Availability, or prediction, of this data about dam breach characteristics, dam characteristics, and reservoir geometry, is crucial in evacuation planning and safe management of reservoir operations. In [40], analytical models for dam breach erosion are developed, with discussing their advantages and disadvantages, and evaluating their applicability. Ref [42] tries to quantify the factors leading to breach and erodibility of dam materials based on historical data put in a database. In [43], existing prediction models for estimating embankment dam breaching parameters are summarized.
For an earthen dam, breaching process often has two phases ([43], see Fig.10):

- Breach initiation phase, with breach initiation time defined as the time spent from the first flow over the dam (in case of overtopping), or the first erosion to form a seepage pipe (in case of piping), and starting the erosion in the downstream face of the dam, to the point of lowering of the upstream embankment crest of the dam or forming a seepage pipe. Breach initiation time is important in determining downstream hazard, warning time, and evacuation planning.
- Breach formation phase, with breach formation time defined as the time spent from the point of lowering of the upstream embankment crest of the dam, or forming a seepage pipe, until the breach is fully formed (the point at which the upstream slope of the dam is fully eroded to the entire depth of the dam).

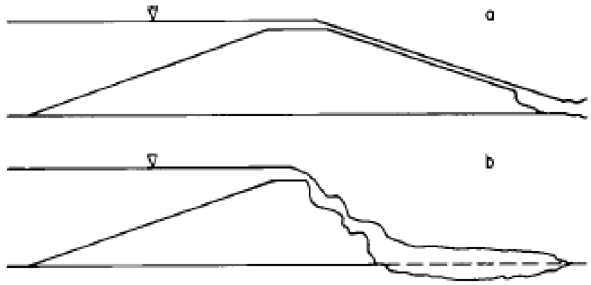


Fig.10: Progressive headcutting breach of a cohesive soil embankment [43]

Dam overtopping, which is one of the major causes of dam failures, is also reviewed in [44]. Reservoir overtops the dam if the inflow exceeds the capacity of the reservoir storage and spillway outflow system. The main challenge is how to predict the performance of the dam in advance of any failure.

Failure of dams can be attributed to a large hydrologic event and the combination of several factors, not only breaching, like [45]:

- Inadequate spillway design,
- Lack of emergency spillway gates,
- Loss of permanent reservoir capacity due to long time of sedimentation,
- Seepage piping failure due to poor dam maintenance, and
- Human factors such as failure to act, wrong procedures, among others.

The most widely used dams in the world, involved in the most historical dam failures, are earthen and rockfill dams. Failure of noncohesive dams, in which materials are removed in layers by tractive stresses, is different than that of cohesive ones, where breaching takes place by headcutting that initiates at the toe of the downstream slope and migrates to the upstream face of the dam. Cohesive embankments rarely have seepage pipes because of the low permeability. On the contrary, seepage pipes take place in granular embankments on the downstream slope resulting in surface slips. Seepage piping is the progressive erosion of particles by percolating water, leading to the development of seepage channels that allow water to flow through the embankment or its foundation, [46].

In the absence of sediment management in many dams, storage capacity loss, which is a long-term progressive process, makes the dam increasingly vulnerable to failure during large flood events. This results in terminating the usefulness of dams and reservoirs, and converting a dam from an asset to a flood control liability [45]. Study of dam failures and flash floods requires modelling the loss of life (LOL), which depends on the time taken by the population at risk

(PAR) to evacuate, that may result due to number of reasons. Ref [47] recommends the following:

- To estimate the benefits of structural modifications and designs that would prevent an existing dam from failure,
- Costs of potential dam failures should be considered in construction decisions,
- To consider the benefits of warning systems that may be installed at dams, and to calculate the expected reduction in fatalities due to these warning systems.

In [41], results of a statistical analysis of failures and accidents of embankment dams are described based on the historic performance of dams. According to [41], the International Commission on Large Dams (ICOLD) has carried out extensive surveys of dam incidents (ICOLD 1974, 1983, 1995).

Management procedures related to safe operation of dams has significant, complex and uncertain social, economic, and environmental factors. The increasing risk posed by failure of dams aroused the need for rehabilitation of current dams. Changes to hydrological safety requirements, changes in downstream of rivers after building dams, and the modified priorities of watershed management are all parts of the risk and should be taken into consideration. Moreover, lack of knowledge of the effects of dams on floods downstream and the worldwide dam accidents puts an additional factor of uncertainty. As a result, and with increasing population and greater development downstream, the overall number of high-hazard dams is increasing. Thus, rehabilitation and/or re-design of aged dams is a must, [48].

Prevention and mitigation processes of dam failures depend on dam risk analysis. So, a quantitative analysis of the dam failures must be conducted.

2.4.1.3 Climatic Factors

Climate conditions affect the dam operation. Winds, precipitation, tornados, and winter ice loading may affect the inflow rates, the reservoir water level, and the operation of different dam components. In [49], the safety of current dams is assessed according to whether or not the effect of the future possible climate changes was taken into account while building them. Climate change may provide increased precipitation and river flows that exceed the capacity of existing reservoirs. Thus, there is a current need in some countries to update the design flood calculations, required for safety assessments which are done every 15-20 years, for their dams. In order to classify dams according to their damage potentials, dams have five classes on a 0 – 4 measure where Class 0 is for dams with minor failure consequences, and Class 4 is for dams with the highest consequences. The design flood is the factor that dams should pass without failure. Design flood for class 2 – 4 dams is required to have a return period of at least 1,000 years, and is 500-year for class 1 dams. Class 0 dams have no specific requirement for design flood, but it is recommended to have a 200 year return period of flood. The dams are also required to withstand a safety check flood, which must be bypassed without causing failure, while some damage may be accepted. The safety check flood for class 1 and class 2 dams is given to be 1.5 of the design flood, [49].

2.4.1.4 Mechanical and Electromechanical Factors

Dams include number of gates for different purposes. Gates are considered mechanical equipment in any dam. Spillway gates, head gates, and service gates are different types of gates that are used in dams. Spillway gates are responsible for releasing water if there is a requirement to spill and in order to prevent overtopping failures. Head gates are used in hydropower dams for generating electrical power from the hydropower turbines by letting the water to flow through penstocks. Service gates are used during maintenance actions. Any failure in operating the gates may result in a failure in the dam operation. Failure may happen due to different reasons, including electric supply problems, ice loading during winter periods, remote control connectivity issues, or manual control problems.

Hydropower turbines are considered electromechanical equipment responsible for generating electric power for different purposes.

Mechanical and electromechanical equipment should have efficient monitoring and maintenance plans in order to reduce their tendency to fail, because this may be responsible for the entire system failure.

2.4.1.5 Economic and Human Factors

The global boom in dam construction reveals that dams are important economic assets that affect people's lives. These assets are supposed to be operated, monitored, and maintained properly in order not to be a liability and a risk for people's lives. Successful operation and maintenance of dams depends on affording economic funds. And if calculating the risk depends of the failure of the system and its consequences, the consequences here are not only economic, but they are about lives of hundreds, if not thousands, of people. Economics are crucial in maintaining proper operation and limiting the failures which may lead to more expensive effects, beside the expected loss of lives.

In the same direction, human factors are important in limiting the failures of dam projects. The humans are operating the dams on site or remotely. They are taking decisions regarding management of dam components (i.e. electric power generation, gates management, and water storage, amongst others). If the human operators of any dam failed to take the right decisions at any time, the dam will have a higher possibility to fail in performing at least one of its operations.

It is also important to mention the economic, social, and societal impacts on people. The aim of [50] is to unify scholarly understanding of dams' social impacts using the analysis of various frameworks. References [51], [52], and [53] present the average need for electric power per person globally, and how some countries are investing in dams to provide economic and societal development and environmental improvement inside and outside their borders. Although the public opposition to hydropower projects because of the risks resulted from the reservoirs impounded by large dams, these projects may play an important role in the future world energy. In [54], break down/failure of the engineering process (which includes planning, design, construction, and operation) is discussed. Three causes are identified: absence of data or theoretical knowledge, ignorance of prevailing practice, and rejection of current technology. It is obvious that the human factor is part of these causes. In [55], two modes of hydropower dams are explained: 1- Reservoir based dams, and 2- Run of the River (RoR) mode. In storage or reservoir based project, the dam may be capable of holding water for sufficient time, in case of flooding, to use it in power generation or other water demands. This also gives some time for people on the downstream side to evacuate before any disaster may take place (warning time). From another point of view, huge reservoirs act like “water bombs” in case of any dam failure, affecting human lives and properties on the downstream side. RoR projects lack the storage advantage, and in case of any emergency due to floods or breakdowns, less time will be available for warning on the downstream side. The strength of RoR projects lies in the fact that they have small reservoirs (or don’t have reservoirs at all), which prevents people from water bombs, [55].

2.4.1.6 Safety Management Factors

A statistical analysis of dam failures from 43 countries in [56] indicated that earth-rock dam failures included 49% due overtopping, 28% due to seepage in dam body, and 29% due to seepage in foundation. Modern dam safety management (DSM) system involves regulations, guidance system, and risk analysis system, safety monitoring system, danger control and reinforcement system, early warning system, and emergency plan system. Two main methods for studies of dam-break process are dam-break experiments and mathematical modeling, [56]. Typically, reasons for dam failures are of two types [56]:

- Natural causes, like heavy rains, hurricanes, and earthquakes, as external natural causes. And aging of materials, dam body defects, and foundation defects, as internal natural causes.
- Human attributes, like global warming (increased precipitation rates), terroristic attacks, inappropriate design (like putting large number of dams on the same river to form system of dams or a flood control system), construction problem, or operational problem.

The purpose of the study in [57] is to investigate the primary causes of the dam failures and the effect of failure of one or several dams on the safety of other dams in a flood control system. Important lesson to be understood from this failure is that powerful warning and emergency response system must be available. Moreover, although flood control system of dams enhances the control mechanism, it poses higher risk during extreme events (e.g. if a dam on the upstream fails). Small dam safety assurance policy benchmarks, that are available from international literature, are reviewed and synthesised in [58] to determine their applicability in developing countries. In [59], the formation and failure of natural dams is discussed. Natural dams are formed from landslides, glacial ice, and late neoglacial moraines after an excessive rainfall, snowmelt, or earthquake. Landslide dams are formed due to mass movements of rock and debris avalanches; rock and soil slumps and slides; and mud, debris, and earth flows. Many landslide dams fail shortly after formation, which should be taken into consideration while designing safety monitoring systems and danger control systems.

2.4.2 Dependability Approaches for Representation of Dam Failures

Dam failures incorporate many different factors. Technical problems in dam construction or operation may lead to environmental and societal problems from one side, or catastrophic events of dam failures from another side. The main concern in this research is to better predict dam failures according to different types of causes, and how to reduce the probability of that failure. Generally, the primary causes of dam failures come from structural failures, inoperable gates, control system errors, operator errors, mechanical failures, or power supply failure. Representing the dam system as cause-effect relation representation is crucial in this case.

Failure prediction is related to the problem of dam aging in the dam safety dilemma, ref [60] mentioned that while dam systems involve multiple failure modes, conventional assessment and prediction models often neglect the correlations among failure modes. Accordingly, the remaining service life of dams predicted by these methods is relatively approximate and could be overestimates. So, there is a certain need for a better method in predicting the remaining service life time for dams, with taking the correlations of different system components and modes of operation into consideration, to predict the risks that might exist. Ref [60] proposes a prediction model of remaining service life for gravity dam systems based on the illustrated correlation analysis and time-varying theory. As an example, in Fig.11, the failure of a dam is viewed as a system and analysed based on Fault Tree Analysis (FTA) technique. FTA is one of many types of dependability analysis techniques that are used for dependency modelling of system components. Ref [61] explains the different types of dependability analysis techniques. Generally, all these techniques share the distinction of being able to represent the cause – to – effect relationships among system components. The principal dependability approaches that are widely used in similar dam studies are: failure modes and effects analysis (FMEA), event tree analysis (ETA), and fault tree analysis (FTA). Ref [7] has provided list of advantages and disadvantages of the three typical methods versus the Bayesian network analysis (BNA). Although still a new approach for engineering applications, Bayesian Networks are found to be suitable for studying complex systems with multiple elements and their interrelationships. Disadvantages of other methods can be overcome by applying the Bayesian network technique, [7].

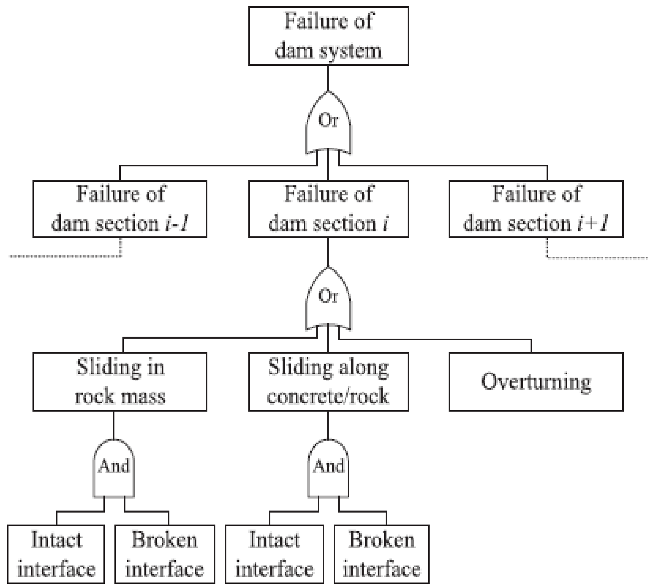


Fig.11: An example of FTA with different dam failure modes [56]

The BN may be considered as a multidisciplinary approach that includes the probability of failure of the geotechnical, hydrological, and structural sub-systems of a dam. Therefore, it provides a promising framework for an integrated system failure analysis in a more global and holistic way, [62] and [63].

2.5 Risk, Reliability, and Uncertainty

There are many definitions of risk. Two common definitions of risk are: (i) probability of failure and (ii) the product of the probability of an undesired outcome (failure) and the consequences of that outcome [3, 64, 65, 66, 67, 68, 69, 70, 71, and 72]. Here in this thesis we generally refer to (i) and occasionally to (ii) depending upon the context. The development of risk estimates or the determination of risks in a given context is called Risk Analysis, while Risk Assessment is the process of evaluating the risks and determining the best course of action. Uncertainty of outcomes is a common concept in all definitions of risk. Uncertainty may be defined as the state of having limited knowledge surrounding existing events and future outcomes, or imperfect ability to assign a character state to a process that forms a source of doubt, [3]. Thus, uncertainty is an intrinsic property of risk and is present in all aspects of risk management (see Fig.12) including risk analysis and risk assessment. Generally, risk analysis is a systematic tool that facilitates the identification of the weak elements of a complex system and the hazards that mainly contribute to the risk. In [73], hazard analysis is described as "investigating an accident before it occurs", with the aim of identifying potential causes of accidents that can lead to losses.

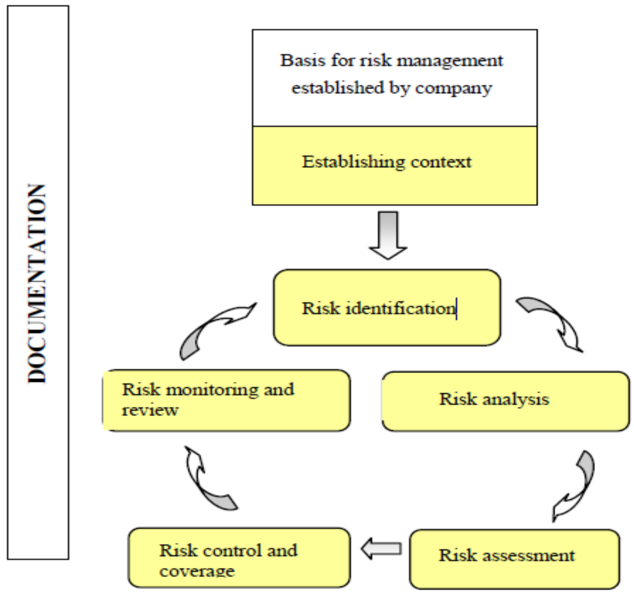


Fig.12: Risk management process [64]

According to [61, 71, 72, and 74], availability is the ability of a component or system to function at a specified interval of time. This is closely related to what is called "Reliability", which describes the ability of a system or component to function under stated conditions for a specified period of time. Reliability engineering is a sub-discipline of systems engineering that emphasizes dependability in the lifecycle management of a product. In reliability engineering programs - where reliability plays a key role in the cost effectiveness of systems - testability, maintainability, and maintenance are parts of these programs. In reliability engineering, estimation, prevention, and management of high levels of lifetime engineering uncertainty and risks of failure are common areas to be dealt with. Theoretically, reliability is defined as the probability of success (Probability of success =1-Probability of failure). Sometimes, probabilistic stability analysis is referred to as "reliability analysis". During failure probability estimation, reliability analysis cannot be used solely, and the results of such analysis must be moderated using engineering judgment and appropriate models as useful tools in estimating conditional probabilities.

Generally, according to [4, 66, 72, and 75], uncertainty – which is a common concept for expressing inaccuracies - means that a number of different values can exist for a quantity, while risk means the possibility of loss as a result of uncertainties. Accordingly, any uncertain variable, which can take various values over a range, should be provided with an uncertainty analysis that is used to assess output uncertainty and to identify the most efficient ways to reduce that uncertainty according to the contributing variables. Hence, in terms of statistical concepts, uncertainty can be thought about as a statistical variable and can be calculated using well verified statistical procedures. In a broad sense, the value reported for a measurement describes the central tendency (mean); while the uncertainty describes the standard deviation (deviation from the mean). Ideally, this measure of uncertainty is calculated from repeated trials, or to be taken from estimates in whole or part in many engineering tests or research experiments. Thus, risk analysis forces the engineer to confront uncertainties directly and to use best estimates and predictions, especially, while taking decisions regarding the safety of large technological (complex) systems. Increasingly, such decisions are being based on the results of probabilistic risk assessments (PRAs), which must be associated with adequate quantification of the uncertainties. Uncertain parameters can be treated as random variables with appropriate probability distributions. Such distributions are assigned on the basis of available data (which is often scarce), combined with the judgement of experts (which can vary widely), adding another element of uncertainty into the uncertainty analysis itself. This means that there might be different sources of uncertainty due to data available, limited knowledge, and subjective judgement, and uncertainty here is assumed to be available in probabilistic terms either from data or from expert judgement or logical inference, [3, 4].

For any given system including inputs and sub-systems, probabilistic failure analysis depends on finding the probability of not getting the required or estimated output of that system. The required output may be the effect that is produced from the system causes (i.e. prediction reasoning), or the determination of causes responsible for certain results and effects (i.e. diagnostic reasoning). Thus, determining the cause-effect relation is an important first step in the probabilistic failure analysis, which allows for better understanding to enhance the system reliability, and take decisions for mitigating the negative effects, or better enhancing the causes. A complex system can be defined as a system structure that is composed of a many components that have complex interactions, and may be represented as a network where the nodes represent system components and the edges (links) are their interactions. Given any complex system that includes inputs, outputs, sub-systems, and boundaries, it is reasonable to assume that all of these system components are interacting either directly with one another, or indirectly. In order to estimate the probability of failure for such system, the interactions should be represented mathematically including any probability measures. A full representation of the system facilitates its analysis from the failure point of view. The main obstacle in failure analysis of complex systems is how to represent the system components and their basic and conditional probabilities. Bayesian Networks (BNs) are found to solve this problem. Bayesian Network provides a graphical representation of any system using basic probabilities, for system inputs, and conditional probabilities, for sub-systems and their interactions. One of the main advantages of using BNs is the ability of integrating all types of data (social, environmental, technical, etc.) seamlessly in one representation. This is because of the probabilistic nature of the BNs, as everything is represented as a probability. The main challenge in BNs is that data must be available in order to estimate probabilities. When the system is fully represented, the failure probability could be estimated using Bayesian equations. An alternative use of the BN is to evaluate the performance of the system components and their interactions to get some information about the failure causes. If the post failure analysis stage is taken into consideration, determination of causes and mitigation or treatment actions should be considered in order to improve the performance and limit the overall system failure. In the next section, Bayesian Networks are defined, with introducing their different types and their probabilistic calculations.

2.6 Bayesian Networks (BNs)

According to [5, 7, 9, 76, and 77], Bayesian networks (BNs), or belief networks, are probabilistic graphical models used to represent knowledge about an uncertain domain using a combination of principles from graph theory, probability theory, computer science, and statistics. In the graph, nodes (vertices) are representing random variables, and the edges (arcs) represent the interrelationships (conditional probabilistic dependencies) among these variables, which can be estimated using known statistical and computational methods. BNs can model the quantitative strength of the interrelationships among variables (nodes), allowing their probabilities to be updated using any new available data and information. BN is a graphical structure known as a directed acyclic graph (DAG), which is popular in some fields of learning (statistics, machine learning, and artificial intelligence). This means that a set of directed edges are used to connect the set of nodes, where these edges represent direct statistical dependencies among variables, with the constraint of not having any directed cycles (i.e. cannot return to any node by following directed arcs). Thus, the definition of parent nodes and child nodes is obvious. The directed edge is often directed from a parent node to a child node, which means that any child node depends on its parent node(s). BNs are mathematically rigorous, understandable, and efficient in computing joint probability distribution over a set of random variables, along with being useful in risk analysis. In BNs, there are two main types of reasoning (inference support): 1- Predictive reasoning (top-down or forward reasoning), in which evidence nodes are connected through parent nodes (cause to effect), and 2- Diagnostic reasoning (bottom-up or backward reasoning), in which evidence nodes are connected through child nodes (effect to cause). Firstly, the topology of the BN should be specified (structuring of graphical causality model), then, the interrelationships among connected nodes should be quantified, i.e. conditional probability distributions using conditional probability tables (CPTs). Also, the basic probabilities of basic (evidence) nodes should be determined using basic probability tables (BPTs). As the number of parent nodes, and/or their states, increases, the CPTs get very large. Fig.13 introduces the different types of reasoning in BNs. Nodes without any arrows directed into them are called root nodes and they have prior (basic) probability tables, while nodes without children are called leaf nodes. Nodes with arrows directed into them are called child nodes, while nodes with arrows directed from them are called parent nodes. The prior basic probability tables, for the root nodes, and the conditional probability tables, for the parent and child relationships, may be obtained from historical database currently available, which can be updated in case of having any new data or information. Generally, quantifying BNs depends on four sources of data: statistical and historical data, judgment based on experience (i.e. expert judgement), existing physical models (or empirical models), and logic inference. Where no such sufficient data exist, either subjective probabilities from experts or detailed simulation models can be used to estimate conditional probabilities, which is discussed in details later in this thesis.

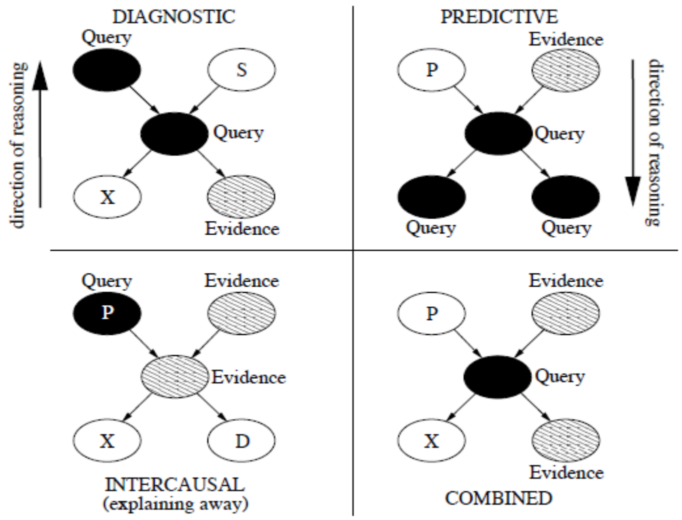


Fig.13: Types of reasoning in BNs [77]

An example of BN with seven variables is shown in Fig.14. The joint probability function of random variables in a Bayesian network can be expressed as shown in equation 2.4:

$$P(x_1, \dots \dots, x_n) = \prod_{i=1}^{n} P[x_i | Pa\ (x_i)] \qquad \text{Eqn. 2.4}$$

Where $P(x_1, \dots \dots, x_n)$ is the joint probability of variables x_1, x_2, $x_{3,..}$ x_n, and $Pa\ (x_i)$ is the parent set of x_i. If x_i has no parents, then the function reduces to the unconditional probability of $P(x_i)$. For more illustration of BNs and their applications, including mathematical relations and equations, see [5, 7, 9, 76, 77, 78, 79, 80, and 81].

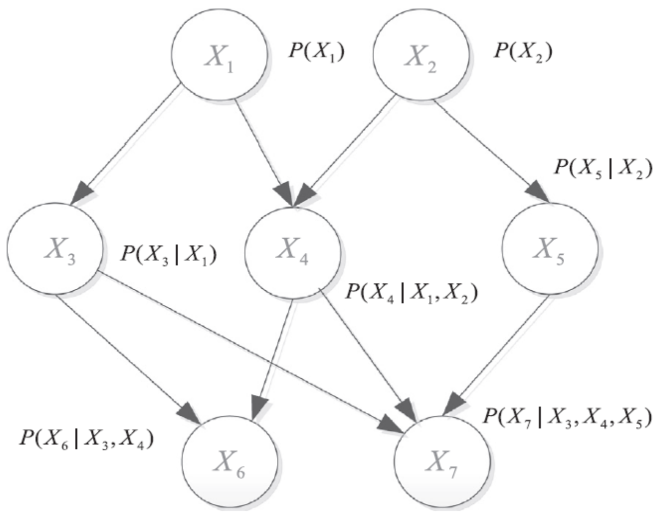


Fig.14: An example of BN with seven variables [78]

In [79], another simple Bayesian network of earthquake-triggered landslides of five nodes (with their possible states) and five arcs is illustrated in Fig.15.

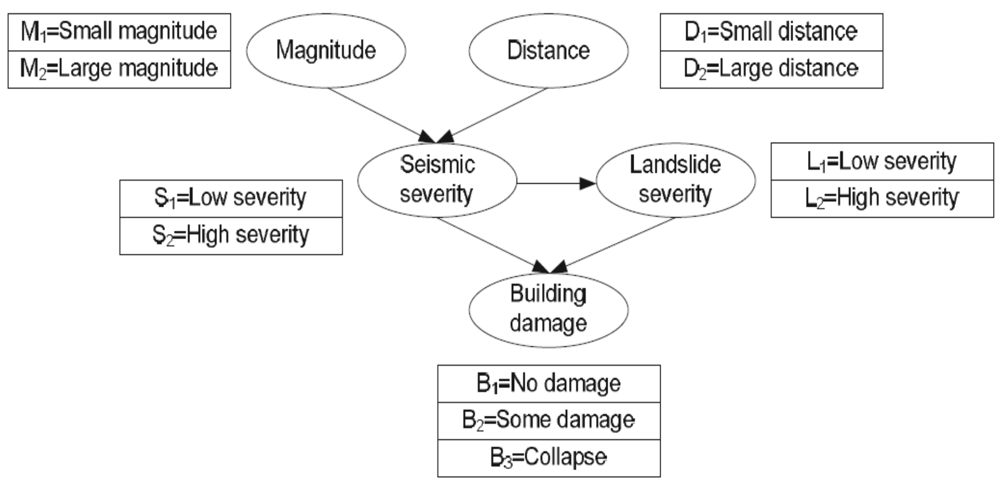


Fig.15: Bayesian network of earthquake-triggered landslides [79]

The marginal prior probability of B having *no damage*, $P(B = B_1)$ can be calculated through marginalization of equation 2.4 by equation 2.5:

$$P(B = B_1) = \sum_{i=1}^{2}\sum_{j=1}^{2}\sum_{k=1}^{2}\sum_{m=1}^{2} P(B = B_1, M = M_\mathrm{i}, D = D_j, S = S_k, L = L_m)$$

Eqn. 2.5

The joint probability can be derived according to equation 2.4, with the conditional probabilities are quantified using available information (e.g., statistical and historical data, expert judgement, and physical and empirical models), [79]. One of the features that BN allows is entering evidence as input, resulting in updating probabilities in the network when new information is available. This information will propagate through the network and the posterior probabilities can be estimated. An example of the posterior probability of $B=B_{1,}$ given that the evidence $M=M_1$ and $D=D_2$ already took place, is shown by equation 2.6:

$$P(B=B1|\,M=M1,D=D2)=\frac{P(M=M1,D=D2|\,B=B1)\,P(B=B1)}{P(M=M1,D=D2)}$$
$$=\frac{P(\,B=B1,M=M1,D=D2)}{P(M=M1,D=D2)}$$
$$=\frac{\sum_{k=1}^{2}\sum_{m=1}^{2}P(B=B_1,M=M_1,D=D_2,S=S_k,L=L_m)}{\sum_{i=1}^{2}\sum_{k=1}^{2}\sum_{m=1}^{2}P(B=B_{\mathrm{i}},M=M_1,D=D_2,S=S_k,L=L_m)}$$

Eqn. 2.6

$$\boxed{\textbf{\textit{Posterior Probability}}\;=\;\frac{\textbf{\textit{Likelihood}} *\ \textbf{\textit{Prior Probability}}}{\textbf{\textit{Evidence}}}}$$

The concept of posterior probability allows for identifying the events which have higher contributing impacts on the undesired/failure event, and then the decision maker may pay more attention to these important factors, [82]. In BNs, the main concern is the cause-effect relationships, and deriving causal inferences from a combination of diverse assumptions. Generally, the use of Bayesian networks helps to answer queries even when no experimental data is available.

The structure of a relatively complex BN of the IEEE-RTS system is shown in Fig.16. This shows how complicated the system interrelationships could be when represented as a BN, especially when large number of system components/nodes need to be represented. This also reveals that BN may be used to represent different applications due to its probabilistic nature.

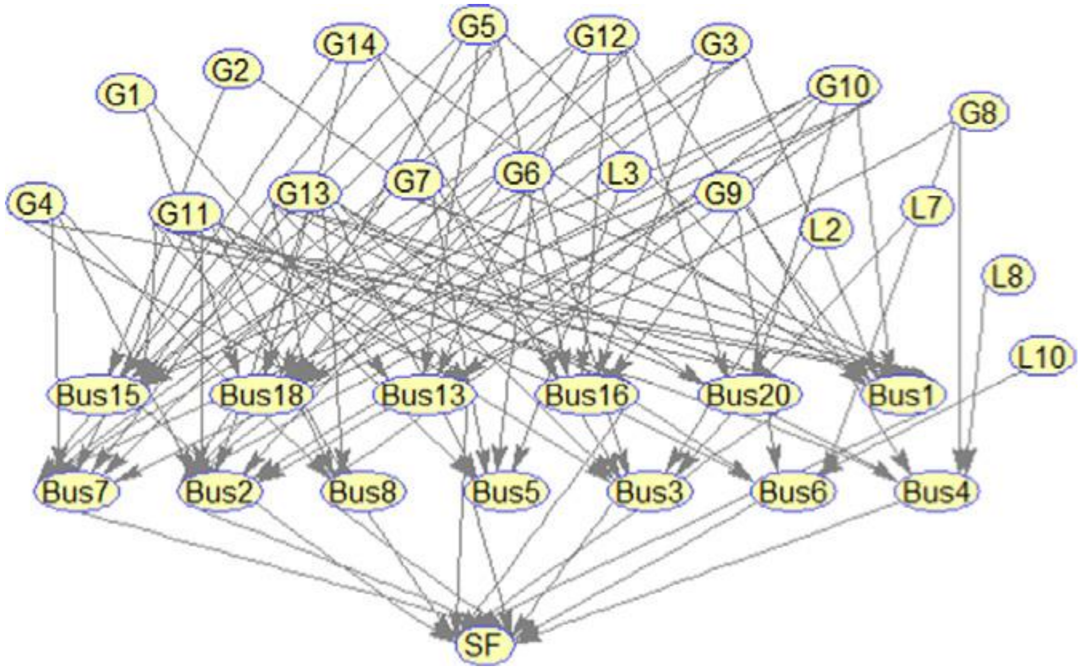


Fig.16: The BN structure of the IEEE-RTS system [83]

2.7 Advantages of BN Over Other Network Representation Techniques

Network representation using sequence diagrams may not be an easy task for complex engineering applications. The two most commonly used sequence diagrams, for representing engineering applications, are Event Tree Analysis (ETA), and Fault Tree Analysis (FTA). This research proposes using Bayesian Networks (BNs) for representing complex systems. Detailed Simulation is another way of representing the engineering system when appropriate amount of data and models are available.

Table 3 shows a detailed comparison, with the advantages and disadvantages of four techniques (methods) that can be used in representing systems. These four techniques are Simulation, Bayesian Network (BN), Event Tree Analysis (ETA), and Fault Tree Analysis (FTA), [7].

Technique	Advantages	Disadvantages
Simulation	• Can represent any system with any number of variables, with detailed states' definitions	• Sampling problem (depends on the sample nature and its size). Sampling mainly depends on randomly generated data • Too complex with multiple number of system variables and their corresponding states. Relations among variables are complicated to be obtained. This may lead to misleading results • Takes much more time to estimate the results in case of huge number of system variables (good for estimation not for risky decision making) • Probability estimation may be computationally complicated
BN	• Depends on historical data and statistics, not on sampling • Can integrate different types of data due to probabilistic nature • It can represent a huge number of variables and states • Estimating probabilities in shorter times • Simplify any system to a number of nodes having interrelationships among each other (nodes and arcs) • Represents basic and conditional probabilities using basic and conditional probability tables (BPTs and CBTs), which facilitates the representation and makes it easier to interpret • Being acyclic makes it faster in solving problems that do not require cyclic representation	• Results depend on connections and topologies used for representing the system as a BN. That is why relying on expert and domain knowledge in representing any system is required. If such knowledge is not available, estimating different configurations that define different scenarios (worst case, best case, and other cases) will be beneficial • Has acyclic behaviour, which is not suitable for dynamic situations which may include cycles

ETA	• Simplifies the system in terms of "yes/no" steps to follow the events that the system may experience • Each step can be represented using probability (conditional probability) if there is a relation between the parent state and the child state	• Not suitable for describing and representing multiple initiating events • Not suitable to represent dependency among different events with multiple number of states, or between any event and a new initiating event.
FTA	• Simple to understand and easy to implement • Qualitative descriptions of potential problems and combinations of events causing specific problems of interest • Lists recommendations for reducing risks • Displays information in a structured, graphic way that makes it easy to interpret and communicate	• Risk of inaccurate information, which compromises the accuracy of the results (because it is mainly based on judgement and subjective opinions) • Can be a relatively time-intensive and complex technique, especially with very large systems • Correlations between basic events are difficult to be modelled

Table 3: Comparison of BN, ETA, FTA, and Simulation

To show the difference between BN and ETA representations, an example of a two reservoir system is represented. Using BNs to represent two dams in series and in parallel, with dependent inflows, is shown in Fig.17 and Fig.18, respectively:

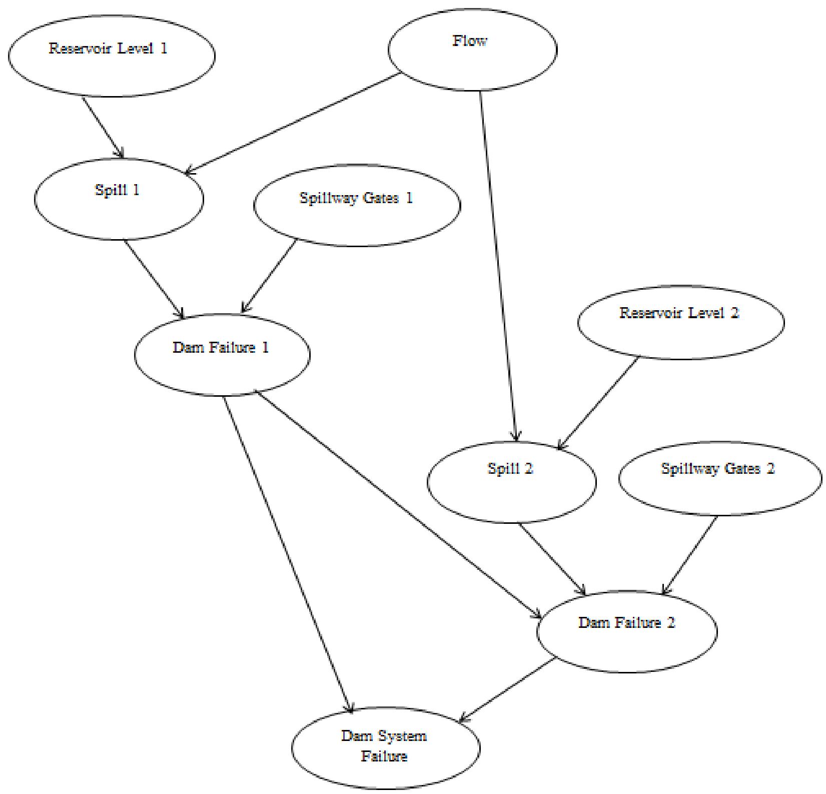


Fig.17: BN of two series dependent dams/reservoirs

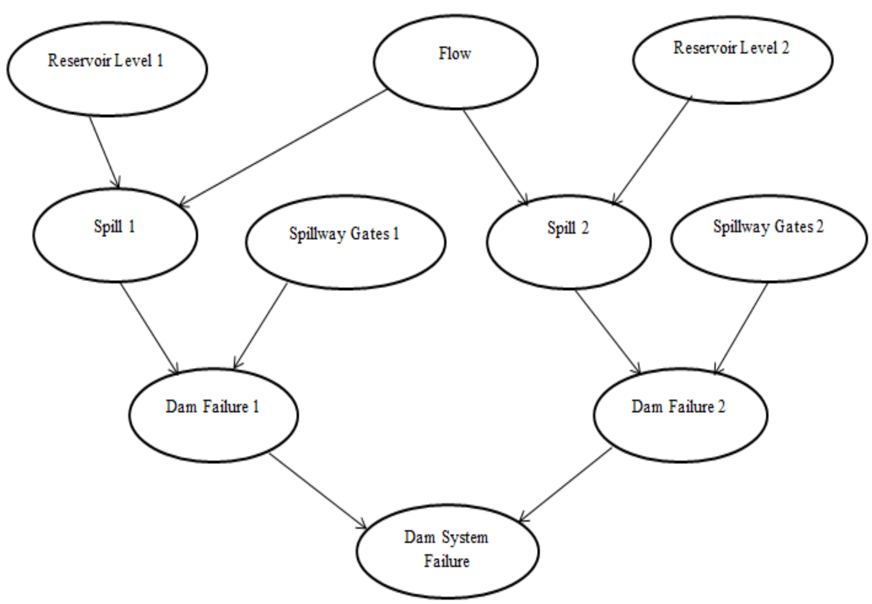


Fig.18: BN of two parallel dependent dams/reservoirs

Both dams in this case are represented by their inflows, reservoir levels, and the event of having excess water more than the reservoir capacity (named spill). If spill took place, and the spillway gates failed to open, the dam will fail due to overtopping. Then, the failures of both dams will represent the system failure probability.

ETA, for example, can also be used to represent the same system of two dams, in series or in parallel, having two dependent inflows (see Fig.19). Both cases, series and parallel, will have the same representation using ETA, which is misleading in terms of the form of representation of the system under study. Moreover, if the two dams are in series, there should be an effect of the outflow and the failure of the first dam on the second one, which is hard to represent in this case. Similarly, for the parallel case, the outflows of both dams should be added to represent the total outflow of the system, which cannot also be represented while using ETA as a representation technique.

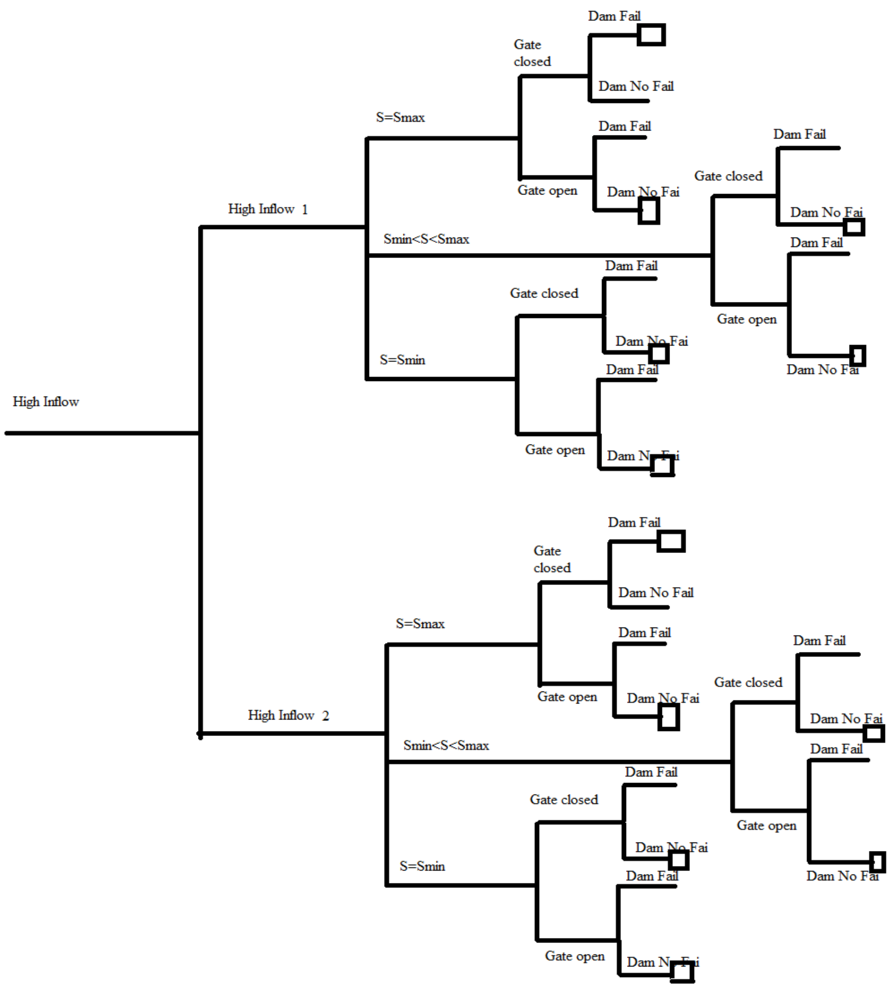


Fig.19: ETA of two dependent dams/reservoirs

Accordingly, when the BN is used to represent the system, the network is found to be more readable and understandable than other representation methods. This facilitates the analysis part of the system, which leads to easier system quantification. Quantifying the sequence diagram depends on available data, expert judgement, logic inference, empirical models, or detailed simulation of the system. BNs need probabilistic quantification for the basic and conditional probability tables of the network, which allows for using the Bayesian inference in predicting the failure probability of any system under study.

2.8 Summary

In this chapter, the different factors affecting the Deep Geological Repository (DGR) disposal system have been reviewed. The diversity of the system's different components needs to be unified in a single representation that includes all the interrelationships among these components. This research focuses mainly on the failure of the Used Fuel Container (UFC) that contains the nuclear fuel bundles. It is shown that there are different causes that may affect the failure of the UFC. The main goal is to limit the failure for such systems, which are not yet applied and don't have any kind of historical databases. As the main purpose of this research is to predict the probability of failure, the way of representation should be probabilistic. BNs have the distinction to represent the different components of the system with their interrelationships, along with defining the different causes leading to certain effect(s) in a probabilistic representation. One of the main advantages of BNs is that they can incorporate any kind of data (pressure, temperature, relative humidity, etc.) because all of them are represented in terms of their probabilities of occurrence, not their values. Similarly, as dams incorporate a huge number of factors of different natures and characteristics (more than that of the NWM case); it would be crucial to have a simplified representation that includes all these factors. Like the NWM case, the different factors affecting dam failures are of different types (technical, man-made, economical, societal, etc.), and for that reason a probabilistic representation like the BN is useful. In the case of dams, BNs are supposed to use the historical databases to determine the different probabilities of the interacting system components and factors.

Probabilistic uncertainty is one of the main sources of inaccuracy in probabilistic results. In complex systems' representations that depend on probabilistic quantification, like BNs, uncertainty propagation is one of the main challenges. While BN is having more advantages over other sequence diagrams and dependability analysis techniques, it is still not mature in representing complex engineering networks having huge number of system variables. In BN representation, uncertainty comes from quantification sources, like expert judgement, logic inference, or empirical models. With that, BNs, as Directed Acyclic Graphs (DAGs), still have the ability to represent any network **quantitatively** (using probability measures), and **qualitatively** (using simple representation and dependency structure). The next chapters introduce different approaches of using BNs when dealing with different types of complex networks, i.e. NWM and SHPD. These proposed approaches try to make the BNs more mature in dealing with such complex networks.

CHAPTER 3

Bayesian Network Approach for Nuclear Waste Management in Canada

3.1 Introduction

This chapter applies the BN to study the Nuclear Waste Management (NWM) system. This future application includes a number of system components that have complex interrelations. According to the literature that has been reviewed, studies and analyses for system components and factors of this application are mostly done for each separate component/ factor. This thesis tries to address an analysis for the combination of most of the interrelated components/ factors of this system in order to predict/ estimate a combined outcome for system failure.

In order to better analyze the system of Nuclear Waste Management (NWM) using Deep Geological Repository (DGR), BNs are used to represent the interrelationships among different system components. Due to the nature of this system as a future project, limited data available and lack of knowledge are the main obstacles in representing the system and its interacting components, which adds some complexity to the system. This chapter focuses on analysing the system, explaining the underlying assumptions, and studying all the related variables and components of the DGR system that will help in predicting the system failure. Moreover, the main contributors to system failure can be estimated in order to better design the project.

3.2 System Assumptions

In the NWM case study, the following key attributes are assumed for the hypothetical site [84, 85]:

1- High- level (HL), long-lived nuclear waste.
2- High volume of spent fuel wastes. Thus, a deep geological repository (DGR) concept is applied (500 m depth).
3- The repository is located at a depth of 500 m, with sufficient volume of rock and depth to host the repository.
4- Groundwater at repository depth provides a chemically reducing environment and a low concentration of potentially corrosive agents.
5- The host rock is capable of withstanding mechanical and thermal stresses.
6- Seismic activity and the risk of volcanism are low.
7- Host rock formation does not contain economically exploitable natural resources at repository depth.
8- Designs are according to the Canadian standards (CANDU fuel bundles, waste container, and bentonite clay buffer boxes).
9- The repository contains a network of placement rooms that are assumed to hold 4.6 million used fuel bundles encapsulated in about 100,000 long-lived used fuel containers, which is the total reference used fuel inventory projected over the expected lifetime of the current fleet of Canadian CANDU power reactors. See Fig.22 and Fig.23 for the layout of the repository and the placement room geometry.

10- The container design consists of an outer corrosion-resistant material (copper), and an inner supporting material (steel), which provides strength for the container to withstand expected hydraulic and mechanical loads. See Fig.20 and Fig.21 for the copper coated used fuel container and its manufacturing process.
11- Used fuel bundles are at least 30-years old at time of placement in the repository.
12- Repository operation (i.e., filling of repository rooms) lasts for 38 years (about 120,000 fuel bundle per year).
13- The post-operation monitoring period, with access tunnels open, lasts for 70 years.
14- Final decommissioning/closure takes up to 30 years.
15- Main goal is to calculate or to estimate the probability of failure of the spent fuel container placed in the repository after the DGR is closed (post closure). This facilitates management and improvement actions in the design stage in order to minimize the failure, and to estimate the main contributors to system failure.
16- Different scenarios are taken into consideration regarding groundwater at repository depth to be of either high or low salinity.
17- Extreme conditions of causal factors such as pressure, water, chemical, biological, and thermal pollutions, can be taken into consideration in probabilistic modeling.
18- The copper coated used fuel containers have a design requirement for a minimum functional life of not less than 100,000 years.
19- Future impacts are assessed over a one-million-year baseline.

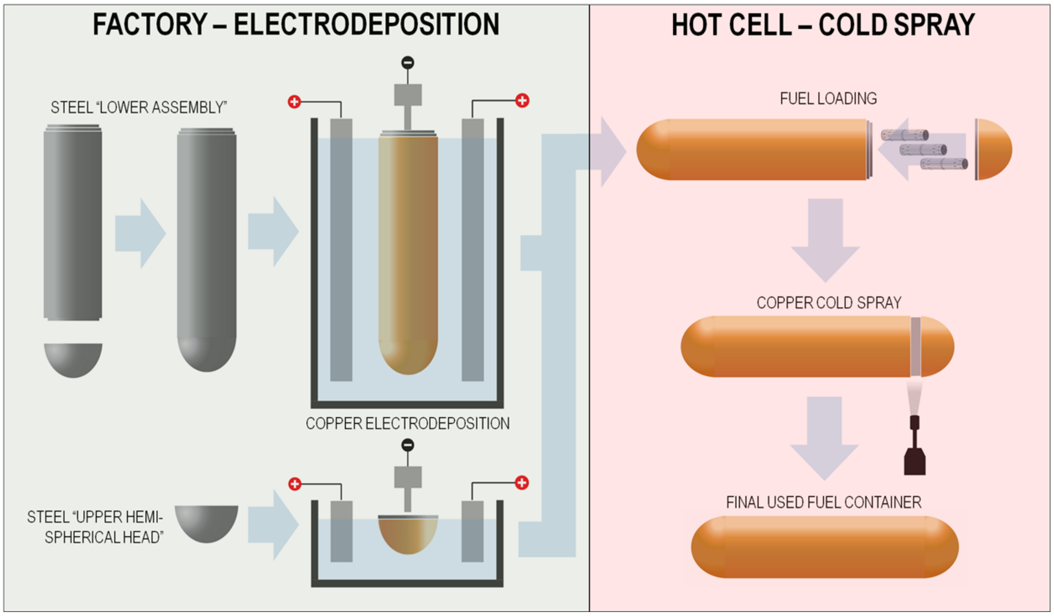


Fig.20: Used Fuel Container Manufacturing Process [85]

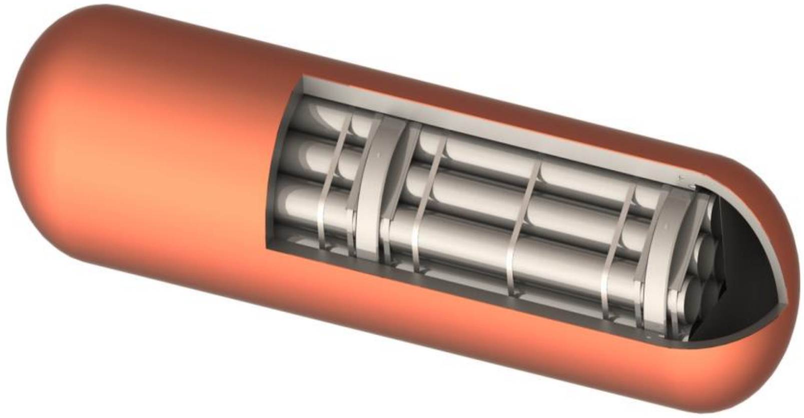


Fig.21: Copper Coated Used Fuel Container [85]

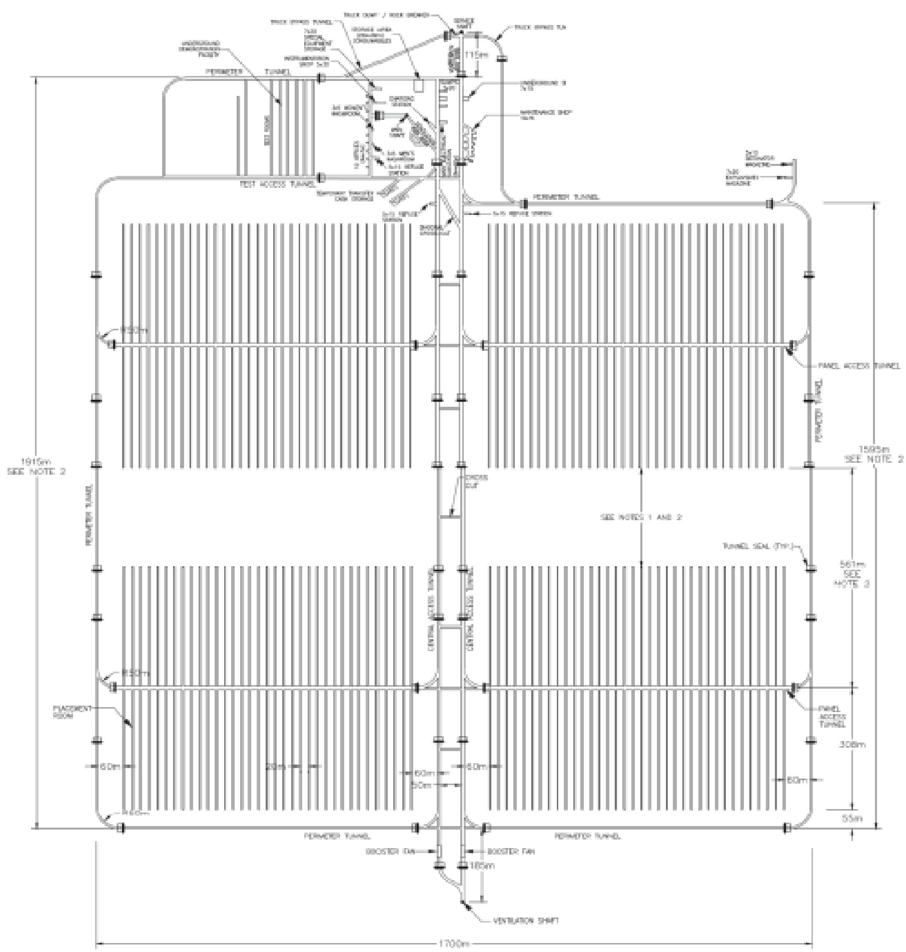


Fig.22: Underground Repository Layout [85]

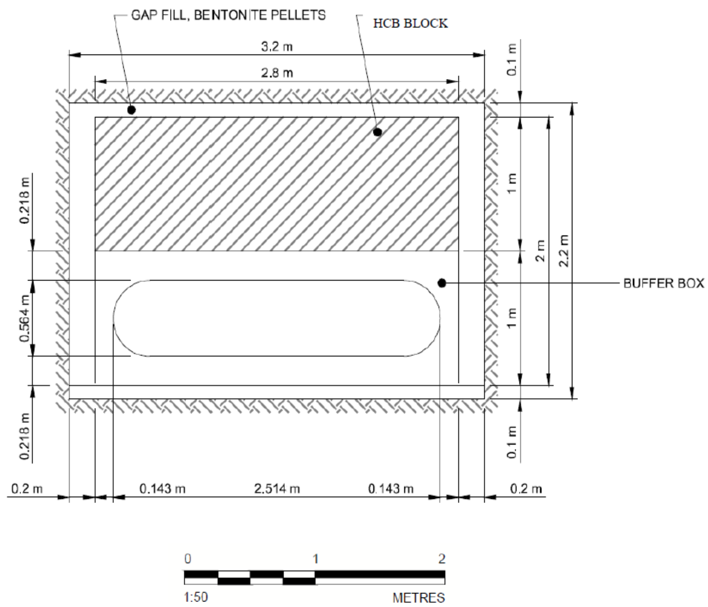


Fig.23: Placement Room Geometry (Vertical Section) [85]

As of June 30, 2017, a total of approximately 2.8 million used CANDU fuel bundles were in storage at the reactor sites (see Fig.24 for major storage locations in Canada). The Nuclear Waste Management Organization (NWMO) has a legal obligation to manage all of Canada's used nuclear fuel, which exists now and that will be produced in the future. The NWMO continually monitors new developments to be prepared to assume its legal responsibility to manage used nuclear fuel, [86].

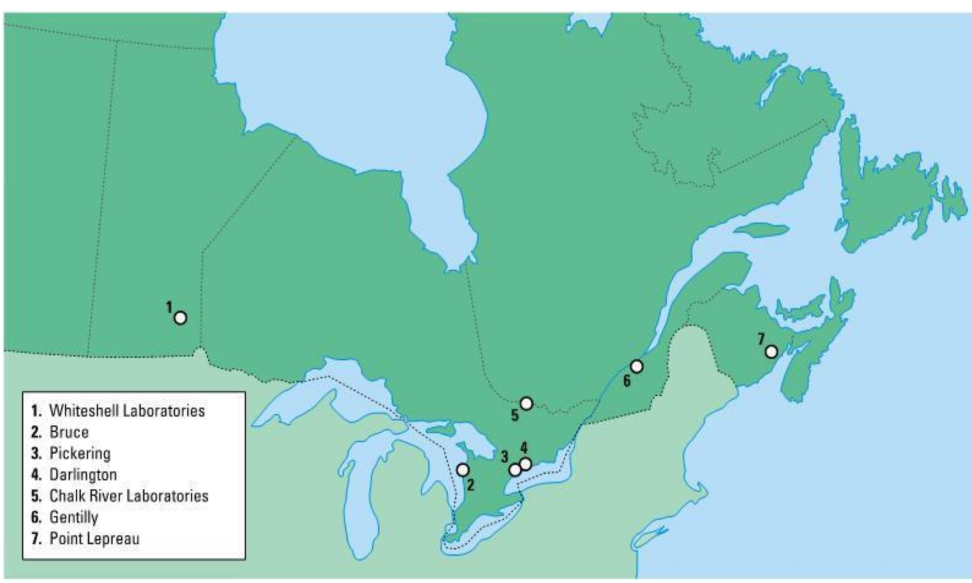


Fig.24: Current Nuclear Fuel Waste Major Storage Locations in Canada [86]

3.2.1 Pressure

The used fuel containers (UFCs) are designed to be corrosion resistant and robust, with an inner steel vessel that is designed to sustain a maximum external isotropic pressure of 45 MPa (including the pressure of a 3 km thick ice sheet above the repository site). Thus, the containers are expected to have a long lifetime. However, there is still a possibility of having unexpected events in the future that could lead multiple containers to fail in the repository, [84]. The UFC incorporates a steel core for structural strength (46 mm thickness to sustain a maximum external isotropic pressure of 45 MPa) and an exterior copper coating for corrosion protection (3 mm thickness), with a capacity of 48 used CANDU fuel bundles for a fuel mass of about 1200 kg. Under repository conditions, corrosion of the copper barrier is predicted to be much less than 2 mm over a period of one million years, which is approximately the time required for the radioactivity of the used CANDU fuel to decay to levels comparable to those of natural uranium deposits, [85]. The total external pressure in the repository accounts for three components: hydrostatic pressure, ice glacial load pressure, and bentonite swelling pressure. The swelling pressure of bentonite backfill is expected to be about 7.1 MPa (maximum of 10 MPa). Major increases in the pressure on the UFC arise during the glaciation period. The bounding limit of the ice sheet loading is the pressure of a 3 km ice sheet thickness above the repository, which counts for about 30 MPa. The UFC will also be exposed to an initial hydrostatic pressure of 5 MPa (at 500m depth). While glaciation will be a significant load, the earliest site coverage due to an ice sheet would be thousands of years in the future (at least another 60,000 years from present), [85]. The basics of calculating the pressure in the repository has been introduced by Eqn. 2.2, where (H) is 500 m depth, and (g) is assumed to still be 9.81 m/s^2 at that depth. It is obvious that the probability of having oceanic pressure in Canada is 8%, with a maximum density of 3300 kg/m^3 of oceanic crust, which leads to a maximum pressure of 16,186,500 N/m^2 or Pa (161.865 bar) at 500 m deep in the repository. It is also understood that the probability of having continental pressure in Canada is 92%, with a maximum density of 3000 kg/m^3 of continental crust, which leads to a maximum pressure of 14,715,000 N/m^2 (147.15 bar) at 500 m deep in the repository. According to NWMO, the bentonite swelling pressure may result in maximum of 10 MPa (100 bar), it means that the total maximum external pressure, without glacial load pressure (maximum of 30 MPa), in the repository may reach 262 bars (26.2 MPa) in oceanic case, or 248 bars (24.8 MPa) in continental crust. And according to NWMO [33], with having the external pressure test on the containers, there was no evidence of damage in the container at 450 bars (design pressure is 45 MPa), and the container started to buckle at 57 MPa. So, with an ice glacial load pressure of 30 MPa, that is supposed to take place in 60,000 years from present, the total maximum external pressure exerted on the container will result in maximum of 56.2 MPa (worst case scenario). For the locations that are being tested by NWMO, the repository is supposed to be built in a saturated rock mass that exerts a maximum of 5 MPa hydrostatic pressure on the repository. One of the main problems is that pressure in the repository may result in increasing the diffusion rate from outside the container to its inside in case of any failure or damage took place in the container.

3.2.2 Temperature

While dealing with temperature, there are two separate temperature factors affecting the DGR:

1- Surface temperature: that may affect the repository through the geothermal gradient in the pre-closure processes, and
2- Radioactive decay temperature: that results from the nuclear radioactive heat decay coming from the used fuel bundles in the containers. This one is dominant during the post-closure conditions.

This research is focusing on the post-closure conditions of the repository. So, the temperature coming from radioactive decay will be the most dominant one in the repository, and the effect of surface temperature should be neglected. However, all the temperature calculations for surface temperatures in Canada - for worst case scenarios - are included in this section. This is to give a general idea about the geothermal gradient concept in the pre-closure conditions, which may also affect the bacterial impacts. In [84, 85], the repository layout is designed such that the temperature remains less than 100ºC at the exterior surface of the UFCs, or in a minimum of 30 cm layer of the buffer surrounding the container. The container surface temperature is expected to initially increase to a peak value of about 120ºC in less than 100 years, decreases relatively rapidly to about 80ºC, moving to 70ºC over about 10,000 years, and then decreases to reach ambient temperatures (~14°C) at about 100,000 years after closure. These values of temperature are determined by thermal modelling, which includes thermal properties of the rock, engineered barrier materials and the heat generated by the fuel, [84]. Thus, temperatures within the repository are anticipated to range from ambient (10 - 20°C) to about 100°C (adjacent to a container). This temperature range will have impact on the culturability (activity) of the microbes, as the microbial activity is reducing with higher temperatures (close to container). Besides, the dry density of the buffer material affects the microbial activity, which will be discussed later in this chapter, [85]. According to NWMO, the outer surface of the fuel container should be kept at a temperature less than 100°C.

To model and quantify the temperature basic probabilities in the BN in the post-closure conditions, three states for the temperature node are considered: 1- Higher than 100°C (low probability in the first 100 years), 2- Lower than 100°C and higher than ambient (within the first 100,000 years), 3- Ambient temperature (starting 100,000 years after closure and lasts until 1,000,000 years). For surface temperature calculation (during pre-closure conditions), it is assumed that the year is split into three seasons:

1- Winter (W) from December – March (12, 1, 2, 3) = 4 months (4/12 = 0.333333)
2- Fall (F) from September – November (9, 10, 11) = 3 months (3/12 = 0.25)
3- SpringSummer (SS) from April – August (4, 5, 6, 7, 8) = 5 months (5/12 = 0.416667)

From [23], historical data of average annual temperatures are given for the largest 33 cities in Canada until 2010. To determine the worst case and getting the extreme conditions, our concern is the morning higher temperatures not the lower ones. According to section 2.3.1, the average geothermal gradient ranges between 25 – 29 $^{\circ}$C / km depth, with actual value of more than 55 $^{\circ}$C / km depth in some regions. Generally, in this research, the higher average value of geothermal gradient (i.e. 29°C / km = 14.5°C / 500 m) is used. The average monthly surface temperatures, their corresponding average seasonal surface temperatures, and the average seasonal temperatures in the repository at 500 m depth, are given in Table 4 (calculated from [23]):

Average Monthly surface temperature (°C)	Average seasonal surface temperature (°C)	Average seasonal temperature in the repository 500 m deep (°C)
Avg. December ≈ -0.4 Avg. January ≈ -3 Avg. February ≈ -1.2 Avg. March ≈ 2.3	(W) = -0.6	(W) = -0.6 + 14.5 = 13.9
Avg. April ≈ 11 Avg. May ≈ 17.6 Avg. June ≈ 22.4 Avg. July ≈ 25.2 Avg. August ≈ 25	(SS) = 20.24	(SS) = 20.24 + 14.5 = 34.74
Avg. September ≈ 19.7 Avg. October ≈ 13.2 Avg. November ≈ 5.4	(F) = 12.8	(F) = 12.8 + 14.5 = 27.3

Table 4: Average seasonal temperature difference between surface and 500m depth

According to NWMO site selection criteria, the repository will be built in a location with an average of 5°C surface temperature, and about 16°C/km geothermal gradient.

3.2.3 Relative Humidity (RH), Water Saturation, Salinity, and Microbial Activity

In sedimentary and crystalline shield environments, the fluid (groundwater) density/salinity can vary by more than 25%. Fluid density and viscosity are functions of groundwater total dissolved solids (TDS) concentrations, which typically increase with depth, [84]. In the repository introduced in [84], microbial activity is suppressed by the presence of very saline groundwater. In [85], three groundwater systems are considered: shallow, intermediate, and deep, where the depth is affecting the TDS concentrations, which affect the density /salinity. The nutrients required for microbial/bacterial growth include N, P, S, K, Mg, Na, Ca and Fe. The dominant species in a given environment tend to be those bacteria that generate the most energy from the available nutrient sources. Acetogens, iron-reducing bacteria (IRB), sulphate-reducing bacteria (SRB), and methanogens, are often the dominant components of the population in Canadian Shield groundwater. In crystalline rock environments, oxygen concentrations have been shown to decrease with depth due to microbial processes, [85]. Another factor affecting the microbial activity is the dry density of the bentonite buffer. The higher the density of the bentonite, the lower the activity of the bacteria. High dry density will prevent the bacteria from being free to grow or move, even if nutrients are available in the host rock, or the bentonite, or carried by groundwater. Jorge Garcia (PhD candidate at the University of Waterloo, Design Optimization under Uncertainty Group, March 2018) has estimated the probability of bacterial activity (SRB) as a function of the dry density of the bentonite buffer in Fig.25 and Table 5. The higher the compaction of the bentonite (i.e. higher dry density), the lower the bacterial activity (i.e. lower sulphide concentrations, and longer container life time).

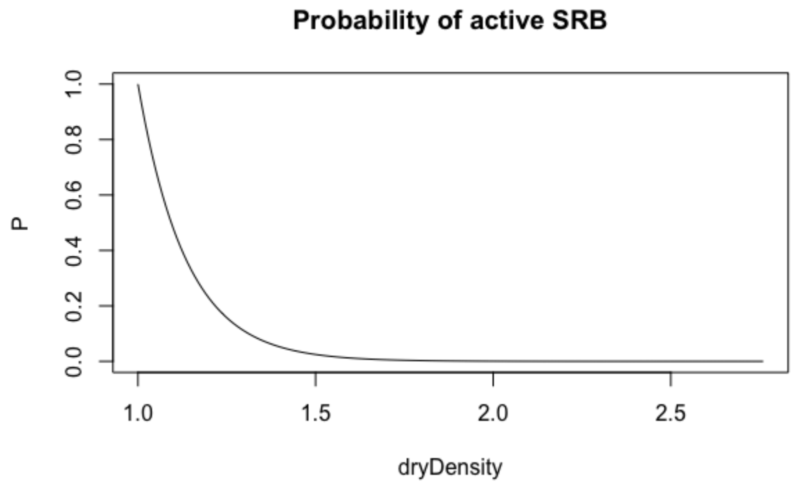


Fig.25: Probability of having active SRB as a function of dry density [87]

Dry density ρ_D in [g/cm^3]	P(SRB)
1	1
1.1	0.477420198
1.2	0.227929436
1.3	0.108817216
1.4	0.051950497
1.5	0.024801111
1.6	0.011839414
1.7	0.005651223
1.8	0.002696848
1.9	0.001286367
2	0.000612973
2.1	0.00029148
2.2	0.000137992
2.3	6.47142E-05
2.4	2.97296E-05
2.5	1.30272E-05
2.6	5.05312E-06
2.7	1.24613E-06
2.76	0

Table 5: Selected values of bentonite dry density versus probability of bacterial activity [87]

With any water diffusion and saturation in the repository at any time, the bentonite buffer will swell, resulting in a swelling pressure that should suppress the microbial activity more and more (compared to the initial dry density before water saturation). But, the amount of nutrient sources, carried by the water diffused, and salinity level of water, are other factors in affecting the microbial growth and activity in the repository. Thus, the relative humidity, in pre-closure conditions, or water diffusion and saturation, in post-closure conditions, is related to the activity of bacteria/microbes in the repository environment. Since the focus in this research is on the post-closure conditions, the relative humidity should not be taken into consideration while quantifying the BN. However, calculations of the relative humidity values in Canada, which are related to the surface temperatures, are discussed in this section in order to provide a general idea about the concept of relative humidity and its relation to surface temperatures. The historical data in [23] is used to estimate the average annual surface relative humidity (RH) over the largest 33 Canadian cities until 2010. In order to take the extreme conditions into account, the main focus should be on the early morning RH, which is higher than that in the afternoon. The average annual surface relative humidity (RH), over the 33 cities, is about 68.3% in the morning, and 51.2% in the afternoon, with maximum of 95% in some cities during sometimes in the year. If the temperature increases according to the average geothermal gradient, which is taken to be 29°C / km = 14.5°C / 500 m, then RH is supposed to decrease with temperature increase when going deeper. As explained previously, relative humidity doubles with each 20 degree **(Fahrenheit)** decrease, or halves with each 20 degree increase in temperature. Table 6 determines the change in RH from surface to 500 m depth according to the temperature differences illustrated in section 3.2.2.

Change in temperature in Winter (W) From surface to 500 deep	**Change in temperature in Fall (F) From surface to 500 deep**	**Change in temperature in SpringSummer (SS) From surface to 500 deep**
-0.6°C to 13.9°C	12.8°C to 27.3°C	20.24°C to 34.74°C
Increase of 27°F, then RH almost halves	Increase of 26°F, then RH almost halves	Increase of 26°F, then RH almost halves

Table 6: Change in RH from surface to 500 m depth in different seasons

Accordingly, if the maximum RH (95%) is reached at the surface, this means that RH will never exceed 47.5% (<50%) at a depth of 500 meters with the temperature increase due to geothermal gradient. In the NWMO site selection process, it is recommended to choose the site, where the repository will be built, to have a lower average value of surface relative humidity in order to have minimal effect in the repository during the operation, monitoring, and decommissioning time (about 150 years to repository closure).

3.2.4 BN Representation

The Nuclear Waste Management Organization (NWMO) is responsible for the implementation of plans for safe long-term management of Canada’s used nuclear fuel, which depends on placing the nuclear fuel within a deep geological repository in a suitable rock formation. A deep geological repository is a multi-barrier system designed to protect people and the environment in the long term. Even though the total radioactivity will increase with placing more used fuel in the repository, it will start to decrease due to radioactive decay with the help of the durable barriers (i.e. corrosion resistant containers, engineered sealing materials, and the surrounding geosphere). After the decommissioning period of the repository, the post-closure period, which may last for 1,000,000 years, starts. In [85], the post-closure period is described in four main timeframes:

1- Up to 1,000 years
2- 1,000 - 60,000 years
3- 60,000 - 1,000,000 years
4- 1,000,000 years and beyond

According to the analysis in the above sections, the proposed Bayesian Network for the NWM case study is shown in Fig.26. Hugin software (www.hugin.com) can be used to help in representing systems as Bayesian Networks, and quantifying their probability tables according to data available in order to use the Bayesian inference in determining the required probability (i.e. probability of failure in this research).

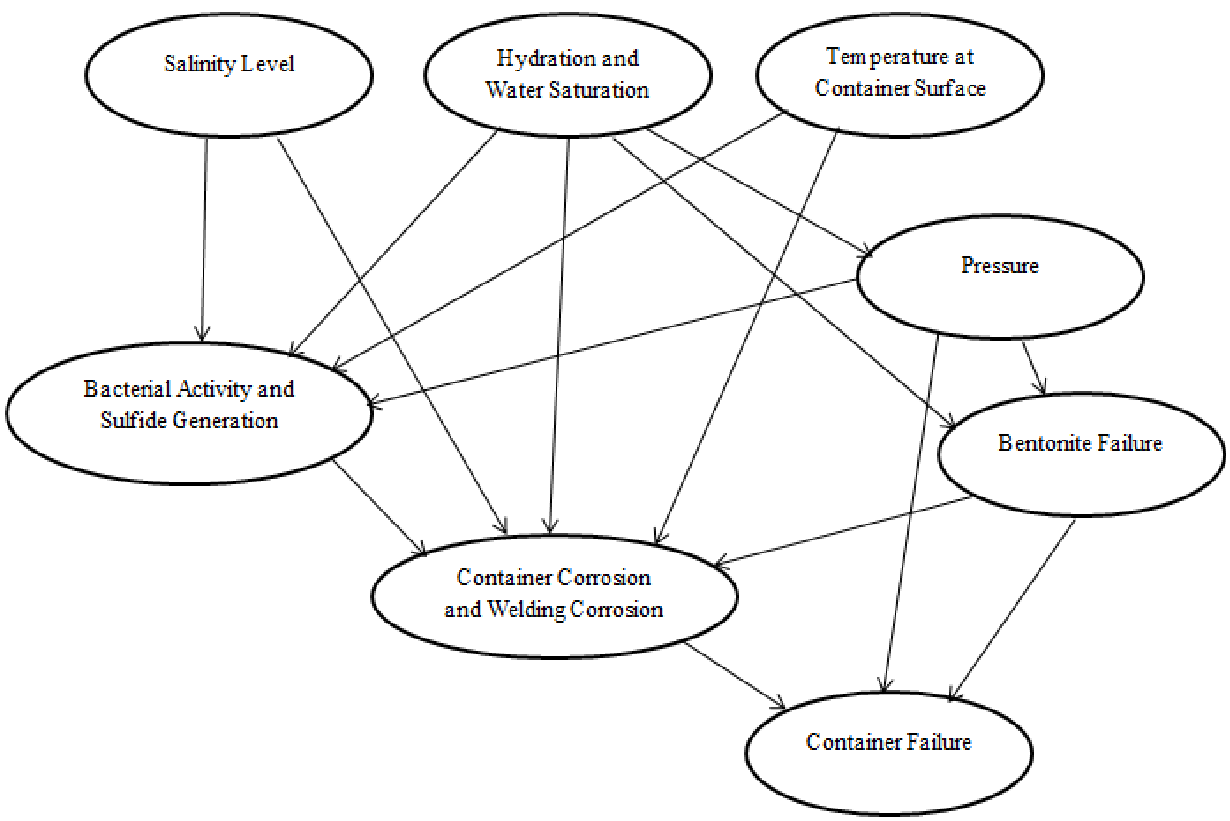


Fig.26: Proposed BN of NWM systems

This BN consists of 8 nodes, which is relatively not complex in terms of representation. But one source of complexity is that each node may include many other internal factors that may act like a nodal sub-network. Another complexity issue is the interrelationships among these nodes. It is not just a series of events that happen consecutively to predict the failure, but rather, it needs a better understanding of the dependability of each node over the others. Every node has states for the event occurrence; the more states the network has, the more accurate the results are. In order to better understand this BN, a description of the BN nodes/events, and their possible states, is provided as follows:

1- **Temperature at Container Surface:** the temperature resulted from the radioactive heat decay from the nuclear bundles inside the container. This is the most dominant temperature factor when dealing with post-closure conditions. The temperature node affects two other nodes: Bacterial Activity and Sulphide Generation, and Corrosion and Welding Corrosion of the container. When the temperature increases, the culturability of microbes/bacteria tends to decrease, so, the bacterial activity decreases, and thus, less sulphide is generated. Moreover, if the temperature increases above design limit (100^{o}C at container surface), the welding of the container may be affected in case of any cracks or defects in the welding, and the whole container may fail due to the new unexpected/undesigned high temperature factors. This node includes three states: higher than 100^{o}C, less than 100^{o}C but higher than ambient temperature, and ambient temperature (starting 100,000 years after closure).
2- **Hydration and Water Saturation:** during the post-closure conditions, there might be sometimes that hydration or water diffusion takes place in the repository. This will affect mainly four other factors: Bacterial Activity, Corrosion and Welding Corrosion, Pressure, and Bentonite Failure. The water diffused in the repository, with a certain salinity level, may be a carrier of bacterial nutrients. In this case, this may help the bacteria to be more active and generate sulphides that help in corroding the container. Moreover, with the high temperature from radioactive decay, the oxygen in the water may contribute in maintaining an oxic condition that contributes in corroding the container. For the bentonite buffer, whenever it is hydrated, it swells and resulting in high swelling pressure (of about 10 MPa). So, hydration, if happens, is a main contributor to the amount of pressure that will be present in the repository, and applied mainly on the UFC. Along with that, the dry density of the bentonite plays an important role in bentonite failure (i.e. failure to perform the operation that it is designed for). The dry density has also an effect on the bacterial activity. If the bentonite is of lower dry density, the bacterial activity is higher, and vice versa. But here, only the bentonite failure is considered. If the bentonite buffer is of low dry density, which means not compacted with the correct process, it will have sealing problems in case of hydration/ water saturation. This may cause water seepage, and water could reach the container resulting in a new corroding factor, besides, being in contact with groundwater of the surrounding environment (i.e. possible nuclear

contamination). If hydration took place, the bentonite will swell trying to seal all the gaps and protect the UFC. With low dry density, along with water diffusion, the bacteria could be more active, generating more sulphides to be carried with the water diffused, and the bentonite may fail to perform the desired task (i.e. failure to safely surround the container and limit its contact with surrounding environment). This node includes two states: hydrated (saturated), and dry.

3- **Salinity Level:** is a property of the intact rock and the groundwater in the surrounding environment of the repository. It may be seen that the groundwater is a carrier of the rock salinity. This depends on the geological region and the rock type. In the DGR, salinity affects both Bacterial Activity, and Container Corrosion and Welding Corrosion. With the salinity goes higher, the bacterial activity is lower, and thus, reducing corrosion possibilities, and vice versa. But in the opposite side, salinity- coming from groundwater if water diffusion and seepage found their way to the container, or found in the host rock or the bentonite buffer - will be one the main contributors in the container corrosion and welding corrosion. In the BN, Salinity node includes three states: High Salinity, Intermediate Salinity, and Low Salinity.

4- **Pressure:** pressure in the repository accounts for three components; ice/glacial load, hydrostatic/geostatic pressure, and bentonite swelling pressure (in case of hydration).
With the pressure increase in the repository, the bacteria/microbes will also be subjected to that pressure. This will limit the activity of the microbes and reduce their culturabilty (in addition to the other factors). Hence, more pressure in the repository results in lower bacterial activity (i.e. sulphide generation). The second node to be affected, by pressure, is the bentonite. The bentonite will fail to perform its operation (i.e. sealing the gaps, and limiting water seepage and bacterial activity) if it has low dry density. If more pressure is present in the repository, with having lower dry density of the bentonite (less compacted), bentonite buffer box may tend to have cracks or weak points that may be the path for water diffusion to the container. Moreover, if the pressure on the container reached a certain limit (57 MPa), the container will buckle and fail to safely encapsulate the used fuel bundles, and this is considered a container failure. The UFC is designed to sustain 45 MPa, and it starts to buckle at 57 MPa. For that reason, the pressure node in the BN includes three states: Less than 45 MPa, Higher than or equal 45 MPa (and less than 57 MPa), Higher than or equal to 57 MPa.

5- Bacterial Activity and Sulphide Generation: in the BN, all the above parent nodes are affecting the bacterial/microbial activity in the repository. Bacterial activity is responsible for generating sulphide, which is considered the main corrodent for the UFC in the DGR. With the higher pressure, higher temperature, higher salinity levels in the groundwater, non-existence of nutrients carried by groundwater (in case of hydration), and higher dry density in the bentonite buffer, the microbial culturability is reduced, and the activity of microbes/bacteria tends to decrease, and thus, sulphide generation is lower. This will also lower the tendency of the UFC, and its welding, to corrode. Bacterial Activity node includes three possible states: Lower Activity (lower sulphide generation), Intermediate Activity, and Higher Activity (higher sulphide generation).

6- **Bentonite Failure:** bentonite failure, mainly due to lower dry density, is affected by two parent nodes/events: the pressure, and water diffusion/saturation. With lower dry density (less compaction), and with water diffusion to the emplacement rooms, the bentonite buffer tends to swell (i.e. swelling pressure) trying to seal the gaps in order to protect the UFC from any possible contact with the surrounding environment. Thus, if the dry density of the bentonite is low, with the increasing pressure from swelling, cracks and weak points may appear in the bentonite buffer, resulting in water seepage and water contact to the UFC. If this happens, the water may be of high salinity, and may contain sulphides (from microbial activity), which may result – with high radioactive heat decay temperatures – in corrosion of the container and the welding. Eventually, this may lead to container failure. There is another limited possibility that may affect the container failure in the case when the bentonite has higher dry density. In case of hydration, seismic, and/or volcanic events, the pressure on the buffer box, and container, may exceed the limit of 57 MPa, resulting in UFC buckling and failure, even with no failure in the bentonite. For these reasons, the possible states of the Bentonite Failure node are: Low Dry Density (Failure), and High Dry Density (No Failure).

7- **Container Corrosion and Welding Corrosion:** Container corrosion takes place affected by hydration (water saturation) with high salinity levels, and bacterial/microbial activity that results in sulphide generation, in the case of having bentonite buffer of low dry density at high temperature (due to radioactive decay). Container corrosion will affect the failure of the container, which means a failure for the whole system (i.e. failure to keep the used fuel not in contact with the surrounding environment). This node includes two possible states: Corroded, and Not Corroded.

8- **Container Failure:** UFC will fail to safely encapsulate the used fuel bundles in case 1- the pressure reaches 57 MPa, with bentonite buffer of high dry density when unexpected events take place (i.e. volcanic and/or seismic conditions), or due to 2- continuous corrosion of the container because of lower dry density of bentonite during water diffusion with high salinity levels and bacterial activity. This may be considered a failure for the entire system. This node contains two possible states: Failure, or No Failure.

In the next section, the numerical quantification for this BN is presented, with possible scenarios that may take place in the repository in the post-closure conditions.

3.2.5 Numerical Evaluations

The Basic Probability Tables (BPTs) and Conditional Probability Tables (CPTs) of the proposed BN are shown in Table 7. These are the probabilistic estimates that are logically inferred, or according to reviewed literature and the data available for the DGR system.

Temp_at_Container_Surface

>100	0.0001
<100.and>Aml	0.0999
=Ambient	0.9

Pressure

Hydration and	Hydrated a	Dry
<45MPa	0.01	1
>=45MPa,<57	0.98	0
>=57 MPa	0.01	0

Salinity_Level

Low	0.333333
Intermediate	0.333333
High	0.333333

Hydration_and_Water_Saturation

Hydrated and	0.5
Dry	0.5

ContainerFailure

Pressure	<45MPa				>=45MPa,<57MPa				>=57 MPa	
Bentonitefailure	Low Dry Density And		High Dry Density And		Low Dry Density And		High Dry Density And		Low Dry Density And	
Container corr	Corroded	Not corroc	Corroded	Not corrod	Corroded	Not corroc	Corroded	Not corroc	Corroded	Not corroc
Failure	0.5	0.2	0	0	0.8	0.5	0.5	0.5	1	1
No Failure	0.5	0.8	1	1	0.2	0.5	0.5	0.5	0	0

Pressure	>=57 MPa	
Bentonitefailure	High Dry Density And	
Container corr	Corroded	Not corroc
Failure	1	1
No Failure	0	0

Bentonitefailure

Hydration and	Hydrated and Saturated			Dry		
Pressure	<45MPa	>=45MPa,	>=57 MPa	<45MPa	>=45MPa,	>=57 MPa
Low Dry Dens	0.3	0.95	0.97	0	0	0
High Dry Dens	0.7	0.05	0.03	1	1	1

Bacterial_Activity_and_sulphide_Generation

Temp at Cont	>100									
Pressure	<45MPa						>=45MPa,<57MPa			
Hydration and	Hydrated and Saturated			Dry			Hydrated and Saturated			Dry
Salinity Level	Low	Intermedia	High	Low	Intermedia	High	Low	Intermedia	High	Low
Low Activity,Lo	0	0.05	1	0	0.1	1	0	0.1	1	0
Intermediate A	0.05	0.95	0	0.1	0.9	0	0.1	0.9	0	0.15
High Activity,H	0.95	0	0	0.9	0	0	0.9	0	0	0.85

Temp at Cont	>100								<100,and>Ambient	
Pressure	>=45MPa,<57MPa		>=57 MPa						<45MPa	
Hydration and	Dry		Hydrated and Saturated			Dry			Hydrated and Saturate	
Salinity Level	Intermedia	High	Low	Intermedia	High	Low	Intermedia	High	Low	Intermedia
Low Activity,Lo	0.15	1	0	0.15	1	0	0.2	1	0	0
Intermediate A	0.85	0	0.15	0.85	0	0.2	0.8	0	0	1
High Activity,H	0	0	0.85	0	0	0.8	0	0	1	0

Temp at Cont	<100,and>Ambient									
Pressure	<45MPa				>=45MPa,<57MPa					
Hydration and	Hydrated a	Dry			Hydrated and Saturated			Dry		
Salinity Level	High	Low	Intermedia	High	Low	Intermedia	High	Low	Intermedia	High
Low Activity,Lo	1	0	0.05	1	0	0.05	1	0	0.1	1
Intermediate A	0	0.05	0.95	0	0.05	0.95	0	0.1	0.9	0
High Activity,H	0	0.95	0	0	0.95	0	0	0.9	0	0

Temp at Cont	<100,and>Ambient						=Ambient			
Pressure	>=57 MPa						<45MPa			
Hydration and	Hydrated and Saturated			Dry			Hydrated and Saturated			Dry
Salinity Level	Low	Intermedia	High	Low	Intermedia	High	Low	Intermedia	High	Low
Low Activity,Lo	0	0.1	1	0	0.15	1	0	0	1	0
Intermediate A	0.1	0.9	0	0.15	0.85	0	0	1	0	0.05
High Activity,H	0.9	0	0	0.85	0	0	1	0	0	0.95

Bacterial_Activity_and_sulphide_Generation

Temp at Cont	=Ambient									
Pressure	<45MPa		>=45MPa,<57MPa						>=57 MPa	
Hydration and	Dry		Hydrated and Saturated			Dry			Hydrated and Saturate	
Salinity Level	Intermedia	High	Low	Intermedia	High	Low	Intermedia	High	Low	Intermedia
Low Activity,Lo	0.05	1	0	0.05	1	0	0.1	1	0	0.1
Intermediate A	0.95	0	0.05	0.95	0	0.1	0.9	0	0.1	0.9
High Activity,H	0	0	0.95	0	0	0.9	0	0	0.9	0

Temp at Cont	=Ambient			
Pressure	>=57 MPa			
Hydration and	Hydrated a	Dry		
Salinity Level	High	Low	Intermedia	High
Low Activity,Lo	1	0	0.15	1
Intermediate A	0	0.15	0.85	0
High Activity,H	0	0.85	0	0

Container_corrosion_and_Welding_Corrosion

Bentonitefailur	Low Dry Density And Failure									
Bacterial Activi	High Activity,High Sulphides									
Salinity Level	Low		Intermediate						High	
Temp at Cont	=Ambient		>100		<100,and>Ambient		=Ambient		>100	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0.1	0.05	0.25	0.2	0.2	0.15	0.15	0.1	0.3	0.25
Not corroded	0.9	0.95	0.75	0.8	0.8	0.85	0.85	0.9	0.7	0.75

Bentonitefailur	Low Dry Density And Failure				High Dry Density And No Failure					
Bacterial Activi	High Activity,High Sulphides				Low Activity,Low Sulphides					
Salinity Level	High				Low					
Temp at Cont	<100,and>Ambient		=Ambient		>100		<100,and>Ambient		=Ambient	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0.25	0.2	0.2	0.15	0	0	0	0	0	0
Not corroded	0.75	0.8	0.8	0.85	1	1	1	1	1	1

Bentonitefailur	High Dry Density And No Failure									
Bacterial Activi	Low Activity,Low Sulphides									
Salinity Level	Intermediate						High			
Temp at Cont	>100		<100,and>Ambient		=Ambient		>100		<100,and>Ambient	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0	0	0	0	0	0	0	0	0	0
Not corroded	1	1	1	1	1	1	1	1	1	1

Bentonitefailur	High Dry Density And No Failure									
Bacterial Activi	Low Activity,Low Sulpt		Intermediate Activity,Intermediate Sulphides							
Salinity Level	High		Low						Intermediate	
Temp at Cont	=Ambient		>100		<100,and>Ambient		=Ambient		>100	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0	0	0	0	0	0	0	0	0	0
Not corroded	1	1	1	1	1	1	1	1	1	1

Container_corrosion_and_Welding_Corrosion

Bentonitefailur	Low Dry Density And Failure									
Bacterial Activi	Low Activity,Low Sulphides									
Salinity Level	Low						Intermediate			
Temp at Cont	>100		<100,and>Ambient		=Ambient		>100		<100,and>Ambient	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0.1	0.05	0.05	0.01	0.01	0	0.15	0.1	0.1	0.05
Not corroded	0.9	0.95	0.95	0.99	0.99	1	0.85	0.9	0.9	0.95

Bentonitefailur	Low Dry Density And Failure									
Bacterial Activi	Low Activity,Low Sulphides								Intermediate Activity,Ir	
Salinity Level	Intermediate		High						Low	
Temp at Cont	=Ambient		>100		<100,and>Ambient		=Ambient		>100	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0.05	0.01	0.2	0.15	0.15	0.1	0.1	0.05	0.15	0.1
Not corroded	0.95	0.99	0.8	0.85	0.85	0.9	0.9	0.95	0.85	0.9

Bentonitefailur	Low Dry Density And Failure									
Bacterial Activi	Intermediate Activity,Intermediate Sulphides									
Salinity Level	Low				Intermediate					
Temp at Cont	<100,and>Ambient		=Ambient		>100		<100,and>Ambient		=Ambient	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0.1	0.05	0.05	0.01	0.2	0.15	0.15	0.1	0.1	0.05
Not corroded	0.9	0.95	0.95	0.99	0.8	0.85	0.85	0.9	0.9	0.95

Bentonitefailur	Low Dry Density And Failure									
Bacterial Activi	Intermediate Activity,Intermediate Sulphides						High Activity,High Sulphides			
Salinity Level	High						Low			
Temp at Cont	>100		<100,and>Ambient		=Ambient		>100		<100,and>Ambient	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0.25	0.2	0.2	0.15	0.15	0.1	0.2	0.15	0.15	0.1
Not corroded	0.75	0.8	0.8	0.85	0.85	0.9	0.8	0.85	0.85	0.9

Bentonitefailure	High Dry Density And No Failure									
Bacterial Activi	Intermediate Activity,Intermediate Sulphides									
Salinity Level	Intermediate				High					
Temp at Cont	<100,and>Ambient		=Ambient		>100		<100,and>Ambient		=Ambient	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0	0	0	0	0	0	0	0	0	0
Not corroded	1	1	1	1	1	1	1	1	1	1

Bentonitefailure	High Dry Density And No Failure									
Bacterial Activi	High Activity,High Sulphides									
Salinity Level	Low						Intermediate			
Temp at Cont	>100		<100,and>Ambient		=Ambient		>100		<100,and>Ambient	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0	0	0	0	0	0	0	0	0	0
Not corroded	1	1	1	1	1	1	1	1	1	1

Bentonitefailure	High Dry Density And No Failure							
Bacterial Activi	High Activity,High Sulphides							
Salinity Level	Intermediate		High					
Temp at Cont	=Ambient		>100		<100,and>Ambient		=Ambient	
Hydration and	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry	Hydrated a	Dry
Corroded	0	0	0	0	0	0	0	0
Not corroded	1	1	1	1	1	1	1	1

Table 7: BPTs and CPTs for the proposed BN

For the nodes in the Bayesian network, the probabilistic quantification is estimated for a repository life time of 1,000,000 years. The probabilities in both BPTs and CPTs are quantified according to logic inference, and limited data available from literature and from NWMO experts. If the site selection procedure, lab tests, or simulation models (performed by NWMO and/or their partners) resulted in updated data and probability estimates, the BN tables can be updated by new probabilistic quantification values, which will help in better estimating the system failure.

3.2.6 Numerical Results and Conclusions

According to the probability tables in the proposed BN, the probability of container failure (system failure) is estimated using Bayesian inference to be 26.48% over 1,000,000 year life time of the repository.

Other scenarios, probability estimates, or network connections may be proposed for different purposes. It is important to state that Bayesian inference can lead to the factors which are more contributing in the container failure (i.e. posterior probability of diagnostic inference). Given the evidence that system failure took place, it can be seen in Fig.27 that pressure of more than 45 MPa, hydration (water saturation), and bentonite failure (of low dry density), are the three main contributors to system failure.

Using the concept of posterior probability in Bayesian inference, which can be compiled in Hugin software, the probabilities can be updated regularly whenever there are new available data, information, or knowledge, which is called evidence in this case. It is shown in Fig.28 that with the evidence of pressure of less than 45 MPa, and the bentonite is of high density and didn't fail, the posterior probability of failure (container failure) [i.e. ***P(failure | Pressure < 45 MPa, Bentonite = High density with no failure)***] is 0% over 1,000,000 years.

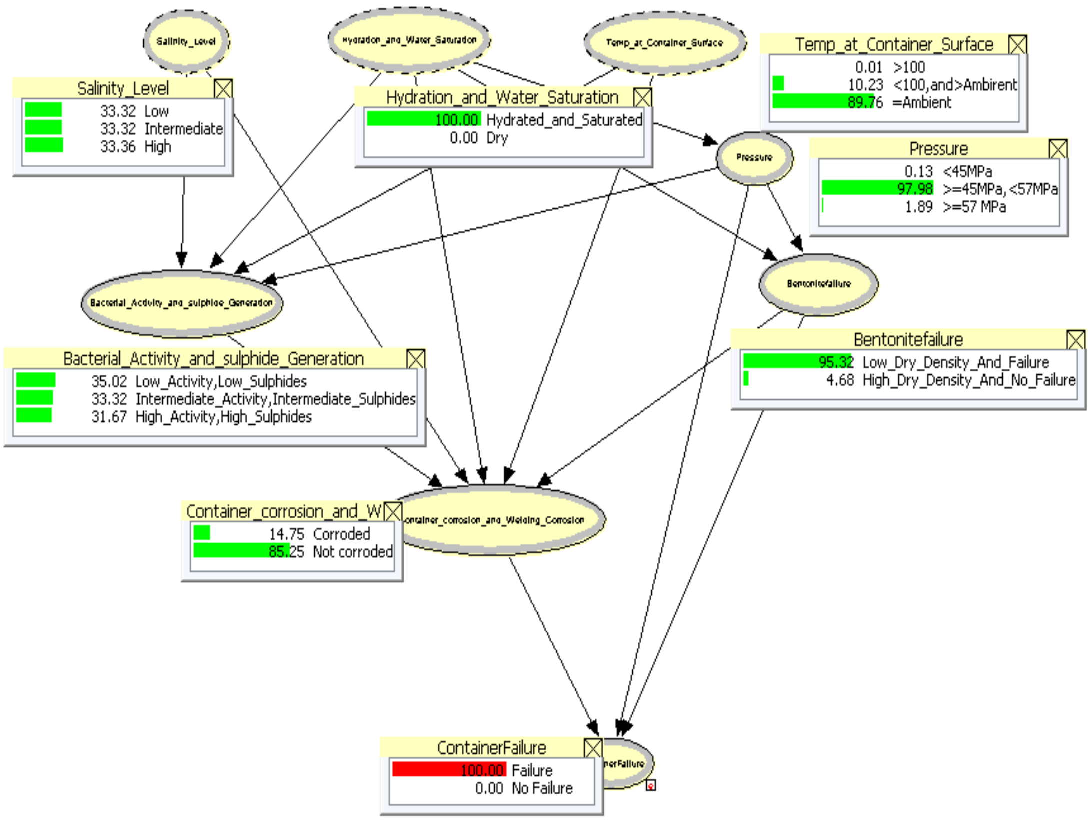


Fig.27: BN determining the main factors contributing in a failure, given a failure took place

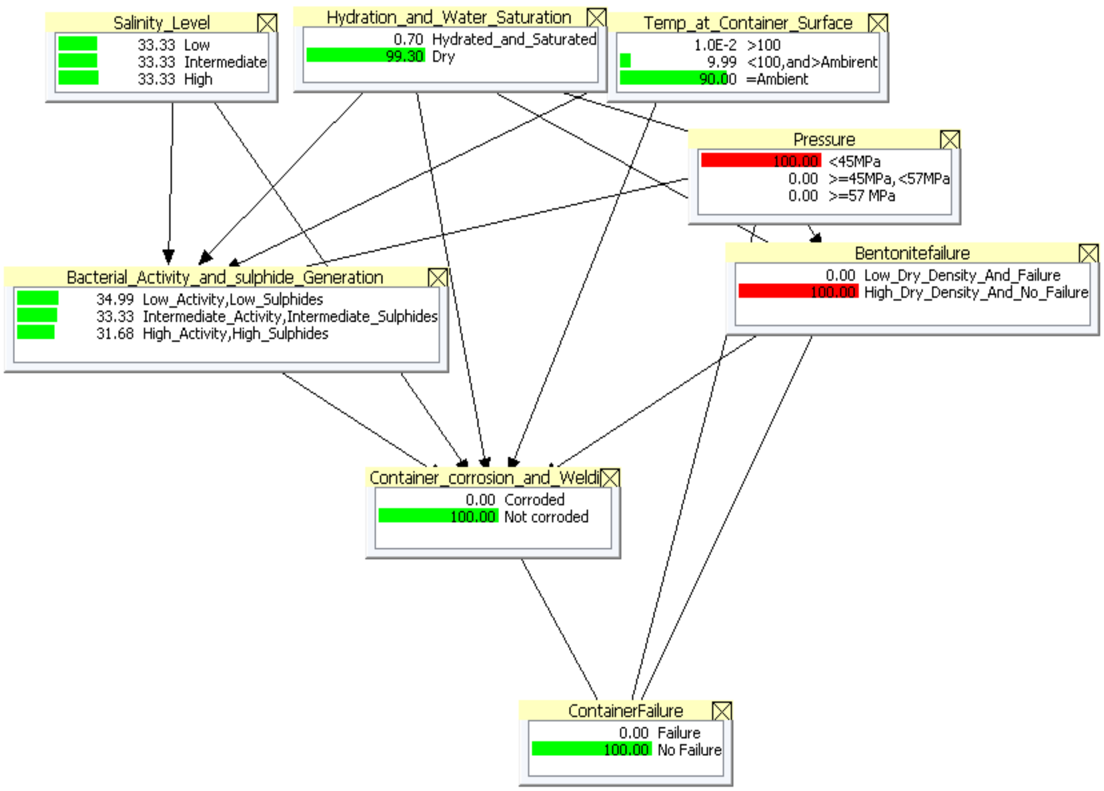


Fig.28: Posterior probability of failure given the evidence of pressure less than 45 MPa and high density bentonite

Thus, all precautions should be taken into consideration during design, site selection, and construction to keep the pressure in the repository less than 45 MPa, and to use high dry density bentonite buffer that will sustain mechanical stresses and limit the diffusion of corrosive materials. This will keep the probability of system failure at its lowest values.

It must be noted that the BN nodes can be represented in many different ways, and the interactions among system components may be re-connected (re-formulated) for different purposes in order to perform prediction or diagnosis for any event of interest. The nodes (i.e. system components) of the BN may also be decomposed to their sub-component nodes in order to represent more states in the network. The previous analysis may also be used to generate some scenarios that reflect different operating conditions of the Deep Geological Repository leading to the failure of the Used Fuel Container (UFC). Each scenario should be described by basic and conditional probabilities for different states.
The results here are reflecting known and assumed input values and hence are only for demonstration purposes and not to be taken literally as representing the current design.

3.3 Summary

In this chapter, related factors, parameters, and variables to NWM case study are explained in details. The BN of the NWM system is then represented and quantified with the currently available data, and with logic inference. The approach of using BNs in predicting system failure is illustrated. The diagnostic capability in the BN is used to diagnose the main contributors to NWM system failure in order to take precautions and mitigation actions into account in the design stage.

In the next chapter, a proposed BN approach supported by simulation and decompositional capabilities is illustrated. Simulation Supported Bayesian Network (SSBN) method is used to aid the quantification of BNs in representing complex systems. SSBN is then applied to systems of dam reservoirs.

CHAPTER 4

Simulation Supported Bayesian Networks (SSBNs) for Failure Prediction of Hydropower Dams

4.1 Introduction

This chapter illustrates the proposed decompositional approach for failure prediction of complex systems using BN-Simulation integration, with some examples to demonstrate how to determine the complexity of engineering networks. Then, Simulation Supported Bayesian Network (SSBN) method is applied to a simple two reservoir system of different configurations.

4.2 Probabilistic Failure Analysis of Hydropower Dams

Dams and reservoir systems are more complex than many civil engineering systems [88]. Studying safety of dams needs a comprehensive multidisciplinary analysis that should consider all the relevant factors and their interrelationships. It is shown in [88] and [89] how complex the decision making process is while dealing with the challenging problem of dam safety. Although past cases of dam failures are taken to diagnose the causes of failure; this is not enough for predicting other dams' failure probabilities as every dam is different in terms of human, environmental, design and technical influential factors. Some of the shortcomings associated with traditional risk analysis and assessment approaches are listed in [89]. The current available approaches such as Monte-Carlo simulation are computationally expensive as they require detailed exhaustive system simulations. Therefore, they are inefficient for complex systems having a large number of elements and highly nonlinear relationships, and any improved practical approach to dam safety analysis and prediction, not just diagnosis, is of significant value. In this line, a paradigm shift has been suggested in [90] and [91] to deal with disaster management by quantifying disaster resilience instead of the traditional risk-based techniques. With these new approaches, system analysis will continue to be a primary approach to understanding the system behaviour under uncertainty and other measures that need to be taken into consideration. This research attempts to address some of these shortcomings, especially in enhancing the way of predicting the probability of system failure using systems analysis while dealing with data scarcity in some engineering applications.

It can be shown in Fig.29 that dam operation and control system models incorporate multiple interrelated sub-systems. High level decision makers may have difficulty in understanding such representations. Decision makers, as humans, focus on “what is important” when facing such complex systems in the case of lack of sureness [88]. They need a simplified system representation to include all the system components, variables, and sub-systems while accounting for different interactions. When they try to evaluate the risk situation and take a control/mitigation action, they become aware of the situation of other system components. This kind of system representation should be at high level, which allows for analysing the system to sub-networks having less number of states instead of dealing with the entire network components. And if needed, these sub-networks should have the ability to be disaggregated to its elemental components. BNs have shown potentials in this direction.

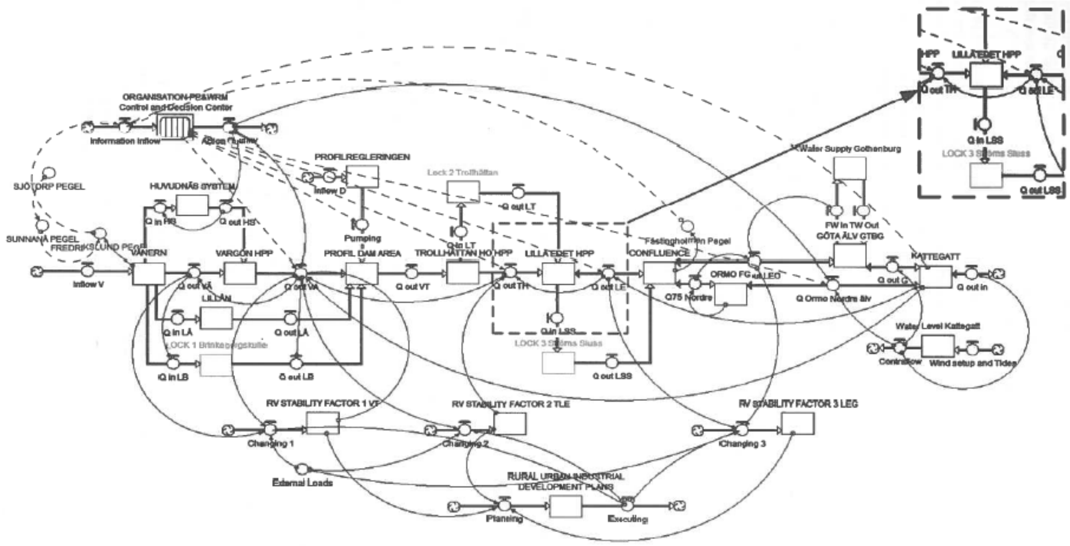


Fig.29: Example of a Dam System Model [88]

A human risk analysis model is presented in [5] using BNs in order to estimate risks to people due to floods from dam-breaks, with the ability to take a large number of parameters and their interrelationships into account, along with their uncertainties. Thus, a BN predicting loss-of-life is constructed, along with using historical data, physical analyses, and existing models, in order to quantify the nodes and their interrelationships (arcs). The network proposed in [5] consists of four main sub-networks: evacuation, sheltering inside buildings, flood severity, and loss-of-life (LOL). The human risk analysis model presented in [5] is applied to evaluate the human risk in the landslide dam failure in [6]. In such studies, it is necessary to divide a flooded area into several subareas of similar parameters. At both the global level (multiple sources of information), and the local level (updating the prior probabilities), the uncertainties of the parameters and their interrelationships are studied. Moreover, there are some differences in the physical models between man-made dams and landslide dams. These differences are taken into consideration in [6]. In [7], dams are classified as follows:

1- First-class dams, that are safe and function normally,
2- Second-class dams, that are safe under controlling conditions and function almost normally, and
3- Third-class dams, which are unsafe with various distresses and cannot function normally as designed (called distressed dams).

As explained earlier, in dam safety studies, three principal approaches are widely used: failure modes and effects analysis (FMEA), event tree analysis (ETA), and fault tree analysis (FTA). Recently, BN analysis has drawn attention as another alternative for dam safety studies. Based on the information in [7], ref [92] attempts to extend the technique of BNs to the diagnosis of a specific distressed dam. The main objective of [7] is to develop a probability-based tool using BNs for the diagnosis of embankment dam distresses at the global level based on past dam distress data. Historical data for dam distresses is used to quantify the interrelations among system parameters. Dam distress is related to the increased potential of structural deterioration, inadequate design, poor construction, poor operation and maintenance practices, or changing hydrological and environmental conditions as shown in Fig.30, Fig.31, and Fig.32. In Fig.31 and Fig.32, the proposed causal network for diagnosing distresses associated with seepage erosion–piping of homogeneous–composite dams include the following nodes [7]: ARS: Abutment rocks or soils, ASS: Abutment seepage situation, CF: Cutoff at foundation, DEW: Designed embankment width, EBI: Embankment–abutment interface, EC: Embankment cracking, EM: Embankment materials, ESS: Embankment seepage situation, FD: Filtered drainage, FSS: Foundation seepage situation, SCF: Sludge cleaning at foundation, SEP: Seepage erosion or piping, SSC: Seepage situation around embedded culverts, and TB: Termite burrows.

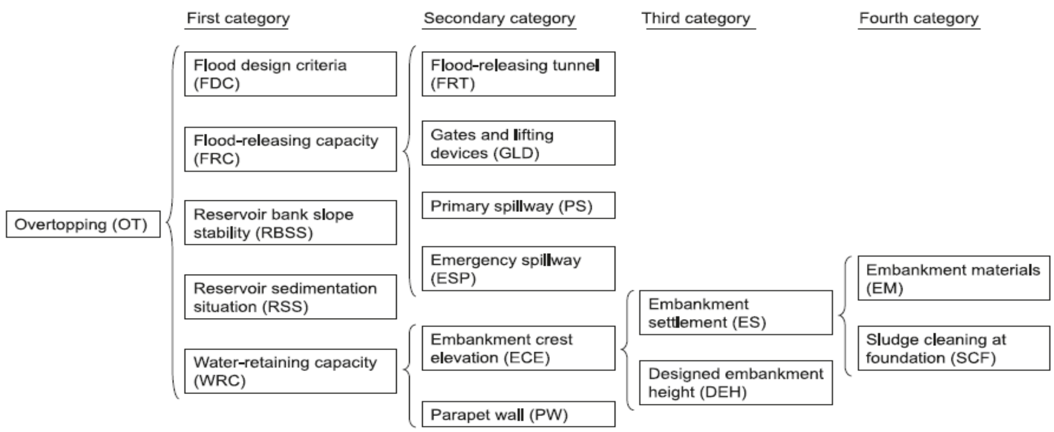


Fig.30: Variables involved in diagnosing distresses associated with overtopping of dams [7]

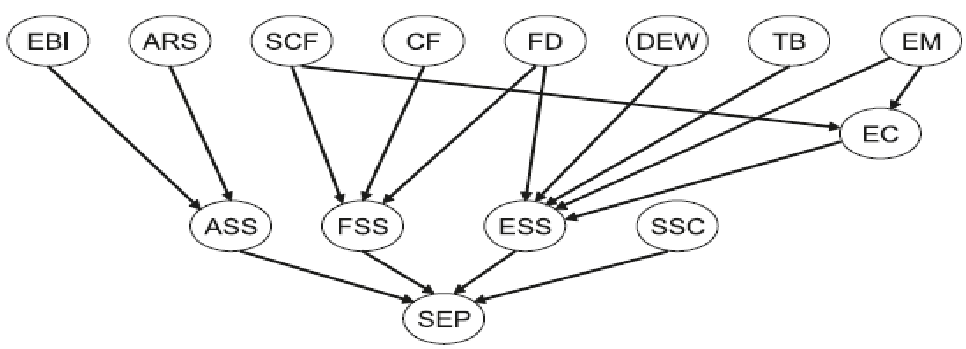


Fig.31: Causal network for diagnosing distresses associated with seepage erosion–piping of dams [7]

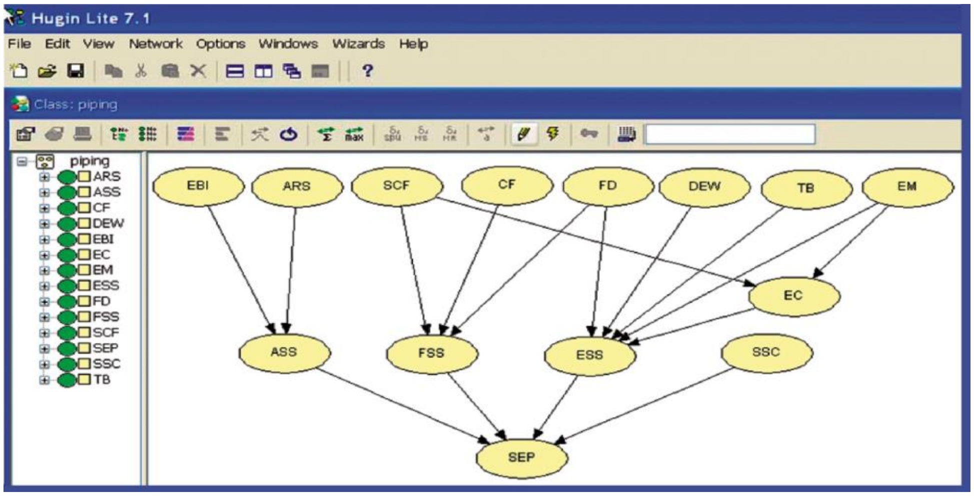


Fig.32: Probability calculation for diagnosing distresses of dams using Hugin Lite program [7]

It is obvious from the networks represented in [7] that only technical failures or causes are incorporated in these representations. The critical step in dealing with safety of dams is that the representation must include the technical factors besides, at least, the human factors. A lot of different environmental, economic, and operational factors are still remaining to be included in the representation. One huge example is what happened in Oroville dam, California in February 2017, [93]. The dam suffered from some economic and operational problems which put the dam structure in a critical situation, and put lives of hundreds of thousands on the edge. It wasn't a pure technical problem in the dam design, but rather, the operation plan and strategy performed by humans was part of the disaster. To better present such cases for future prevention, more than just technical factors should be considered in the failure analysis.

A simple example for applying the BN representation on the safety of hydropower dams, to predict the failure probability, is what was illustrated in Fig.17 and Fig.18 (section 2.7). Two dams are connected in series or in parallel, and the inflows of both dams are statistically dependent (and can be independent in other configurations). The inflow and the reservoir level of each dam are affecting the spill event (i.e. to have excess water more than the reservoir capacity), and if the spillway gates failed to open at the spill event (due to any electromechanical failures), the dam will experience an overtopping failure, and affect the system failure according to the connection between both dams (serial or parallel). For this kind of systems, it is supposed to have the basic and conditional relations among system components/nodes from historical and operational data, if available, in order to feed the basic and conditional probability tables (i.e. BPTs and CPTs) of the BN to predict the failure probability. This can be used for the sake of prevention of any future failure that may affect the dams or the population at risk (PAR) living around dams. The two dam reservoir example is the main pilot case study for the purposes of this thesis. Different approaches that use BNs to represent engineering systems and predict their failure probabilities will be applied to this system with its different connections/topologies. The two dam reservoir system will be used to provide a general case study that is used to demonstrate the methodologies developed in this thesis.

The next section explains a novel approach that uses simulation to support BNs in probabilistic quantification and failure prediction, i.e. Simulation Supported Bayesian Network.

4.3 Simulation Supported Bayesian Network (SSBN)

This section introduces the Simulation Supported Bayesian Network (SSBN) decompositional approach for probabilistic failure analysis and quantifying risks of complex systems. Complex systems are reviewed to have different interacting factors and components. These interactions can be in the form of cause – to – effect relations, which defines all the causes and evidences that may lead to certain effects. The complexity of a system is determined by the number of interacting components and the interrelationships among causes and effects. Two case studies in nuclear and hydropower industries were explained. Both case studies are of complex systems, but with different complexity measures. The complexity in the nuclear waste management system lies in being a new project which is not yet applied in reality, while the hydropower dams are well-defined systems with a huge number of inputs. The aim of this research is to simplify the representation of such complex systems, to predict the failure probabilities of the systems, and to estimate the factors that are responsible for limiting the probability of failure in both systems. To simplify the representation of complex systems and their components, Bayesian Networks (BNs) are found to be useful in defining the interrelationships among system components depending on evidence basic probabilities, and conditional probabilities among system components (nodes). BNs are found distinctive in representing any kind of information as the representation is being done in a probability form. This section aims to build a probabilistic methodology for any complex system, whether pre-existing or to be constructed. As the network representation needs to be quantified, running system simulations is integrated to the quantification process.

4.3.1 Simulation

Simulation is defined in [94] as "the process of designing a model of a real-world process or system and conducting experiments with this model for the purpose either of understanding the behavior of the system or of evaluating various strategies (within the limits imposed by a criterion or set of criteria, e.g. time) for the operation of the system". Any real-world process studied by simulation techniques is viewed as a system, which is, in general, a collection of entities that are logically related and are of interest to a particular application. While investigating a real-world system, detailed simulation model should include the entire system. This may be computationally expensive especially in systems having large number of variables. During simulation, system variables are sorted into two groups: 1- uncontrollable variables: which are considered as givens, and 2- controllable variables: that can be manipulated to find a solution, [95]. In general, simulation enables the study of internal interaction of sub-systems within a complex system. A simulation model helps to gain knowledge about improvement of a system. Simulating different capabilities can help determining the requirements. These capabilities allow analysis and understanding of how individual elements interact and affect the simulated environment. In conclusion, simulation is a representation of the functioning of a system or process. Through simulation, a model may be implanted with unlimited variations, producing complex scenarios. However, simulation results may be – sometimes – difficult to interpret.

4.3.2 Integration of BN and Simulation for Uncertain Complex Systems

Complex systems in Engineering include unlimited disciplines, like hydropower dams, electric networks, nuclear power generation, nuclear waste management, water distribution networks (shown in Fig.33 as a dynamic Bayesian Network), and waste water management, among others.

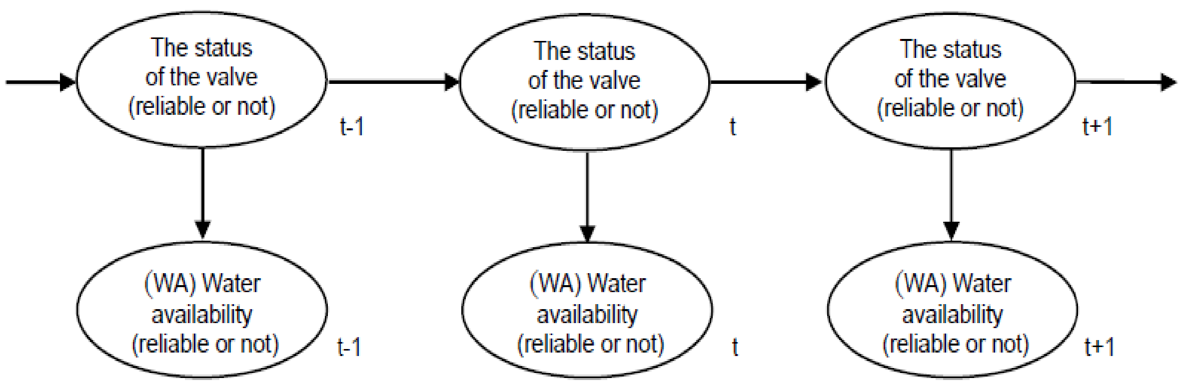


Fig.33: Dynamic Bayesian network for predicting water availability in a water distribution network [96]

While BN represents the interrelationships among system components qualitatively through nodes and arcs (i.e. dependency structure), there is a quantitative part of the BN which is responsible for defining the probabilistic, uncertain, values. Quantifying the arcs of the BN with probability measures is the main challenge in this kind of system analysis. For some blue print projects (systems) like the one of nuclear waste disposal, there are no data for operations or any historical and statistical data. For this kind of systems, the decision makers may rely on expert judgement and logically inferred data, along with mathematically accepted empirical models. On the contrary, there are pre-existing complex systems that are operating for decades like hydropower dams, waste water sewage systems, or water supply piping systems. In this kind of systems, there are lots of operational, historical, and statistical data that can be estimated to quantify the BNs that represent these systems. The question is, can the simulation be used as another source of information to quantify the complex systems represented by BNs?

In [97], reassessment of dam safety events using BNs is illustrated. The BNs are built based on the event tree analysis, and were supplemented with Monte Carlo simulations. This combination, BN-Simulation, with enough number of sample runs, can be an effective tool to narrow down the range of probabilities, and may cover a wide range of uncertain events leading to failures. However, it can be seen in the approach of [97] that simulation is performed for relatively small networks (not that complex). Moreover, the basic data and statistics are known from the beginning for the system under study. So, if we are updating (reassessing) the network using simulation models, why not we provide the network with the probability estimates using simulation from the beginning?

If sufficient historical and statistical data are available, there should be no need for simulation. Such data is not available in two cases: in future systems (i.e. blue print projects), or for networks that don't have an efficient monitoring system to save the operational data with time. In both cases, relying on the logic inferencing, expert judgement, or empirical models may be misleading and may add another source of uncertainty, especially in very complex systems. That is why simulation may be integrated as a useful source of data. But the challenge is that simulating a very complex system may be computationally expensive for the purpose of identifying the probabilistic interrelationships among systems' variables and sub-components. On the other hand, simulation results of decomposed sub-systems may provide the BN with probability estimates that are used to estimate probabilities of whole systems. The proposed methodology of this section - Simulation Supported BN (SSBN) for a complex system - is summarized in Fig.34. The simulation will be computationally complicated if performed for the entire network, especially in complex networks with huge number of states. For that reason, SSBN proposes to have the network decomposed to smaller sub-networks (sub-trees). Each sub-network will have its own simulation according to the data available, or from random sampling in case only basic data are available (e.g. lower and upper bounds). For every sub-network, simulation results are all about probabilistic quantification of this sub-network's BN. Thus, probability values are estimated from simulation and fed into the BN of the sub-network.

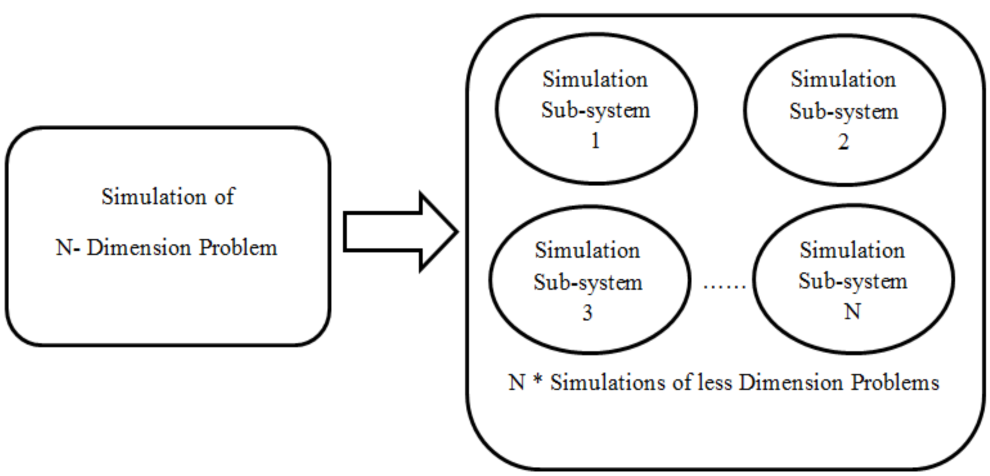


Fig.34: Proposed Methodology of SSBN

Once all Bayesian sub-networks are probabilistically quantified with their basic and conditional probability values, the sub-networks are ready to be re-combined as one whole network representation. SSBN makes the complex system more readable for both the operators and decision makers. SSBN overcomes the following obstacles:

- Complex, time consuming simulation models,
- Complex representation of systems,
- Propagation of uncertainty measures in a complex network, and
- The integration among different sources of data, including simulation.

As an example, in Fig.35a and Fig.35b, a 23 node BN is represented to show how complex system components can be interrelated. Each node includes at least two states, which means at least 2^{23} states in that system. The more states the nodes have, the more complex the system is. When the analysis of the system is enhanced using the SSBN method, rather than simulating the entire system (in Fig.35a), smaller sub-systems may be simulated instead. In Fig.35b, the BN is decomposed to six different sub-entities (sub-systems, sub-networks, or sub-trees). Each sub-system is less complex than the whole system, which means less number of states. In general, a system of **N** nodes/components, two states each (i.e. $\mathbf{2^N}$ possible states) can be decomposed to **n** sub-systems and the number of possible states becomes $\mathbf{n*(2^{N/n})}$, which is less than $\mathbf{2^N}$ [i.e. if N=12, n=4, $2^N = 4096$, and $n*(2^{N/n}) = 32$]. The sub-system components are interrelated, and the sub-systems may also have interrelations among each other. By applying the SSBN concept, every sub-system is simulated separately, using the appropriate methods, to get the probability estimates needed for quantifying the BN.

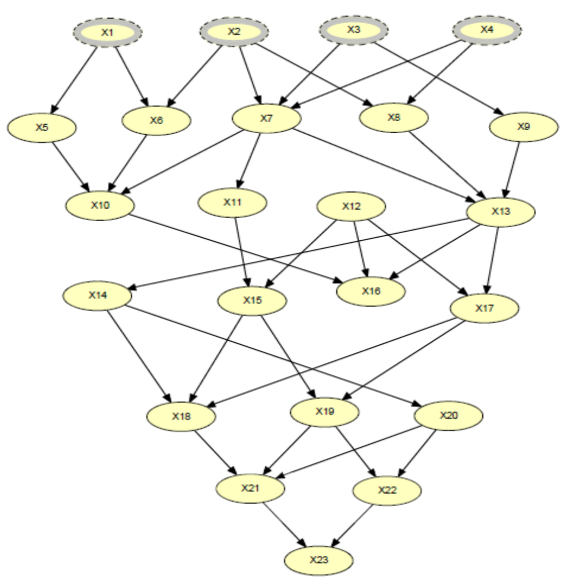


Fig.35a: A 23 node BN using Hugin software

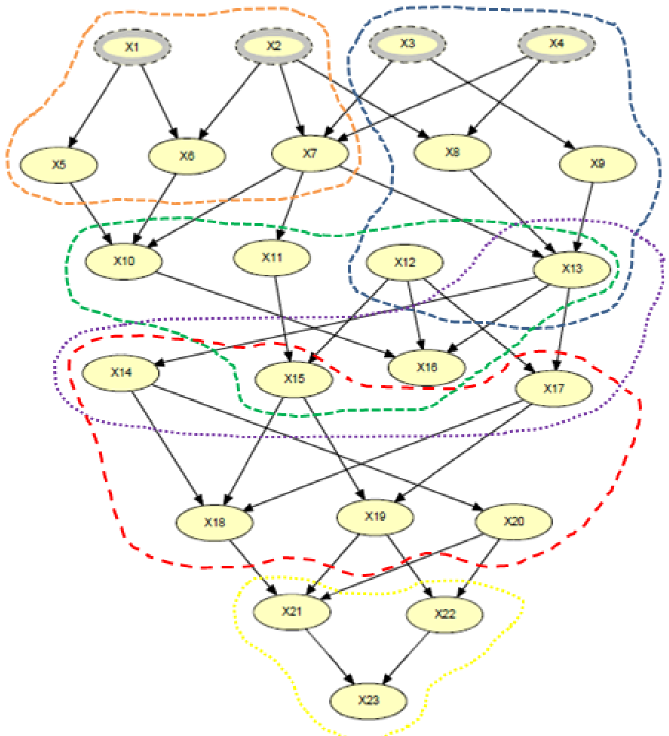


Fig.35b: A 23 node BN decomposed to 6 sub-entities ready to be simulated

In order to quantify the conditional interactions among sub-system decompositions, domain knowledge and expert judgement may be required. If this kind of judgement is not available, assuming different scenarios/states can be used instead. This means that different interactions among sub-system decomposition are quantified by assuming worst case scenarios, best case scenarios, and normal case scenarios in order to estimate the system failure probabilities in different situations.

According to [93], in 2009, the American Society of Civil Engineers (ASCE) issued a report titled “Guiding Principles for the Nation’s Critical Infrastructure.” Risk management of critical infrastructure depends on four interrelated guiding principles, identified as follows:

1. To quantify and communicate risk,
2. To employ an integrated systems approach,
3. To exercise leadership, management, and stewardship in decision-making processes,
4. To adapt critical infrastructure in response to dynamic conditions and practices.

This thesis focuses mainly on the first two guiding principles, which is of how to represent all interrelated system components in a combined representation (integrated systems approach), while enhancing the ability to quantify this kind of system representation in order to better predict the failures for many purposes (risk management, risk reduction, etc.).

Bayes-Markov chains introduced in [98], along with reassessment of safety events using BNs and supplemented with Monte Carlo simulations illustrated in [97], which are both proposed for relatively small networks, may assist in conceptualizing a new methodology. Fig.36 shows an overview of a Bayes-Markov chain, which integrates Markov Chains and decomposed BNs to acquire cyclic behaviour of the BNs. In Fig.36, the clear circles represent Markov states; and grey circles represent nodes of a BN.

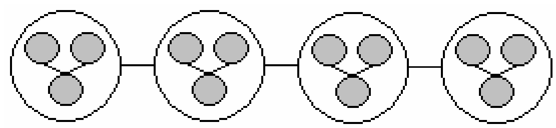


Fig.36: Bayes-Markov chain [98]

BN-simulation integration (i.e. Simulation Supported Bayesian Networks (SSBNs)), presented in this chapter, has a distinction of being able to deal with large systems of large number of system components, unlike the relatively simple network presented in [97]. The sub-system decompositions are interrelated through conditional probabilities, unlike the one presented in [98], which deals with one BN decomposition, instead of a large BN, through Markov states. SSBN may also be integrated with Markov Chains to acquire cyclic behaviour of the BN. This is presented in details in Chapter 5 in this thesis.

An example of a real-world case study is shown in Fig.37a and Fig.37b by representing the proposed BN for probabilistic failure analysis of Mountain Chute hydropower dam in Ontario, Canada, operated by Ontario Power Generation (OPG). In this network, there are 21 nodes representing system components for the purpose of analyzing the failure of this system. This includes Probable Maximum Precipitation (PMP), ice loading, earthquake and seismic actions, water pressure, geology and rock type, flood severity, adequacy of discharge capacity, sluice gates, drainage, vegetation control, seepage, and other components. If more than two states are defined for every node, the system will turn to be a huge complex network to analyze. However, the more states the system components have, the more accurate the results are. But, the main problem faced is having limited historical, operational, and monitoring data. Only basic data of lower and upper bounds of inflows, outflows, and flooding events may be available, along with expert opinions and logic inferencing, with using some accepted empirical models of reservoir system analysis. In such cases, mathematical modeling and simulation may be a first step to get probabilistic estimates. The distinction of the decompositional approach is obvious when dealing with such networks. Decomposing the system to new entities is shown in Fig.37b, and SSBN method can be applied. Accordingly, simulation results, logic inference, and expert judgement, may provide probabilistic data that can be fed to the re-composition of the entire network (in Fig.37a) to estimate/predict the probability of failure for the entire system.

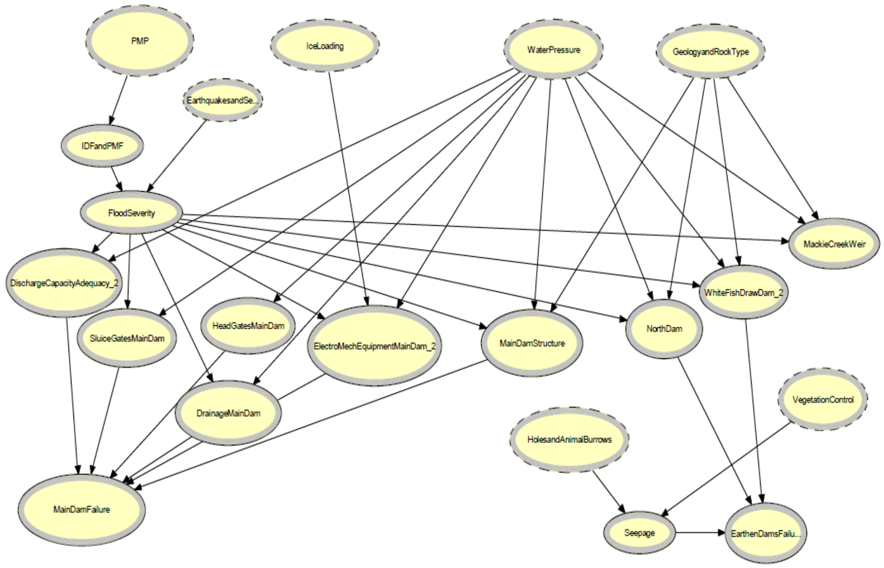


Fig.37a: BN for probabilistic failure analysis of Mountain Chute Dam

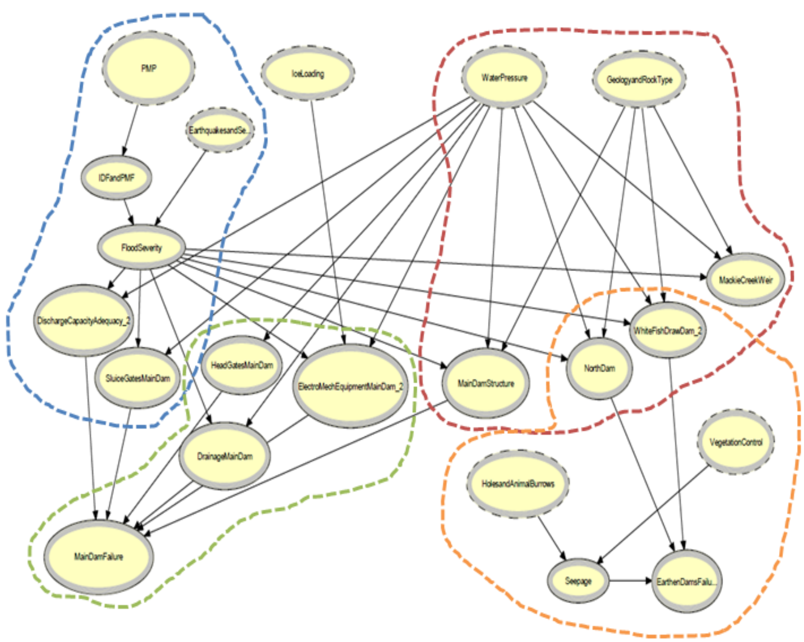


Fig.37b: BN of Mountain Chute Dam decomposed to sub-entities ready to be simulated

Mountain Chute main dam is 55 meters high (above its foundation), and almost 50 years old, having an electric power generation capacity of 150 MVA coming from two hydropower turbines. It doesn't have an emergency spillway, and its inflow is controlled by another dam of Madawaska River System in its upstream. Although the sluiceway discharge capacity of Mountain Chute main dam covers less than 50% of its peak outflow, which should be considered a risk, the inflow is controlled by upstream dams in Madawaska River System of dams, which decreases the probability of failure. In this dam, there is leakage in the drainage gallery (inspection tunnel) of the main dam (which is a concrete dam). The Inflow Design Flood (IDF) for Mountain Chute dam may result in the Loss of Life (LOL) of 381 persons. IDF can't be passed through sluice gates with the current deficiency and inadequacy in its discharge capacity.
Fig.38 and Fig.39 are site pictures for the downstream and the penstock and power house of Mountain Chute dam, ON, Canada, taken in October 2017. Fig.40 also shows a proposed BN for probabilistic analysis of the safety of Mountain Chute dam [Population at Risk (PAR), & Loss of Life (LOL)].

Fig.38: Downstream of the Mountain Chute Dam (including roads, a bridge, and electric transmission lines)

Fig.39: Penstock and Power House of Mountain Chute Dam

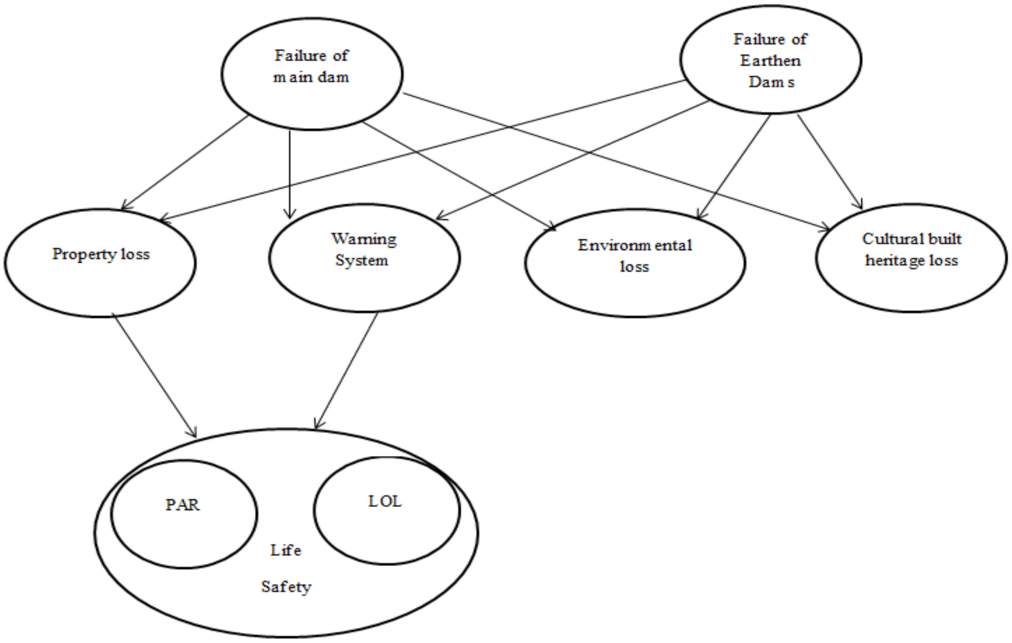


Fig.40: Probabilistic Analysis for Safety of Mountain Chute Dam

4.4 SSBN: Application, Methods, and Results

In order to apply the concept of SSBN, a two dam reservoir system analysis is conducted. This system is a less complex system, which means that exhaustive simulation can be performed to the entire system without having any concerns regarding the random sampling problems, uncertainty propagation problems, or spending too much time to perform the simulation. This is because the system is relatively having a lower number of nodes/variables. The main purpose of using the two dam reservoir system is to compare the results from detailed simulation with the results that come from the BN when supported by simulation. If both results are similar or close to each other with no huge difference, it means that BN may use the simulation as a useful quantification source for less complex networks, and for large complex networks while applying decompositions. Using the SSBN concept, the complex system may be decomposed to smaller less complex networks; each is having a separate simulation in order to feed the BN with probability estimates, and in order to predict the failure probability for the entire BN of the complex system. This is expected to reduce the number of possible states to deal with while representing the system using BN. The specifications, characteristics, and underlying assumptions of the two reservoir system, being simulated, are as follows (see Appendix 1):

- For each dam, dead (minimum) storage capacity, and maximum storage capacity of the reservoir are known.
- The designed outflow from the dam is assumed to be the mean of the inflow in each year.
- The inflow to the dam reservoir in each season is a uniformly distributed sampled random value using known lower and upper bounds. Of course, any other distribution can be used.
- The dam is assumed to have a spillway gate that is to be opened or closed. If there is a spill (excess water more than the reservoir capacity) at any time, the gate should be opened, and there will be a spill release from the dam that can go to the same channel of the outflow, or to be diverted to any other channel. If there is a requirement to spill and the gate is closed (failed to open or to operate), the dam will fail due to overtopping over the dam crest. The state of the gate is a randomly generated value (0 or 1).
- The dam failure is assumed to happen if the inflow is higher than certain limit, the storage state in the reservoir is high, which will result in having excess water more than the reservoir capacity (spill), and the gate is closed (failed to open) at the spill event.
- The aim is to estimate the probability of failure of each dam (i.e. the probability that all the above events happen at the same time).
- Then, each dam can be connected in series or in parallel with another same dam with the same characteristics and operational conditions, but with its inflow is dependent or independent on the inflow of the first dam. The outflow and spill release that are released from the first dam may also be added to the inflow of the second dam (according to the way of connection between the two dams).

- The system is assumed to fail if any dam fails or both dams fail at any time (in case of series connection), or if both dams fail (in case of parallel connection).

The reservoir operation simulation model (mass balance and governing equations) used for simulating each dam operation/management, are presented and explained below:

$$U = mean(I) \qquad \text{Eqn. 4.1}$$

$$S(t+1,m) = S(t,m) + I(t,m) - U(m) \qquad \text{Eqn. 4.2}$$

Such That:

$$Smin \le S(t+1,m) \le Smax$$

$$Water\_Available(t,m) = S(t,m) + I(t,m) \qquad \text{Eqn. 4.3}$$

$$Controlled\_Release(t,m) \le U(m) = \begin{cases} Water\_Available(t,m) - Smin & , Water\_Available(t,m) - U(m) < Smin \\ U(m) & , else \end{cases}$$

Eqn. 4.4

$$Spill(t,m) = Water\_Available(t,m) - Controlled\_Release(t,m) - Smax \qquad \text{Eqn. 4.5}$$

$$Spill\_Release(t,m) = \begin{cases} Spill(t,m) & , Spill(t,m) > 0 \ \ and\ Gate(t,m) = 1, Success \\ 0 & , Spill(t,m) > 0\ and\ Gate(t,m) = 0, Failure \end{cases}$$

Eqn. 4.6

Where:

t: season of the year {1,2,3,4}. The unit time in this simulation is one season.
m: year {1,2,3,4,……..,1000}
I: randomly generated inflow of the dam according to the lower and upper bounds known from historical data (uniformly distributed) [units of water volume/time].
I(t,m): inflow of the dam at a certain year (m) and season (t) [units of water volume/time].
U, U(m): designed outflow from the dam for steady river flow regulation. It is assumed that the designed outflow equals the mean of the dam inflow throughout one year (m) [units of water volume/time].
S: storage of the reservoir in a unit time [units of water volume]

S(t,m): storage of the reservoir in a unit time in the current season of the year [units of water volume]
S(t+1,m): storage of the reservoir in a unit time in the next season [units of water volume]
Smin: minimum storage limit of the dam reservoir (dead storage) [units of water volume]
Smax: maximum storage limit of the dam reservoir [units of water volume]
Water_Available: the water available at the reservoir at a unit time. This is the inflow at a unit time plus the stored amount of water at the reservoir [units of water volume].
Water_Available (t,m): the water available at the reservoir at a unit time in every season of the year.
Controlled_Release: the actual release from the dam with gates control/management, to keep the storage levels of the dam reservoir above the minimum value (Smin) and in order not to go lower than this value. Controlled release should be less than or equal the designed value of the outflow (U) [units of water volume/time].
Controlled_Release (t,m): the controlled release at every season and year.
Spill: the amount of water that exceeds the maximum storage level of the reservoir (Smax) at a unit time (one season) after releasing all the required release (controlled release) [units of water volume].
Spill (t,m): the spill amount at a certain season and year.
Spill_Release: if the spillway gates are opened, the spill release will equal the amount of spill over the time (per unit time or season). If the gates are closed (failed to open), the spill release will equal to zero and an overtopping failure is taking place [units of water volume/time].

In simulation, more samples give more stable results. So, it is important to check different number of samples (years) in order to check at which number of samples the results will stabilize and reach steady state. Matlab simulations, for the two reservoir system, have shown more stabilized results at 1000 years sampling period. Thus, in order to get the steady state estimates, the simulations are conducted for 1000 years, four seasons each.

Using the connection of both dams to each other (series or parallel), with the inflow dependency on each other (dependent or independent inflows), the simulation results for different configurations are shown in Table 8. Failure probability of the system of dams depends on the connection topology. In case of series connection, the failure is assumed to happen if any of the dams fail (dam1 fails <u>or</u> dam2 fails <u>or</u> both of them fail). In the parallel connection, the failure happens if both dams fail at the same time (dam1 fails <u>and</u> dam2 fails). It is also assumed that the inflows are highly correlated in the configurations having dependent inflows for both dams.

Simulation Results	Dam 1 Probability of Failure	Dam 2 Probability of Failure	Probability of System Failure
Series Connection , Dependent Inflows	0.0123	0.001	0.013
Series Connection, Independent Inflows	0.0123	0.0147	0.027
Parallel Connection, Dependent Inflows	0.0123	0.0022	0.0018
Parallel connection, Independent Inflows	0.0123	0.0112	0.00025

Table 8: Simulation results for two reservoir system with different configurations

Different results may be obtained with different inflow rates, different initial conditions of the reservoirs (initial water levels in the reservoirs), and different spillway gates' operation/management.

It was important to make sure that our code in Matlab produced results that are comparable to a software that OPG and many others use. For that reason, the software focusing on the reservoir systems and their management/control was used **"GoldSim simulation software"**. While processing the same simulation using the same equations 4.1- 4.6, Matlab and GoldSim had exactly the same results for 1000 years, 4 seasons each.

Fig.41 shows the simulations used to estimate the probability of having spill from the system of dams (two dams in this case) using GoldSim simulator software for all four configurations a) in series with dependent inflows, b) in series with independent inflows, c) in parallel with dependent inflows, and d) in parallel with independent inflows. Matlab software was also used to conduct the same simulation. Matlab and GoldSim had exactly the same results. See Appendix 2 for more clear figures of GoldSim system representation.

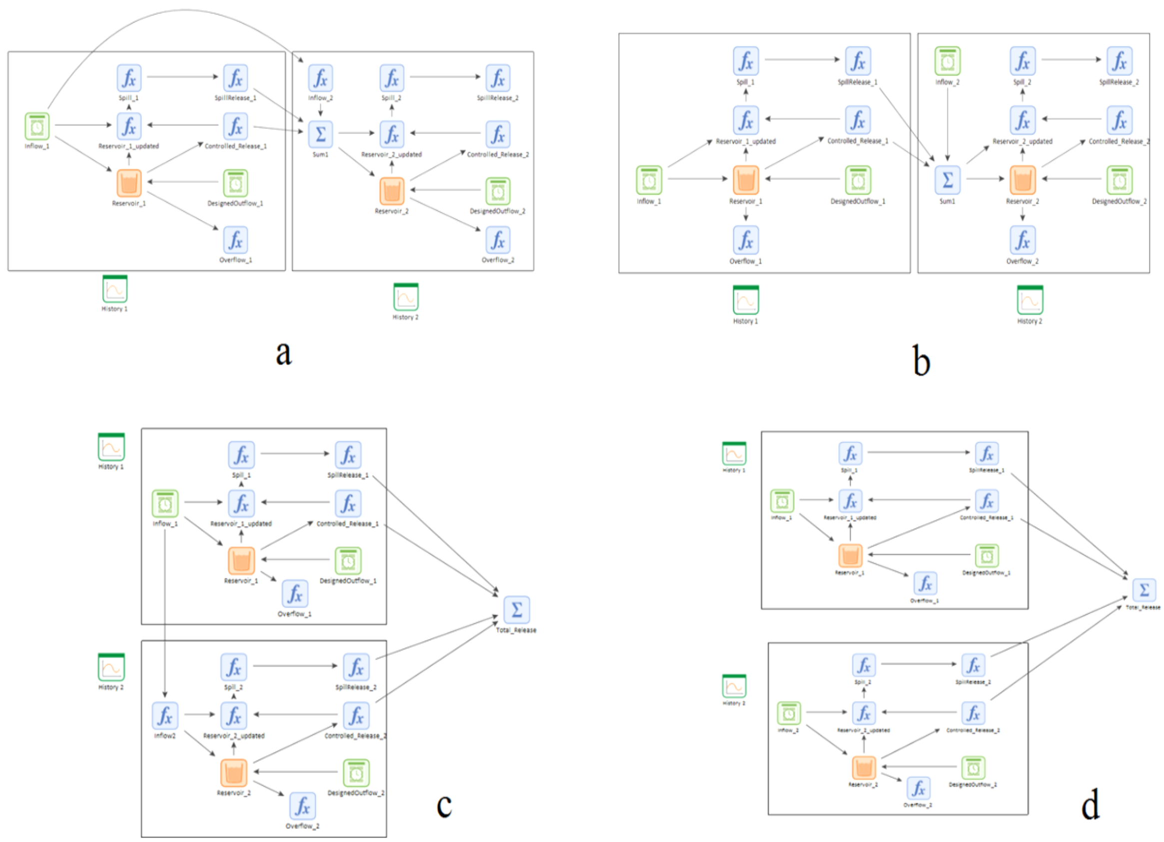


Fig.41: GoldSim simulations of two reservoirs of different configurations for estimating the probability of spill

To represent the two dam reservoir system using BN, Fig.42 shows the BN representations of different configurations of the two dam reservoirs used in the simulation, a) in series with dependent inflows, b) in series with independent inflows, c) in parallel with dependent inflows, and d) in parallel with independent inflows. This representation is conducted using Hugin software for BN representation and calculations.

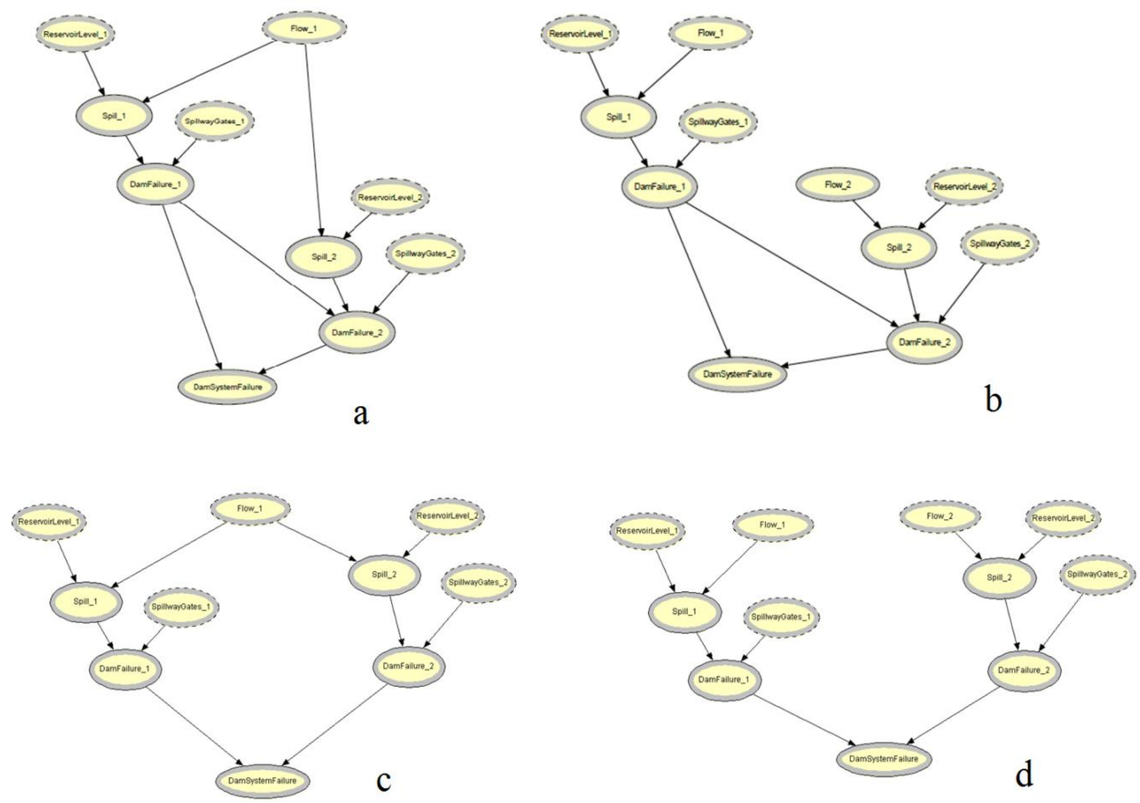


Fig.42: BNs of two reservoirs having different configurations

In these BNs, each dam is represented using five nodes/variables that include different states. These nodes and their states are explained as follows:

- **Flow node:** the inflow of the reservoir. It includes two states, high inflow, or low inflow. The inflow, with the reservoir level, affects the spill event (excess water more than reservoir capacity) of each dam. The probability values of each state (high and low inflows) are defined and estimated from the simulation according to the proper system analysis.
- **Reservoir Level node:** The level of water in the reservoir in every time step. It contains two states, high level, or low level. Definition of high state or low state depends on the system analysis, and the probability of each state can then be obtained from simulation.
- **Spill node:** affected by the inflow and the reservoir level nodes, there would be a spill or deficit in the reservoir. But because the water level in the reservoir is governed/regulated to be higher than or equal the minimum value (Smin), the states for this node will be taken as spill, or no spill. This node determines the probability of having excess water more than the reservoir capacity, which needs to be released from behind the dam in order not to result in an overtopping failure. Given the states of both the inflow and the

reservoir level in every time step, the spill state depends on both parent nodes with conditional probabilities that can be determined from the simulation process.

- **Spillway Gate node:** the spillway gates are supposed to open during the spill event in order to release the spill amount from behind the dam to avoid overtopping failures. If these gates fail to open for any reason during the spill event, a failure is assumed to happen. So, this node includes two states, open, or failed to open. According to the spillway gates maintenance schedules, there should be an estimate for the percentage of time during the year that the gates tend to fail or not operate, which may be conditioned on other conditions, for example, reservoir water level. In simulation, random generation of 1's and 0's indicating the gates to be opened or closed, respectively, at every time step is helpful in determining the probability of dam failure according to the state of the gates during spill events.
- **Dam Failure:** at the spill events, if the spillway gates failed to open, dam failure occurs. The two different states of this node are failure or no failure.

Another node called **"Dam System Failure"** is added to the BN to predict the probability that the system of dams will fail according to the way of connection (series or parallel). Fig.43, Fig.44, Fig.45, and Fig.46, show the BN representations for different connections/topologies of the two dam reservoir system under study using Hugin software.

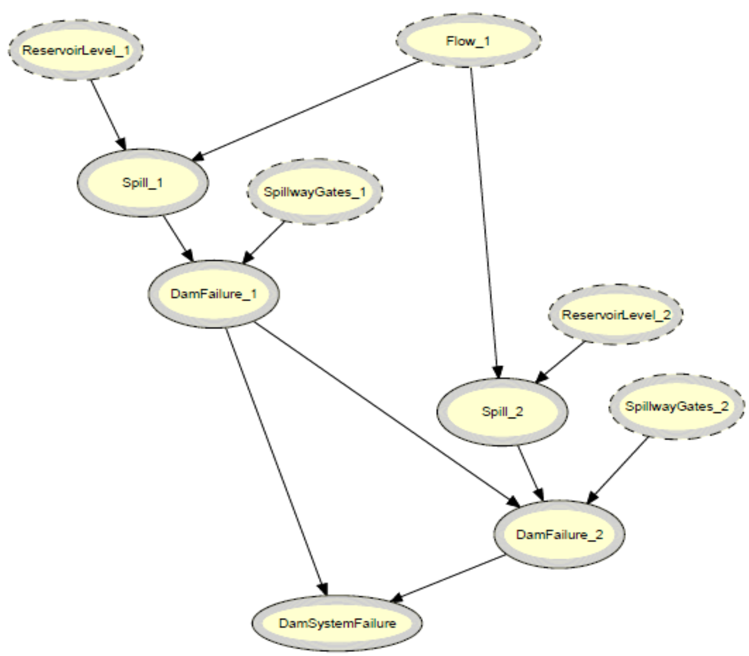


Fig.43: BN of two reservoirs in series with dependent inflows

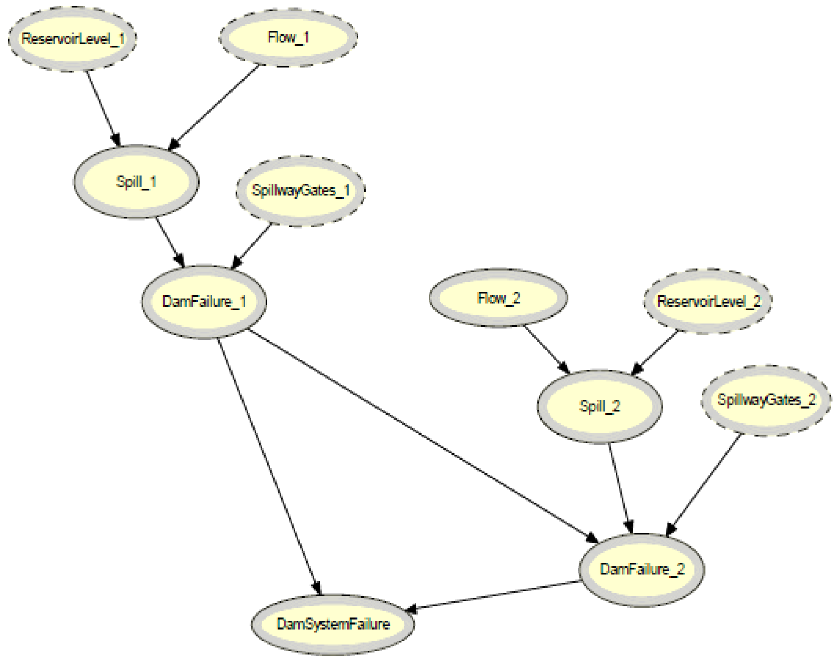


Fig.44: BN of two reservoirs in series with independent inflows

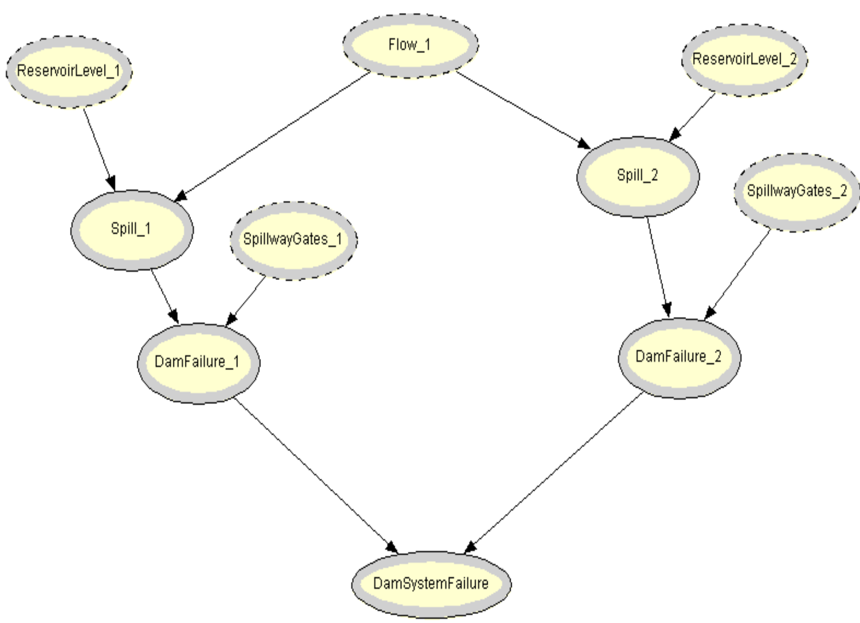


Fig.45: BN of two reservoirs in parallel with dependent inflows

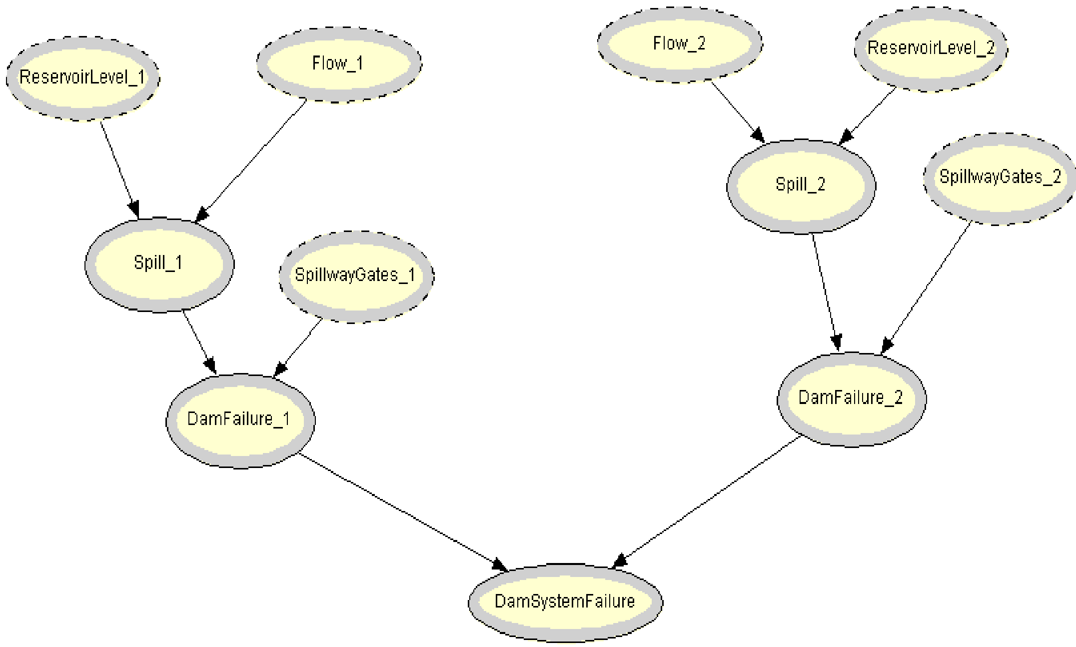


Fig.46: BN of two reservoirs in parallel with independent inflows

When the probability estimates obtained from simulation are fed to the BNs represented in Fig.43, Fig.44, Fig.45, and Fig.46 through their probability tables, the probabilities of failure can be estimated using the Bayesian equations (i.e. equations 2.4 – 2.6). According to the work presented in this chapter, the simulation for this system, which is relatively of low complexity, resulted in failure probabilities that were close to those estimated from BNs when supported by simulation. Table 9 shows the Basic Probability Tables (BPTs) and Conditional Probability Tables (CPTs) for the BN representation of two reservoirs in series with dependent inflows using the probability estimates from the simulation stage. The results of failure probabilities, using BN-simulation integration (i.e. SSBN), are shown in Table 10 and Fig.47.

DamFailure_1

SpillwayGates	Open		FailedtoOpen	
Spill_1	Spill	NoSpill	Spill	NoSpill
Failure	0	0	1	0
NoFailure	1	1	0	1

DamSystemFailure

DamFailure_2	Failure		NoFailure	
DamFailure_1	Failure	NoFailure	Failure	NoFailure
Fail	1	1	1	0
NoFail	0	0	0	1

SpillwayGates_1

Open	0.4982
FailedtoOpen	0.5018

ReservoirLevel_1

Fulllevel	0.465
Lowlevel	0.54

Spill_1

Flow_1	Highflow		Lowflow	
ReservoirLevel	Fulllevel	Lowlevel	Fulllevel	Lowlevel
Spill	0.0883	0	0	0
NoSpill	0.9117	1	1	1

Flow_1

Highflow	0.511
Lowflow	0.489

DamFailure_2

DamFailure_1	Failure				NoFailure			
Spill_2	Spill		NoSpill		Spill		NoSpill	
SpillwayGates	Open	FailedtoOp	Open	FailedtoOp	Open	FailedtoOp	Open	FailedtoOp
Failure	0.5	1	0	0.5	0	1	0	0
NoFailure	0.5	0	1	0.5	1	0	1	1

SpillwayGates_2

Open	0.4962
FailedtoOpen	0.5038

Spill_2

Flow_1	Highflow		Lowflow	
ReservoirLevel	Fulllevel	Lowlevel	Fulllevel	Lowlevel
Spill	0.0027	0	0	0
NoSpill	0.9973	1	1	1

ReservoirLevel_2

Fulllevel	0.76
Lowlevel	0.245

Table 9: BPTs and CPTs for the BN representation of two reservoirs in series with dependent inflows, using probability estimates from simulation

BN Results	Dam 1 Probability of Failure	Dam 2 Probability of Failure	Probability of System Failure
Series Connection , Dependent Inflows	0.0105	0.0032	0.011
Series Connection, Independent Inflows	0.0105	0.0162	0.024
Parallel Connection, Dependent Inflows	0.0105	0.001	0.001
Parallel connection, Independent Inflows	0.0105	0.0097	0.0001

Table 10: BN results for a two reservoir system with different configurations, fed from simulation (SSBN)

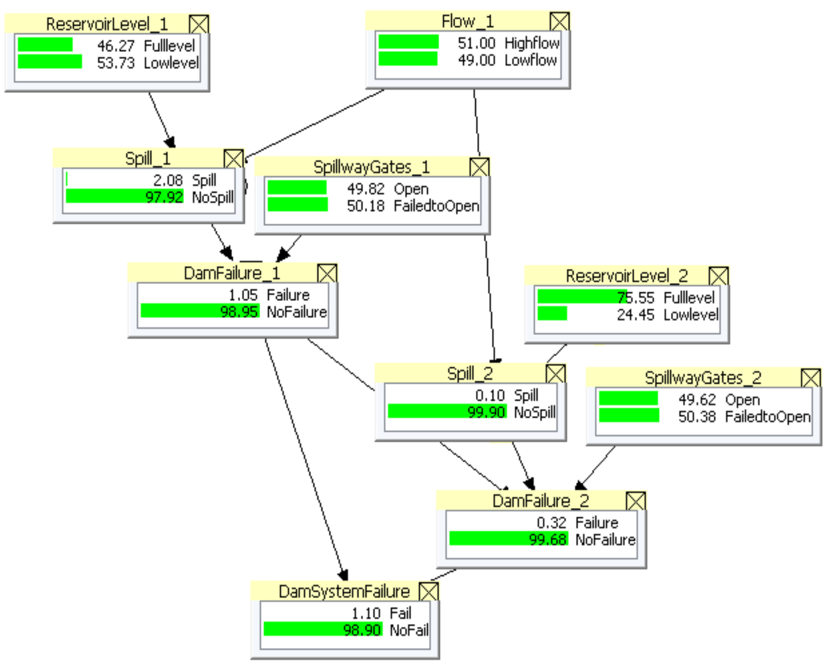


Fig.47: Probabilistic data and results of the BN of two reservoirs in series with dependent inflows

The difference in the probabilistic results is coming from the estimated definition of states' margins in the BN (i.e. discretization of states). The detailed simulation is supposed to give the exact results. In simulation, for example, the inflow rate may be of intermediate value (neither very high nor low), and with a high storage level in the reservoir, spill may be taking place, and with the gates closed, failure occurs. But, when the states were defined in the BN, the intermediate state of the inflow was not considered (i.e. only high inflow and low inflow were considered). Accordingly, the probability of high inflow was obtained from simulation and fed into the BN. However, there is another state called "intermediate inflow" that was not defined from the beginning because of the states' discretization. This also applies to the storage reservoir level (High, Intermediate, and Low). In simulation, the more the number of random samples, the higher the accuracy of the simulation results. Similarly, for a better accuracy of BN results, a higher number of states for every event is expected to provide a higher accuracy of the BN results. So, the number of defined states per event/variable should be increased, and the probability of every state is estimated from the simulation stage. Then, the probabilities are fed to the basic and conditional probability tables of the BN for prediction of system failures.

To test the effect of states' discretization on the probability estimates from SSBN, the SSBN is conducted for both cases of independent inflows (i.e. parallel dams of independent inflows, and series dams of independent inflows). Three states are used for inflow of the first dam (i.e. high, intermediate, low) instead of two. The second inflow is of three states, in the parallel case, and four states, in the series case (i.e. low, intermediate, high, and very high). In the series connection, the outflow of the first reservoir affects the inflow of the second one, and this is why there is a fourth state called "very high". For both reservoirs, the reservoir level has three states instead of two (i.e. full level, half level, and low level). Table 11 compares the probability estimates of system failure from Simulation, SSBN of two states per event, and SSBN of more number of states per event (i.e. 3-4 states).

	Probability of System Failure (Simulation)	**Probability of System Failure (SSBN, 2 states)**	**Probability of System Failure (SSBN, 3-4 states)**
Series Connection, Independent Inflows	**0.027**	**0.024**	**0.025**
Parallel connection, Independent Inflows	**0.00025**	**0.0001**	**0.00014**

Table 11: Effect of increased number of states on the SSBN results for a system of two dams

It is obvious from Table 11 that increasing the number of states affected the system failure probability. In the series connection, it is clear that the increased number of states led to an increase in the failure probability and reduced the difference between the results of simulation (i.e. exact results) and the SSBN results. In the parallel case, the probability of failure from simulation is 0.00025 over 4000 seasons (the system failure happens only in one season). This kind of low estimate makes it hard for the SSBN to converge to the simulation results unless a large number of discretized sates are used in the BN representation. However, the results are better with the increased number of states illustrated in Table 11. Accordingly, to have more accurate estimates from the SSBN, more number of states for every variable should be defined.

Here, the advantage of simulation over BN is clear, that is, there is no discretization error in simulation unlike in BN.

The SSBN concept starts with decomposing the complex system/network to smaller less complex networks, like the one proposed in the two dam reservoir system. Once all the smaller networks are simulated and represented probabilistically, they are ready to be re-composed/aggregated to the whole network for prediction of the system failure. And in worst cases, which is the one considered in this section, with defining only two states for every BN node (i.e. less accurate), the results of the simulation versus the SSBN are close.

It must be noted that the probabilistic estimates from simulation or SSBN (in Table 8 and Table 10) are steady state estimates that can be used in predicting failure probabilities in future time periods (e.g. 20, 50, 100, or 200 years). The following equation 4.7, which depends on binomial distribution, can be used for that purpose:

$$P(failure)_{in\ n\ years} = 1 - [(1 - P(failure)_{s.s})^{n}] \qquad \text{Eqn. 4.7}$$

Table 12 shows the results of using the above equation to predict the probabilities of system failure in different future time periods using the steady state probability estimates of SSBN in Table 10.

	Probability of System Failure (S.S)	Probability of System Failure (20 years)	Probability of System Failure (50 years)	Probability of System Failure (100 years)
Series Connection , Dependent Inflows	0.011	0.1985	0.425	0.6692
Series Connection, Independent Inflows	0.024	0.385	0.703	0.912
Parallel Connection, Dependent Inflows	0.001	0.0198	0.0488	0.0952
Parallel connection, Independent Inflows	0.0001	0.001998	0.004988	0.00995

Table 12: Predicting failure probabilities for future time periods from SSBN steady state estimates

4.5 Summary

A proposed methodology for representing and quantifying complex engineering systems is developed based on simulation and BN techniques for the purpose of probabilistic failure analysis. The proposed methodology deals with the whole system as sub-entities that are analysed using simulation models, with the integration of other different sources of data. This methodology adds another potential in facilitating the way by which complex systems are represented and probabilistically quantified as BNs. The proposed SSBN concept has been applied to a pilot case study of two dam reservoirs, and results are compared to detailed simulation results in order to analyse the difference for a relatively small system, that may act or be presented as a BN sub-entity. It was shown that performing simulation for this system, which was relatively of low complexity, resulted in failure probabilities that were, in worst cases, close to those estimated from BN-simulation integration.
It is also shown how the SSBN can be used to decompose a complex system to a number of less complex sub-systems (sub-networks) simulated together in the meantime. The BN of the entire system is then fed by the probabilistic information from simulations, resulting in a representation that can be used for failure analysis of complex systems (i.e. failure prediction and identification of causes).

The acyclic behaviour is one limitation in the BN representation. Moreover, updating the networks when any new data becomes available is challenging especially in the intermediate nodes (i.e. neither root nodes nor leaf nodes). The update should be in both directions (i.e. top-bottom, and bottom-top), which is not possible while using the BN, that only relies on one direction. In the next chapter, a novel concept is developed to overcome these obstacles using Markov Chains.

CHAPTER 5

Markov Chain Simulation Supported Bayesian Network (MCSSBN) Concept for Probabilistic Failure Analysis

5.1 Introduction

Simulation Supported Bayesian Network (SSBN) can help solve complex systems using a flexible decompositional method. But the BN has one limitation, that it is an acyclic graphical representation. In order to take decisions regarding any complex system that has many interrelationships among its components, different scenarios/states of the system should be represented. The scenarios/states of the system may be cyclic, and not only acyclic like in BNs. For the scenarios/states to be cyclic means having transitions from one scenario/state to a new one, with the chance to get to the first scenario/state again creating one cycle. To overcome only acyclic limitation of the BN, this chapter adds Markov Chain (Markov Analysis) to the SSBN to form the **Markov Chain Simulation Supported Bayesian Network (MCSSBN)**. This is considered an approach that develops integration between cyclic (Markov Analysis) and acyclic (BN) networks. In this chapter, MCSSBN concept is explained in details by representing its different approaches. The MCSSBN will then be applied on a system of two series reservoirs of independent inflows, having the same constraints of the system used in the SSBN application procedure. There are mainly two approaches to apply MCSSBN, 1- First approach: low level BNs and high level Markov Chains, and 2- Second approach: low level Markov Chains and high level BNs.

5.2 Cyclic and Acyclic Graphical Representations

An acyclic graph is a graph without cycles, where a cycle is a complete circuit. When following the graph from node to node, the same node will never be visited twice, unlike the network in Fig.48, which shows a cycle for a number of nodes/vertices.

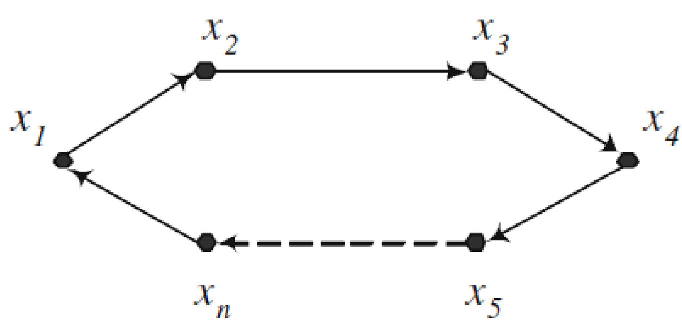


Fig.48: A cycle with *n* vertices [99]

A path in a directed graph can be described by a sequence of edges having the property that the ending vertex of each edge in the sequence is the same as the starting vertex of the next edge in the sequence. A path forms a cycle if the starting vertex of its first edge equals the ending vertex of its last edge. A directed acyclic graph is a directed graph, through direction of arrows/edges, which has no cycles. Bayesian Networks (BNs) are Directed Acyclic Graphs (DAGs). Fig.49 shows a DAG for a number of nodes.

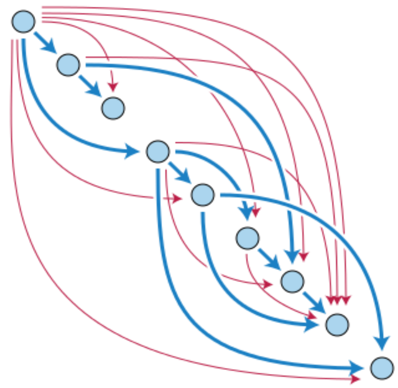


Fig.49: Directed Acyclic Graph (DAG)

Accordingly, cyclic graphs are those which have complete cycles, means the same node can be visited twice. Fig.50 shows different directed cycles (blue) that are included in an upper layer of directed acyclic network (orange).

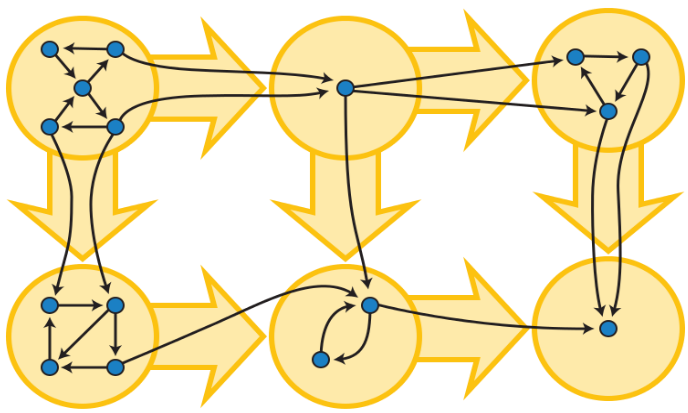


Fig.50: Directed Acyclic Graph (orange) of Directed Cyclic Graphs (blue)

The graphical representation in Fig.50 shows that for every node in the acyclic network (e.g. BN) there might be directed cycles for all the possible states within this node. Markov Chain Analysis is a mathematical probabilistic representation that can be used to describe these directed cycles.

5.3 Markov Chain Analysis

The Markov process is a random process in which changes occur continuously over a period of time, where the future depends only on the present state, and is independent of the past history. Markov Analysis (MA) is a probabilistic technique that provides probabilistic information about a decision situation that may help the decision maker, but without providing a recommended decision. It can be used to model system performance, dependability, availability, reliability, and safety. So, Markov Analysis is a descriptive technique, not an optimization technique, which results in probabilistic information, and is applicable to systems that exhibit probabilistic movement from one state/condition to another, over time. MA may also be shown as a mathematical abstraction to model simple or complex concepts in a computable form. It is a tool for modeling complex system designs involving timing, sequencing, repair, redundancy, and fault tolerance, along with determining the system availability in order to identify the flow of the system and enumerate the failure rate (forward), repair rate (backward), and the probability of failure of the different components. Any Markov model can be graphically represented using Markov diagram, which consists of the states and transitions of the model. The transition probabilities, and transition rates, among the different states, within the system diagram, are of a great importance in the Markov Analysis. Transition rates represent the rate at which the Markov chain moves from one state to another. The transition rate from a working state to a failed state is represented by the failure rate, whereas the transition from a failed state to working state is represented by the repair rate. The transitions are represented by the connections linking the circular states, with arrows indicating the transition direction (directed graph).

In reliability analysis, MA has the following advantages:

- The Markov model allows for modelling and investigating the system in terms of model parameters, along with assessing the probability of failure (probability of decreased performance),
- Markov graphical representation helps in understanding the system behavior,
- Modelling systems with their state diagrams, and in terms of the interdependencies of states, is more accurate in specific situations,
- For observation purposes, MA allows for specifying different types of states and state groups.

A Markov chain is a sequence of random variables $X_1,.., X_n$ such that, given the present state, the future and past are independent. It is formally written as follows in equation 5.1:

$$Prob\ (X_{n+1} = x \mid X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) = Prob\ (X_{n+1} = x \mid X_n = x_n) \qquad \text{Eqn. 5.1}$$

In other words, the conditional distribution of X_{n+1} in future depends only upon the present state X_n. Usually, the chain is defined by specifying the probabilities of transitioning from one state to another. The state space may be considered to be continuous and sometimes discrete. For a continuous state space where a probability density can be defined, the transition probability can be written as $P(x, y) = Prob\ (X_{n+1} = y \mid X_n = x)$. For a discrete state space, the transition probability is a matrix and is written as Pxy, [100].

So, if the chain is currently in state $\boldsymbol{s_i}$, then it moves to state $\boldsymbol{s_j}$ at the next step with a probability denoted by $\boldsymbol{p_{ij}}$, then, this probability does not depend upon which states the chain was in before the current state. The transitions among different states in the Markov Chain are represented by the Transition Probability Matrix (TPM). This matrix is also called the matrix of transition probabilities, or the transition matrix. For a Markov Chain of three states, the Transition Probability Matrix (TPM) can be represented as follows (see Fig.51 for a three state Markov Chain showing their transition probabilities):

$$\text{TPM} = \begin{pmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{pmatrix}$$

Where, for example, P_{22} is the probability that the variable is currently in the second state, and will remain in the second state in the next step. While P_{32} is the probability that the variable is currently at the third state and will move to the second state in the next step (moves to second state given that it was at the third state).

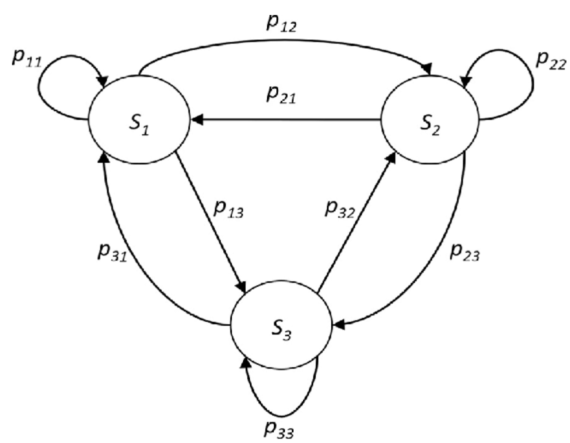


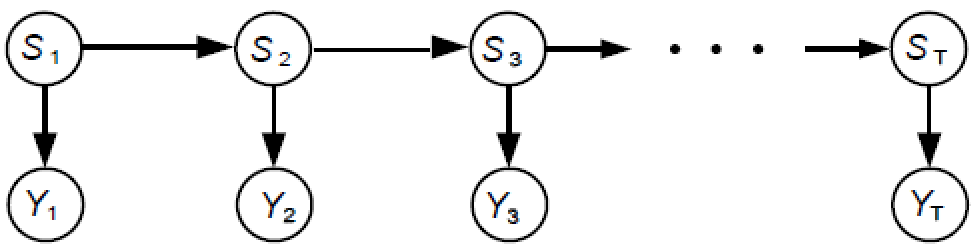
Fig.51: Markov Chain of three states S_1, S_2, S_3

5.4 Markov Chain Simulation Supported Bayesian Network (MCSSBN)

The decompositional approach conducted in [97] and [98], allowed the researcher in this thesis to conceptualize and formulate a new concept and methodology in dealing with BNs of complex systems. The concept of Simulation Supported Bayesian Networks (SSBNs), developed in this thesis, is expected to be an efficient method of applying decompositions to complex networks. Moreover, the Bayes-Markov (Cyclic-Acyclic) combination, proposed in [98], represents a way of supplementing Markov chains with additional low-level features taken from multiple sources, and are efficiently combined using Bayesian Networks. Since quantification of BNs depends on basic and conditional probabilities, and Markov Chains are represented by transition (conditional) probabilities among different states, the Markov-Bayesian combination is a probabilistically quantified representation. Adding Markov Chains, which may represent different scenarios, states, or events in a cyclic representation, to the BNs, of which the acyclic

nature may not be suitable for all complex structures, will result in a more generalized approach that fits most of the large complex system structures. Such structures, with their complex interrelations among system components, usually have slow processing for calculating failure probabilities. Bayes-Markov combination is estimated to reduce this problem in such systems.
Now, with the decompositional approach, represented by SSBNs, the question is how to incorporate Markovian analysis to determine different scenarios, states, or events, which may take place at different times in the system network. In this section, the concept of Markov Chain Simulation Supported Bayesian Network (MCSSBN), cyclic-acyclic approach, is introduced.

Hidden Markov Chains, and Markov Chain Monte Carlo (MCMC) models, are not new concepts/methods. Hidden Markov Chains are used in different applications to introduce the states' transitions while taking time into consideration. Such models are known to be dynamic models because of the time representation. Differently, MCMC models are providing a combination of simulation results, and simulation updated results, to the Markov Chain to produce more efficient updated output results. See [99], [100], [101], and [102].
According to [101], hidden Markov model is a tool for representing probability distributions over sequences of observations in which time is incorporated. Fig.52 shows a BN with a hidden Markov model depending on output observations.



$$P(S_{1:T}, Y_{1:T}) = P(S_1)P(Y_1|S_1)\prod_{t=2}^{T} P(S_t|S_{t-1})P(Y_t|S_t)$$

Fig.52: A BN with a hidden Markov model [101]

The combination of hidden Markov models and BNs may be called Dynamic Bayesian Network (DBN), which is simply a BN that models time series data. Fig.53 is for a BN structured hidden Markov model depending on input observations (X's) and output observations (Y's). It is shown that a number of Markov Chains may be required to represent this system. Every system variable is supposed to have its own Markov Chain, which makes the system representation more complex especially in large system structures.

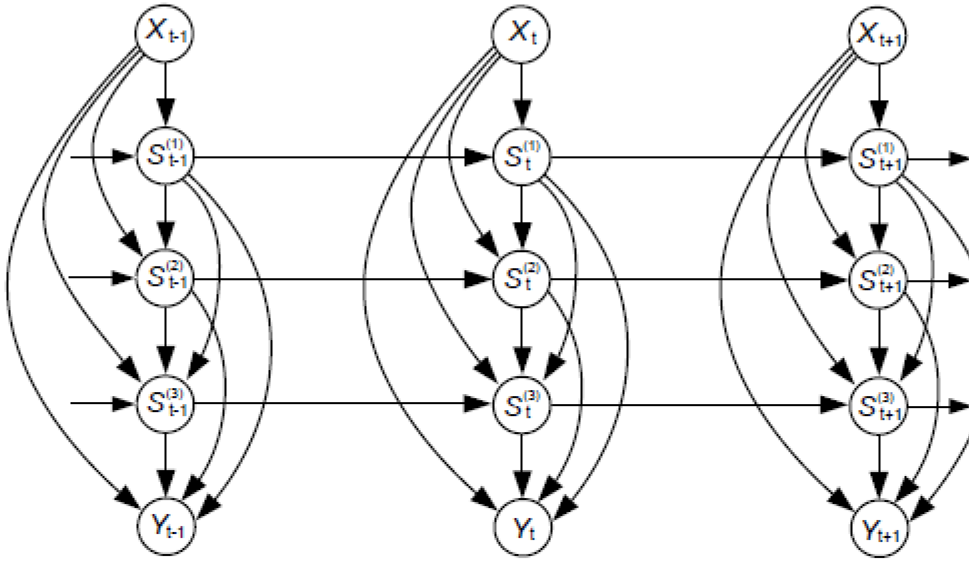


Fig.53: A BN structured hidden Markov model [101]

References [101] and [102] use hidden Markov models with Bayesian Networks to update information/data of the system network using any available evidences, with incorporating time dependent states into the network. Ref [99] is trying to mathematically prove a generalization for Bayesian Networks to allow directed cycles using the case of an isolated cycle. References [103], [104], [105], [106], and [107] show different methodologies to solve some problems using Markov Chains and/or Bayesian Networks from different perspectives for different engineering applications.

There is a need for a general global methodology to be applied to all engineering applications for risk and reliability problems. It can be shown from the reviewed literature that the relation between Markov models, representing cyclic networks, and Bayesian Networks, representing acyclic networks, is still vague and needs clarification, especially for many complex networks of different engineering applications. The missing link between Markov Chains and BNs may be the simulation. The distinction of the concept proposed in this research is that it combines the three concepts together: BN, Simulation, and Markov Chains in one combination in order to be applied to almost all of the engineering applications. This forms the Markov Chain Simulation Supported Bayesian Network (MCSSBN) cyclic-acyclic approach in systems analysis. Like SSBN, the system is decomposed to smaller sub-networks to be simulated in smaller scale in order to estimate their probabilities. Then, they can be re-combined to the unified larger scale BN. In this section, combining Markov Analysis to the SSBN is of interest. Within the smaller scale sub-networks, that are being simulated, there might be some scenarios of interest, or time variant states/variables that need to be considered in the process of failure prediction (forecasting), or even in the decision making. The proposed MCSSBN methodology depends, theoretically, on two different approaches:

5.4.1 First Approach of MCSSBN

In this approach, the system is represented with high level Markov Chains, and low level BNs, for different scenarios. The SSBN concept is the corner stone. Decomposing the BN to lower level BN sub-networks, with running simulations for them, according to available data, is the first step of this approach. Running the simulation for every sub-network makes it obvious that it may experience more than one scenario. Scenario is a combination of states for all the nodes included in every sub-network. According to that combination, the scenario is defined. So, the results from simulating every BN sub-network are used to define at which scenario the sub-network is, or to define different scenarios that the sub-network may experience. Then, given the scenarios and simulation probabilistic results for all the sub-networks, sub-networks will be re-combined/aggregated back to the higher level network. The Bayesian inference in the higher level, larger scale BN will result in the probabilistic output that is required (for example, the probability of failure). While the transition probabilities among different scenarios in every sub-network are estimated from simulation, the most probable scenario to take place in the next time step can be predicted for every sub-network. Then, the probability of failure of the system can be predicted in the next time step. Moreover, the scenarios that have more contribution to the failure can be obtained, and the scenarios of sub-networks which result in higher failure probability can also be identified. Fig.54a and Fig.54b show a 23 node BN before and after being decomposed to four BN sub-networks, respectively. In this network, every BN sub-network should be simulated using its available data. By running simulations, different scenarios of every BN sub-network may be defined or identified with different states of the sub-network nodes. The probabilistic results of each scenario should be estimated from the simulation stage. Moreover, the transition probabilities among different scenarios should be obtained while simulating the sub-networks. A Markov Chain should then be built for every BN sub-network. Fig.55 and Fig.56 show Markov Chains having transition probabilities for a three scenario BN sub-network and a two scenario BN sub-network, respectively, which are parts of the BN shown in Fig.54b.

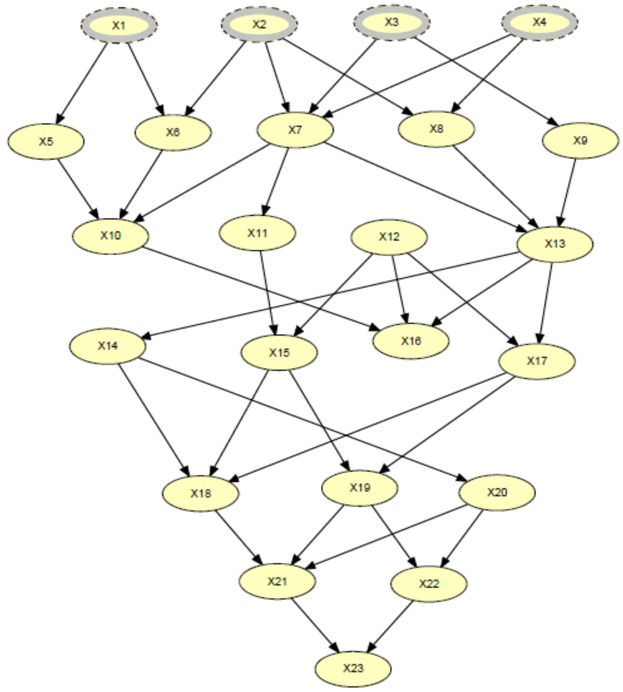


Fig.54a: A 23 node BN

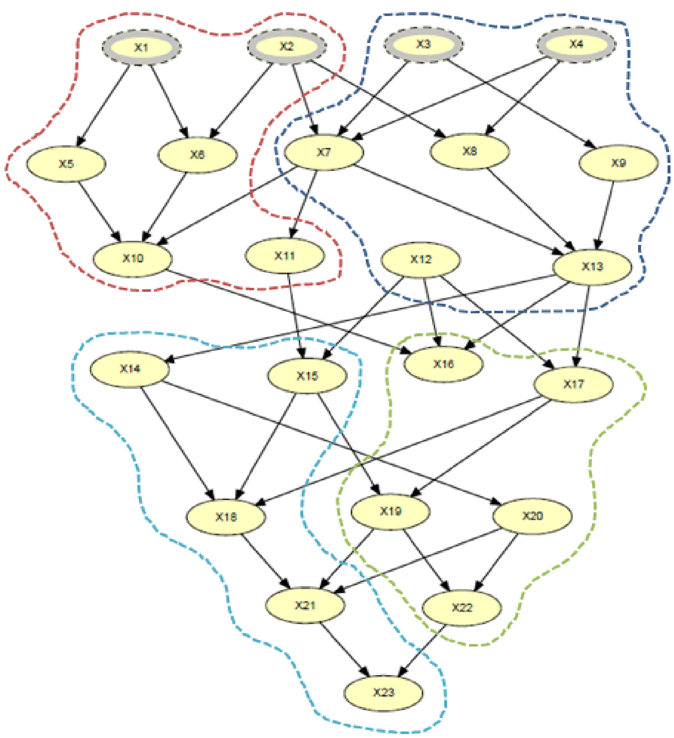


Fig.54b: A 23 node BN being decomposed to 4 BN sub-networks

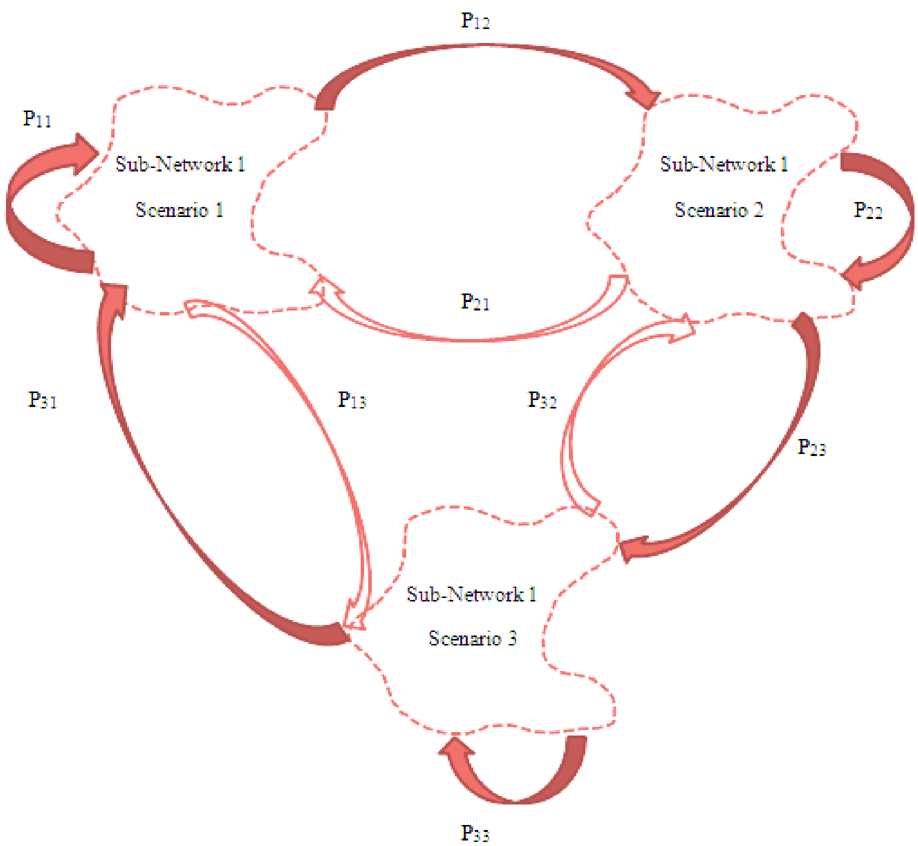


Fig.55: Markov Chain of a three scenario BN sub-network

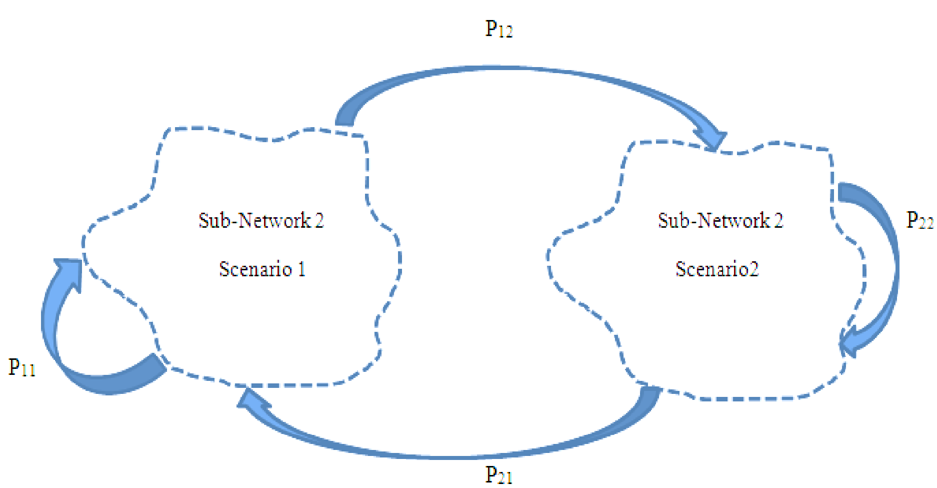


Fig.56: Markov Chain of a two scenario BN sub-network

In conclusion, in this approach, the processing steps for the system network are as follows:

1- The BN of the system is decomposed to BN sub-networks, 2- Every BN sub-network is simulated according to its available data, or with random sampling. Simulation results in probabilistic information (basic and conditional probabilities) of the nodes and their interrelationships. Simulation is also used to identify different scenarios for every sub-network, steady state probability distribution of the scenarios, and the transition probabilities among these scenarios. At steady state, the relation between steady state probability distribution of Markovian states and the steady state transition probability matrix is given by the following equation 5.2:

$$\pi \, TPM_{s.s} = \pi \qquad \text{Eqn. 5.2}$$

where:

$TPM_{s.s}$ is the steady state transition matrix, and π is the row vector of steady state probability distribution of the Markovian states.

3- The BN sub-networks are re-combined back to the entire system BN, and the probability of system failure can be predicted using Bayesian inference,

4- Then, by using the transition probabilities from a scenario to another, for every sub-network, the probability of failure can be predicted according to the new scenarios, and linked probabilistically, through transition probabilities, to the initial scenarios,

5- With any evidence in the BN of the entire system, the posterior Bayesian inference facilitates determining the main contributing scenarios/states to the evidence (failure in this research). This will make it easier to determine which BN sub-network had more contribution in the failure, and which of its scenarios, represented by Markov Chains, is more contributing to the failure.

In this approach of MCSSBN, the driving force is the BN sub-network simulation. The simulation results, according to different data inputs, identify at which scenario the sub-network is operating, and also reflect the transitions among different scenarios. In this case, MCSSBN can be seen as a clustered SSBN. Every cluster represents a sub-network, which has different scenarios linked through sequence of transitions.

5.4.2 Second Approach of MCSSBN

In this approach, the system is represented with low level Markov Chains and a high level BN. In this case, Markov states are the driving force for the probabilistic prediction process in the whole network. For every node in the BN, there are at least two states. The node's states may be represented as a low level Markov Chain that controls the states every time step within the node. For example, in a reservoir problem, if the node of inflow of the dam is represented by three states, high, intermediate, or low inflows. The transitions among the three states may be known from the historical data that, for example, the inflow is higher in the spring and fall than winter, and the inflow of fall is higher than that of the spring. The data available in this case defines the transition probabilities of this sequence. This means that every node takes its state from its own lower level Markov Chain. Running simulation is the start point. Decomposing the network to smaller sub-networks is used to facilitate the simulation process. Then, simulation is used to estimate the steady state probability distribution of the Markov states in every node and the transitions among Markov states within every node/variable. Fig.57a shows a 17 node BN, which has nodes that include two states each (at least), as shown in Fig.57b. Fig.57c shows the same network with a lower level two state Markov Chain (shown in Fig.58 with transition probabilities) for the states inside every state variable. At every time step, the state of the lower level Markov Chain will be reflected to be the state of the BN node.

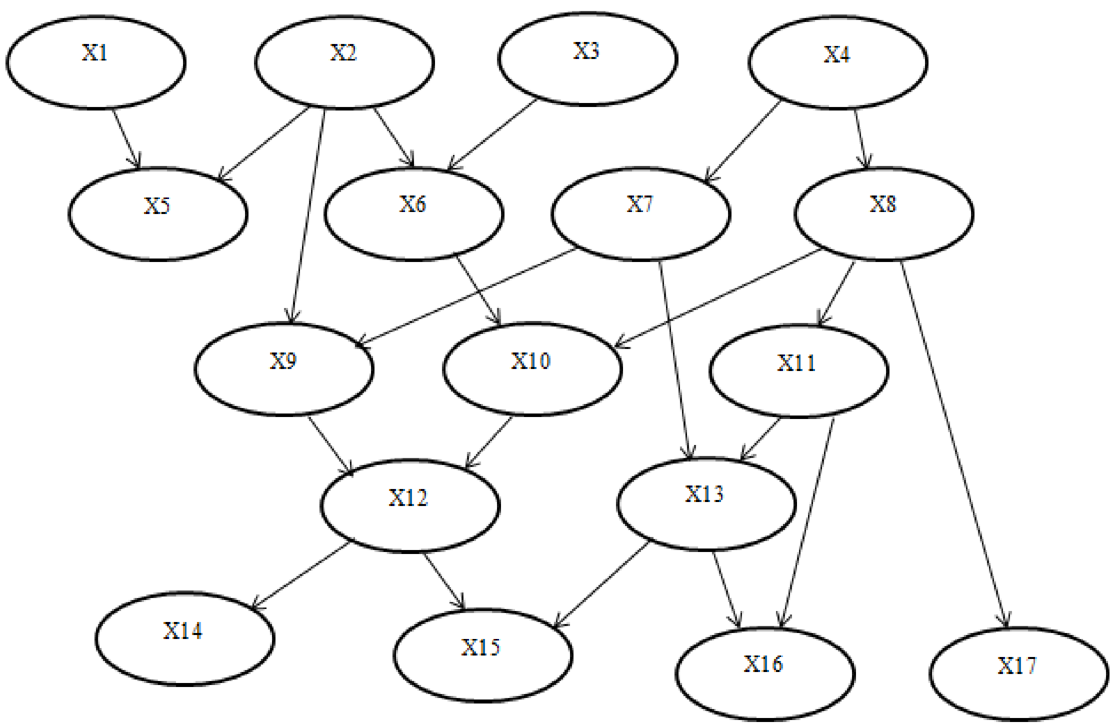


Fig.57a: A 17 node BN

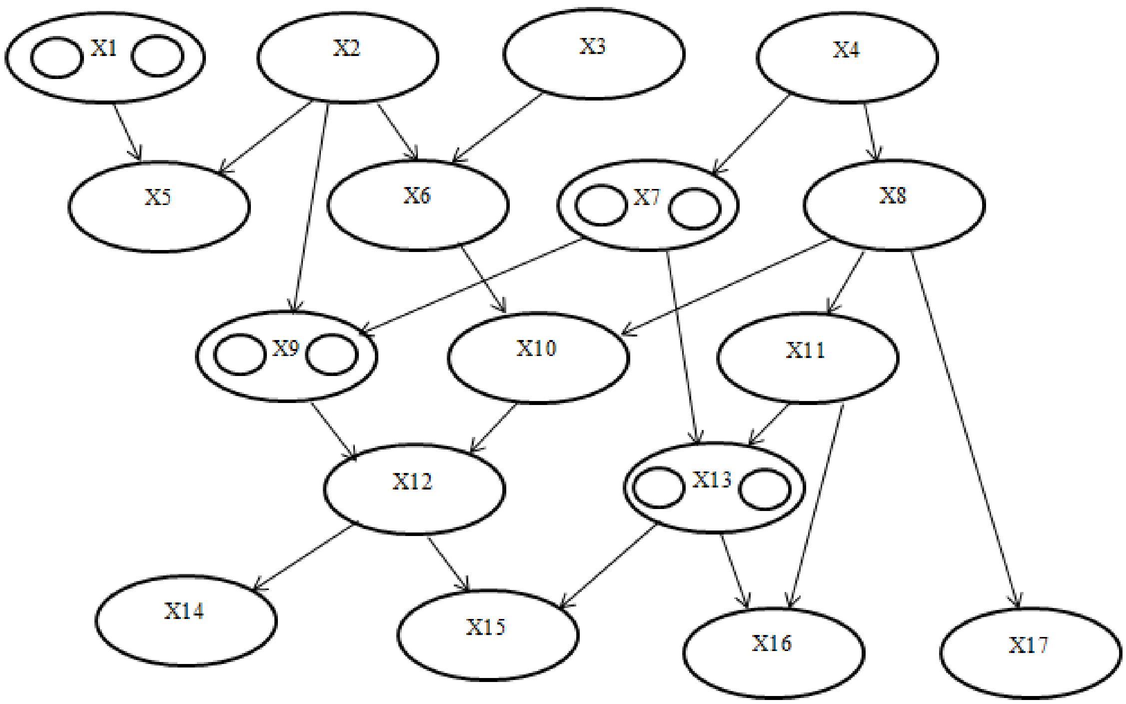


Fig.57b: A 17 node BN, with every node includes two states (at least)

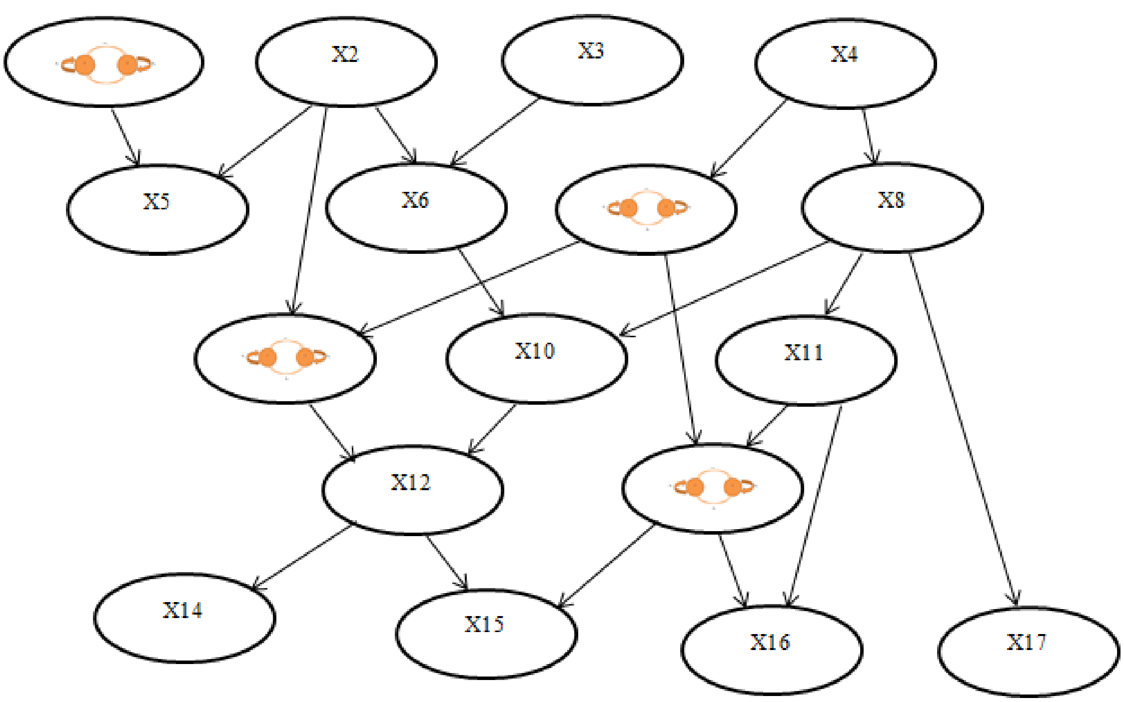


Fig.57c: A 17 node BN, with every node includes a two state Markov Chain

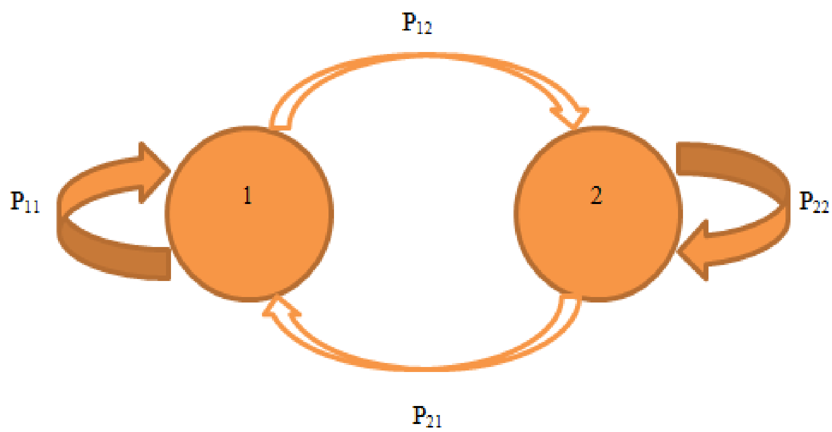


Fig.58: Two state Markov Chain for every node

In conclusion, in this approach, the processing steps for the system network are as follows:

1- The states of every node in the BN are defined. A Markov Chain is constructed for the states in every node, with defining transition probabilities from available data (or from the simulation stage),
2- The decompositional SSBN approach is applied using available data, or using randomly generated samples. The purpose of applying SSBN is to determine the probability estimates of all the states in all the nodes included in the BN. In that order, the whole BN is decomposed to smaller sub-networks that are simulated separately to estimate the required probabilistic information for all possible states, and to identify the transition probabilities among states in every node,
3- Now, every Markov state is defined by its steady state probability, and the transition probabilities among different states within the same node, are also identified using equation 5.2.
4- All the probabilistic information are combined to the entire high level network in order to estimate the probability of failure (the required probability),
5- At every time step, the failure probability of the system's entire BN can be estimated, and linked probabilistically, through transition probabilities, to the initial states. For the next time step, the most probable state to take place in every node can be predicted using the transition probabilities of Markov Chains within system nodes. Then, the required probability (i.e. failure probability) of the BN is dynamically estimated at this point.

5.5 Methods of Applying MCSSBN to a System of Three Dam Reservoirs

In this section, the two approaches of MCSSBN are applied, theoretically, on a system of three series reservoirs, with three independent inflows. The purpose is to show that the method can be expanded to more number of system components. The aim is to estimate the probability of failure of the whole system according to the operating conditions/events of the three dams. Fig.59 shows a BN for three dam reservoirs connected in series.

Fig.59: A BN of a three reservoir system

The specifications, characteristics, and underlying assumptions of the three reservoir system, are similar to those reservoirs defined in section 4.4. The three dam reservoirs, of the same characteristics and operational conditions, are connected in series, with their inflows to be independent. The controlled outflow (actual outflow) and spill release, which are released from the first dam according to the gates management, may also be added to the inflow of the second dam, and so forth for the third dam. In this case, the system fails if any of the dams fails at any time (i.e. Dam1 or Dam2 or Dam3 or all fail), as it is a series connection. In the BN of this system, each dam is represented using five nodes/variables that include different states. These nodes and their states are explained in section 4.4. The node that is named **"Dam System Failure"** is added to the BN to predict the probability that the system of dams will fail according to the way of connection (series in this case). The proposed MCSSBN concept can be applied, theoretically, on this three reservoir system, using both MCSSBN approaches, in the next sections.

5.5.1 MCSSBN First Approach

By applying the first approach of MCSSBN, the BN of the three dams can be decomposed to four BN sub-networks as shown in Fig.60. It can be seen that every dam reservoir is taken as one BN sub-network. The last sub-network is for the dams' failure and the system failure.

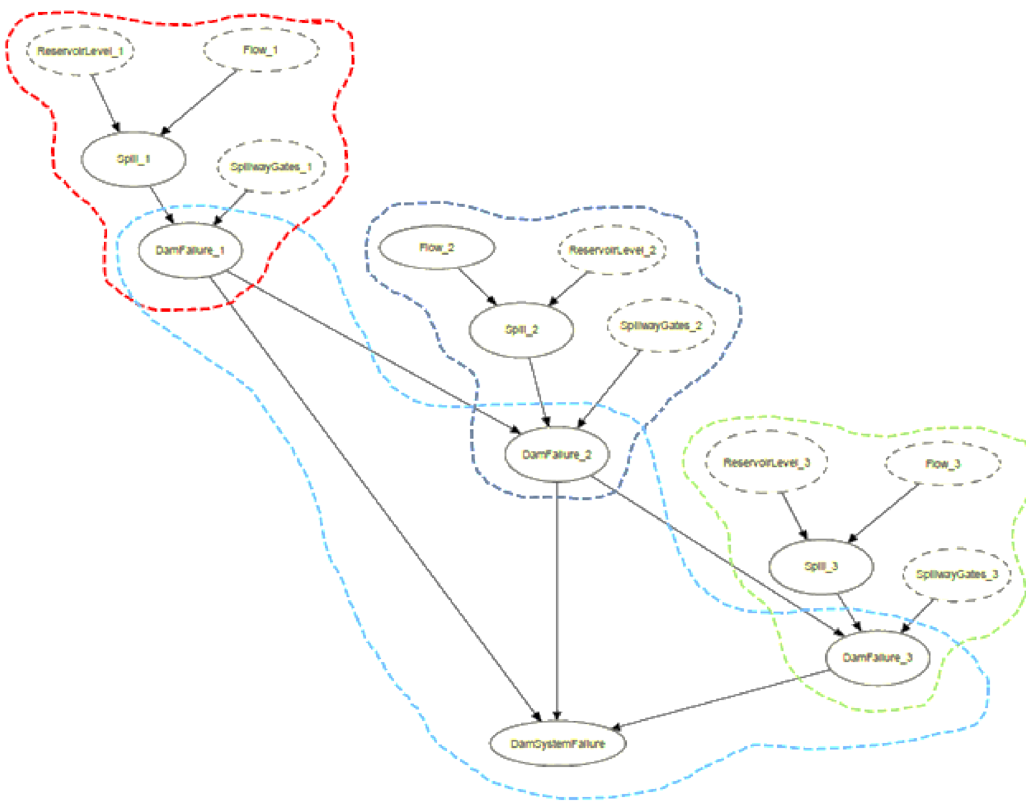


Fig.60: Three reservoir system BN decomposed to four sub-networks

From Fig.55 and Fig.56, it can be seen that a Markov Chain can be constructed for different scenarios of every sub-network. The system shown here, in this section, is for the overtopping hazards, so, each scenario is considered a combination of states that results in an overtopping failure with higher or lower probability. For example, the first scenario (i.e. combination of states) may be with high inflow, intermediate reservoir level, and the spillway gates are closed, while the second scenario is for high inflow and high reservoir level, with the spillway gates closed, and so forth. Different scenario for every dam will result in a different scenario for the system failure. Then, the BN sub-networks are used to construct a high level BN for the system as shown in Fig.61.

This approach may also be generalized for dam failure events. In a more general BN, the first scenario for each dam may be overtopping, the second is sliding, and the third scenario is seepage piping, and these scenarios may be represented by a three state Markov Chain as shown in Fig.62.

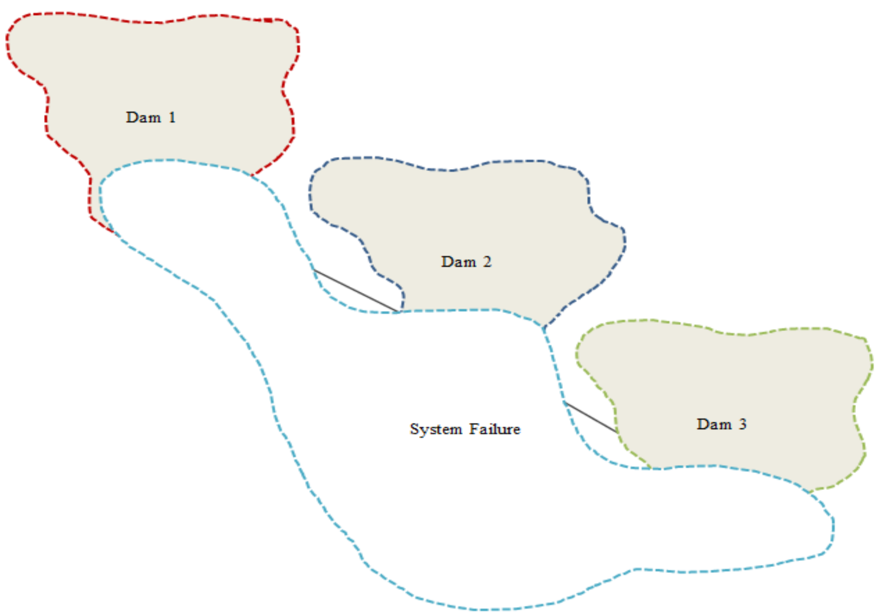


Fig.61: General three reservoir BN, decomposed to four sub-networks

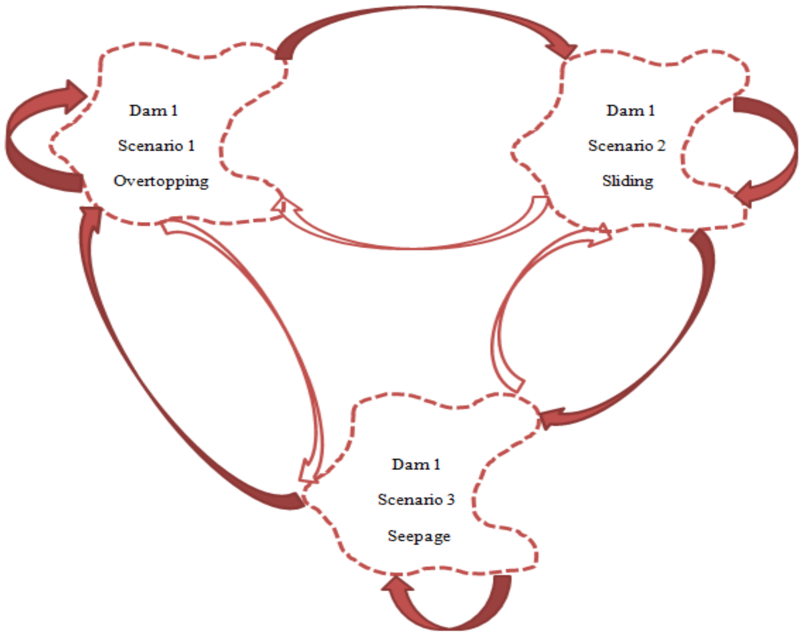


Fig.62: Markov Chain of a three scenario reservoir BN sub-network (Overtopping, Sliding, or Seepage)

5.5.2 MCSSBN Second Approach

For the three reservoir system in Fig.59, the second approach of MCSSBN can be applied as shown in Fig.63, where each node or state variable in the BN may include a lower level Markov Chain with at least two states. The Markov Chain takes the decision for the state of every node/variable. When the states change at every time step the output results from the BN will also change.

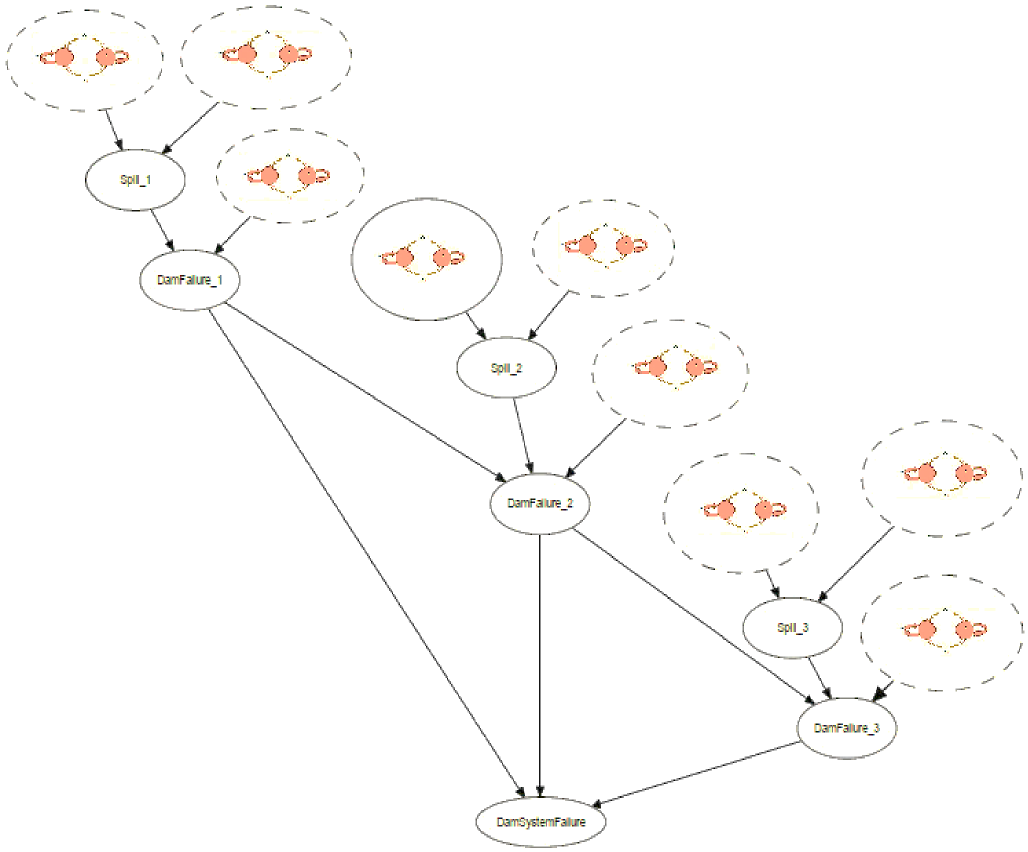


Fig.63: BN of a three reservoir system, with every node includes a lower level Markov Chain

As an example, assume that at a certain time, the first dam is of low inflow, low reservoir level, with open gates, and the second dam is of high inflow, low reservoir level, with closed gates, while the third dam is of high inflow, high reservoir level, and open gates. For this case, failure probabilities will be totally different than another combination of states of the entire network after a number of time steps. It can be seen that this approach takes the combination of states to produce a scenario for the entire network, not for just a sub-network like in the first approach. The sub-networks here are only used for simulations to identify probabilistic information for the nodes and their states.

In conclusion, the system is decomposed to four sub-networks, shown in Fig.60, to be simulated in order to get all the probabilistic information for all the possible states of the nodes. When the transition probabilities among states in the lower level Markov Chains are defined, at every time (i.e. *t-1, t, t+1, etc.*) the state of every node can be predicted. Thus, at any time, the states of the nodes, their probabilities, and transition probabilities from previous states, are defined. This information is combined to the entire network to estimate the probability of failure of the system of the three dams. A higher level Markov Chain may be constructed for the entire network to show the transitions among different BN cases/scenarios as shown in Fig.64 for the BN of Fig. 60. In Fig. 64, the combination of states of the state variables of the BN (i.e. scenario/state for the entire network) changes at every time step. In other words, at every time step, there is a different situation that the entire network experiences. Markov Chain represents the transitions among different situations/scenarios (i.e. Markov states) for the entire network. In the next time step, the entire network may remain in the same scenario (Markov state), or make a transition to another scenario (Markov state).

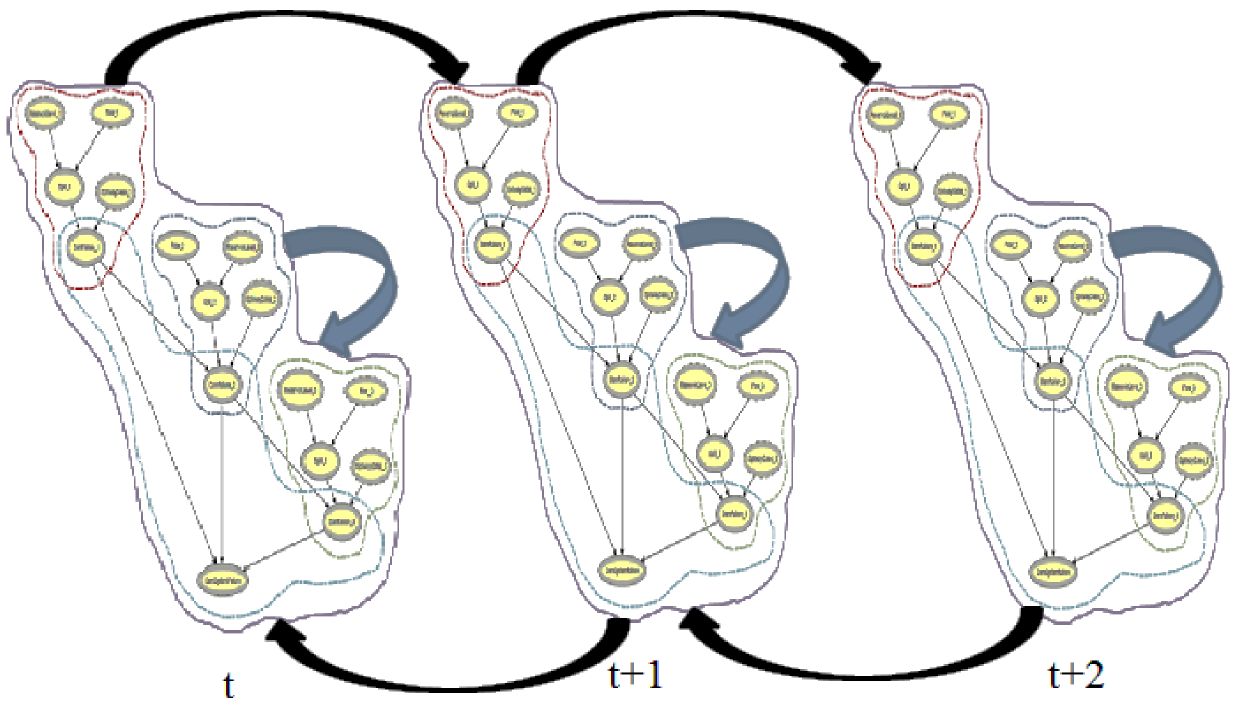


Fig.64: Higher level Markov Chain for the three reservoirs BN, MCSSBN second approach

5.6 MCSSBN First Approach for Two Series Reservoirs

In this section, the first approach of MCSSBN, i.e. low level BNs, high level Markov Chains, and higher level BN, is applied to a system of two series reservoirs of independent inflows. In order to apply the MCSSBN concept with this approach, the following steps are followed:

1- The two reservoir system is decomposed to three sub-systems (sub-networks), the first reservoir sub-system, the second reservoir sub-system, and the system failure sub-system, as shown in Fig.65

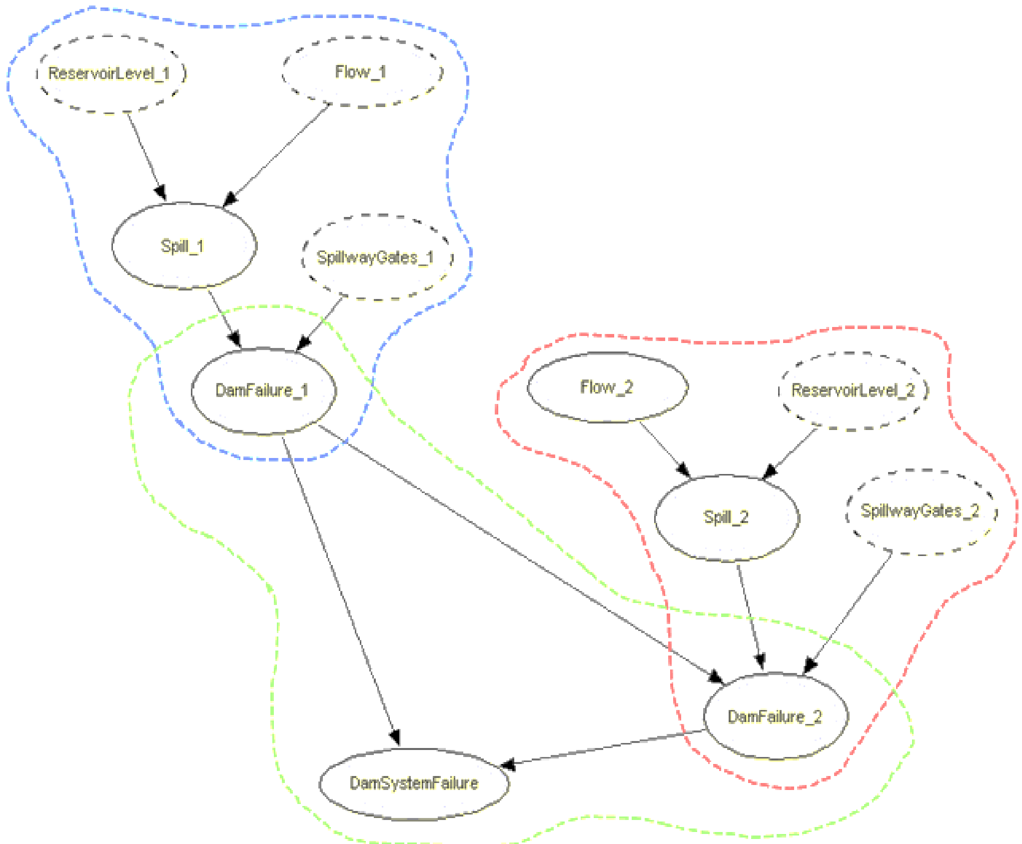


Fig.65: BN of two series reservoirs of independent inflows decomposed to three sub-networks

2- The system is simulated according to the system constraints (minimum and maximum reservoir capacities) and with randomly generated data for inflows and the states of the spillway gates over a period of 4000 seasons.
3- While simulating each dam, it is obvious that the dam failure may happen at different states of inflows and reservoir levels. So, combinations of these states are taken into consideration.
4- In this simulation, inflow of the first dam is supposed to have three different states (low, intermediate, and high), and reservoir level of the first dam is also having three different states (low, intermediate, and high). Combination of states means, for example, to have a combination of high inflow with intermediate reservoir level with a failed gate at the spill event.
5- While defining the states of the first dam in the simulation stage, we may have five combinations of states (i.e. scenarios) of interest for the first dam. These five scenarios, which are all counting for the failure probability of the first dam, are defined as follows in Table 13:

	Inflow	Reservoir Level	Gates
Scenario 1	Low	Low	Failed to open
Scenario 2	Intermediate	Intermediate	Failed to open
Scenario 3	High	High	Failed to open
Scenario 4	Intermediate	High	Failed to open
Scenario 5	High	Intermediate	Failed to open

Table 13: Scenarios of the first dam reservoir

6- For these combinations of states (scenarios), a Markovian Transition Probability Matrix (TPM) should be constructed for the first dam scenarios, and steady state probability distribution, of possible scenarios of interest, should also be estimated. In real world, TPM can be concluded from the operation of the dam, or from its exact simulation. It is also possible to mimic the possible scenarios by randomly generating the Markov TPM for the first dam with five Markovian states. Fig.66 shows an example of a five state Markov Chain for the scenarios of interest of the first dam. Fig.67 also shows a randomly generated Markov Chain for the five scenarios of interest of the first dam.

7- The steady state probability distribution of the five different states of Dam1 (Dam1 scenarios, or combinations of states) is estimated from simulation and fed into the BN representation of the first dam. This accounts for the steady state probabilities of occurrence of each of the five scenarios for the first dam.

8- For the second dam, the same procedure is followed to simulate the dam, and to estimate or randomly generate the Transition Probability Matrix for its possible scenarios of interest. But, this dam will contain seven scenarios (combinations of states) of interest, as the inflow of this dam depends also on the outflow of the first dam, which may add two more states of interest with the increased inflow rate. Fig.68 shows an example of a seven state Markov Chain for the scenarios of interest of the second dam. Fig.69 also shows a randomly generated Markov Chain for the seven scenarios of interest of the second dam.

9- At this point, the simulation results of both dams and the steady state probability distributions of the scenarios of interest (combinations of states) of both dams are ready to be fed into the higher level simplified BN shown in Fig.70 and Fig.71 to start predicting system failure.

10- The simulation results, and steady state probability distribution of Markovian states (estimated from simulation) are the main sources of quantifying the basic and conditional probability tables of the higher level BN shown in Fig.71, see Table 14 for basic and conditional probability tables of the higher level BN. Quantification is about determining the probabilities of occurrence of the states (scenarios) at which the first dam fails, the probabilities of occurrence of the states (scenarios) at which the second dam fails, and the probabilities of occurrence of the states (scenarios) at which both dams fail.

11- According to the simulation procedure that was followed, and the **randomly generated Markov Chain Probability Matrices**, the probability of system failure estimated from the higher level BN is 0.42%. This probability value is different than what was estimated from the SSBN approach because of the use of randomly generated Markov Transition Probability Matrices. These randomly generated data add another source of uncertainty that affects the final results. If more data is available about probability distribution and actual transitions among states, instead of the randomly generated Markov Chains, more accurate results will be obtained from the MCSSBN. The use of randomly generated Markov Chains here mimics the dependence on logic inference and/or expert judgement that may affect the results by adding sources of uncertainty that may lead to overestimates or underestimates.

12- Till this point, a low level BN was represented and decomposed to sub-networks [Fig.65]. The decomposed sub-networks are simulated; a high level Markov chain is constructed for every decomposed sub-network to represent different scenarios of interest (combinations of states) [Fig.66 and Fig.68]. A higher level BN is represented for the entire system and fed from simulation of both dams, and Markov Chains (which should also be estimated from simulation) [Fig.70 and Fig.71].

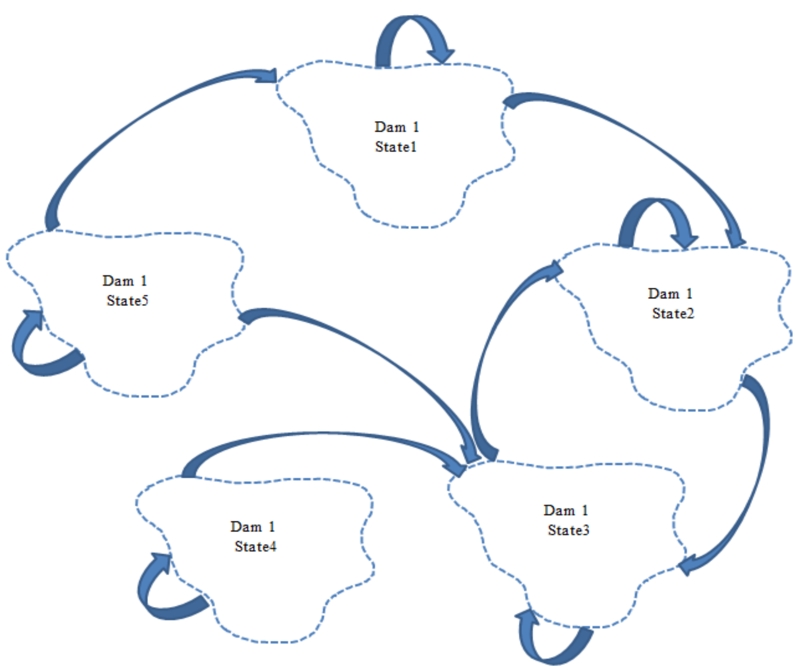


Fig.66: An example of a Markov Chain for a five scenario BN sub-network of the first reservoir

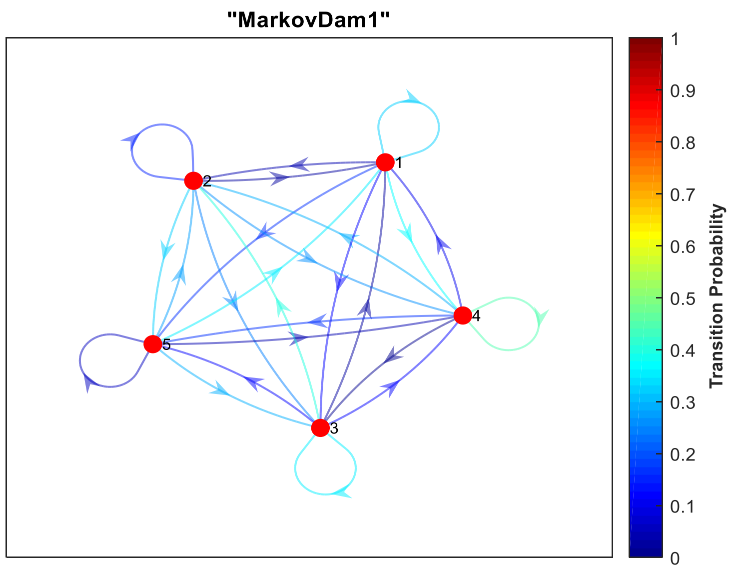


Fig.67: Randomly generated Markov Chain for the five scenario BN sub-network of the first reservoir

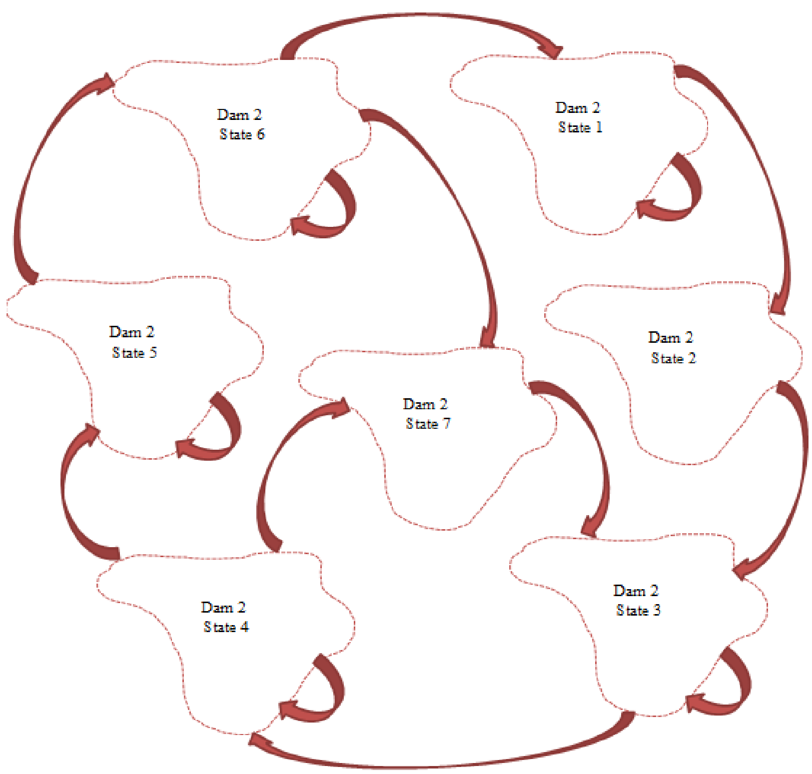


Fig.68: An example of a Markov Chain for a seven scenario BN sub-network of the second reservoir

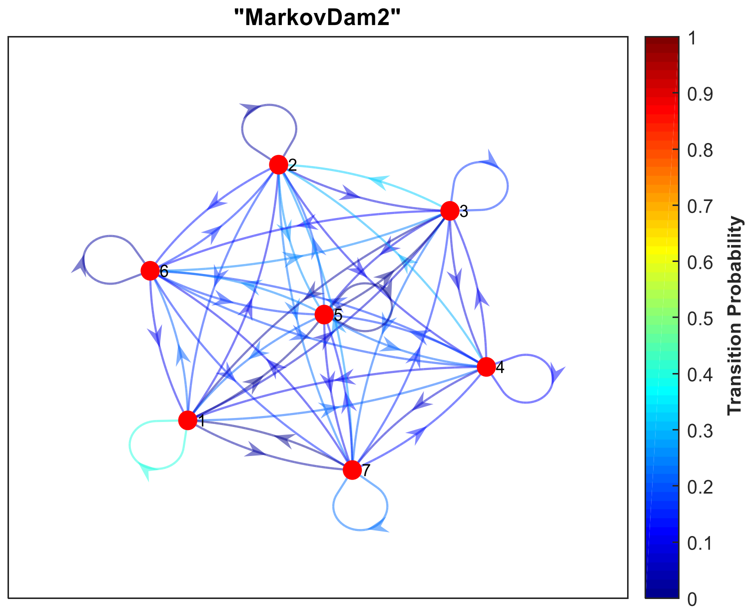


Fig.69: Randomly generated Markov Chain for the seven scenario BN sub-network of the second reservoir

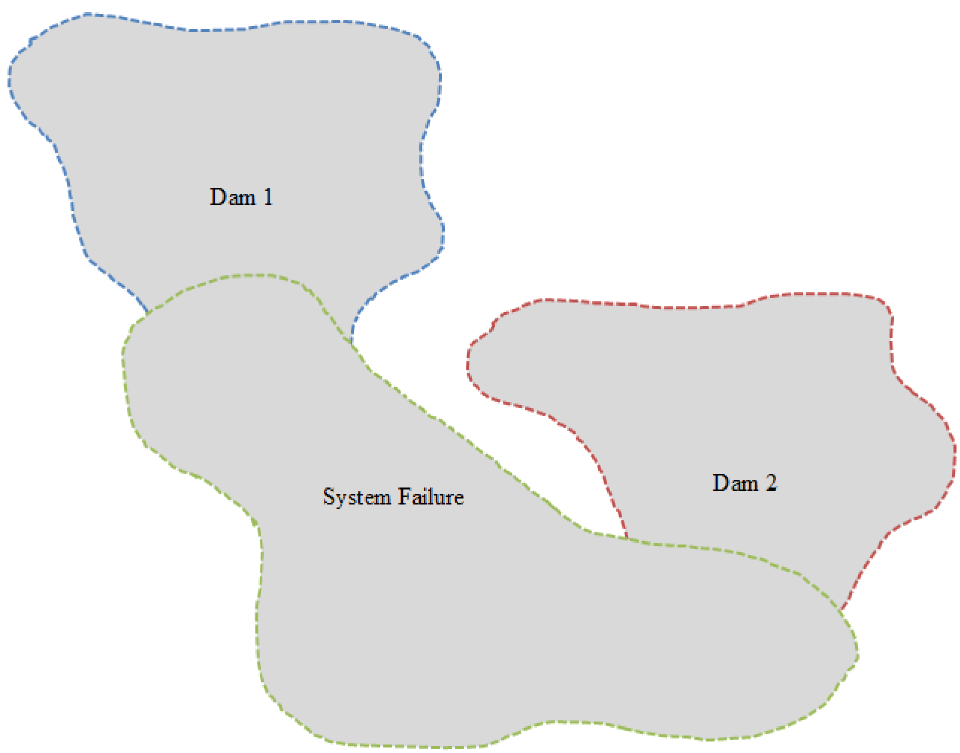


Fig.70: Higher level BN for two reservoir system with three sub-networks

13- In the higher level BN in Fig.71 and with the evidence that the system has failed, the states of both dams that are more contributing to the system failure can be identified. Knowing the main contributors to the system failure, and going back to the simulation and state definition stage, will let the decision maker know more information about the contributors to system failure. In Fig.72, it can be seen that, with the evidence of system failure, and according to the randomly generated transition probability matrices, the main contributors to system failure are STATE 3 (high inflow, and high reservoir level) in the first dam of more than 38% probability, and STATE 7 (very high inflow, and high reservoir level) in the second dam of more than 38% probability.

14- If any new data are available and the system is required to be updated, the sub-network of the dam that was affected by the change will be re-simulated, not the entire network. This will allow for building a new TPM for the dam (sub-network) having updated data, and getting all updated probabilistic results from its simulation. Then, the new probabilistic data is fed to the higher level BN for updated prediction of system failure. It is up to the decision makers, according to their expertise, to re-simulate the system sub-networks every season, every year, or even every month, to have more updated data and more accurate and reliable prediction results.

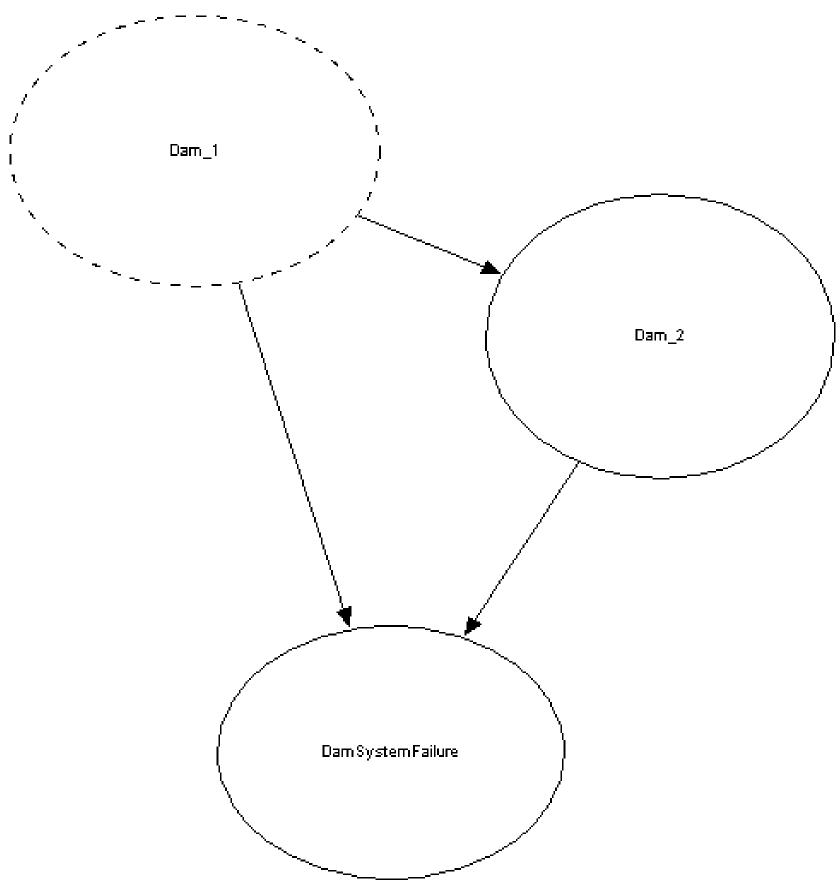


Fig.71: Higher level BN for two reservoir system in Hugin Lite

Dam_2

Dam 1	state1	state2	state3	state4	state5
state1	0.1497	0.1497	0.1497	0.1497	0.1497
state2	0.1799	0.1799	0.1799	0.1799	0.1799
state3	0.1179	0.1179	0.1179	0.1179	0.1179
state4	0.1448	0.1448	0.1448	0.1448	0.1448
state5	0.1227	0.1227	0.1227	0.1227	0.1227
state6	0.14	0.14	0.14	0.14	0.14
state7	0.1451	0.1451	0.1451	0.1451	0.1451

Dam_1

state1	0.1389
state2	0.24
state3	0.1945
state4	0.2543
state5	0.1724

DamSystemFailure

Dam 2	state1					state2				
Dam 1	state1	state2	state3	state4	state5	state1	state2	state3	state4	state5
Failure	0	0	0.0065	0.002	0.0037	0	0	0.0065	0.002	0.0037
NoFailure	1	1	0.9935	0.998	0.9963	1	1	0.9935	0.998	0.9963

Dam 2	state3					state4				
Dam 1	state1	state2	state3	state4	state5	state1	state2	state3	state4	state5
Failure	0	0	0.0065	0.002	0.0037	0	0	0.0065	0.002	0.0037
NoFailure	1	1	0.9935	0.998	0.9963	1	1	0.9935	0.998	0.9963

Dam 2	state5					state6				
Dam 1	state1	state2	state3	state4	state5	state1	state2	state3	state4	state5
Failure	0	0	0.0065	0.002	0.0037	0.0037	0.0037	0.0102	0.0057	0.0075
NoFailure	1	1	0.9935	0.998	0.9963	0.9963	0.9963	0.9898	0.9943	0.9925

Dam 2	state7				
Dam 1	state1	state2	state3	state4	state5
Failure	0.0088	0.0088	0.015	0.0108	0.0125
NoFailure	0.9912	0.9912	0.985	0.9892	0.9875

Table 14: Basic and Conditional Probability Tables for the higher level BN for two dam reservoirs

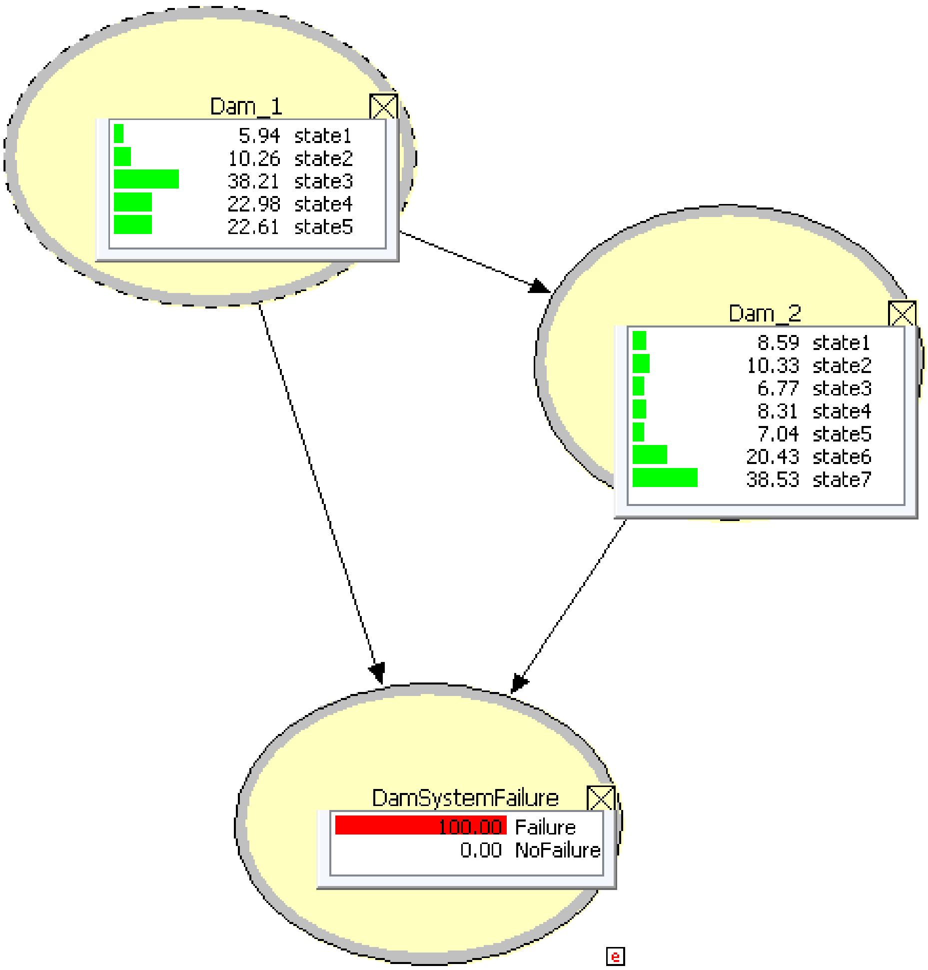


Fig.72: The higher level BN given the evidence that system failure took place

15- To compare the MCSSBN and SSBN results while **using probability estimates from exact simulations**, the steady state probability distributions of the different scenarios of interest of Dam1 and Dam2 are estimated from the simulation stage, and used to quantify the BN probability tables. **It is found that the system failure probability under the same operational conditions is about 1.21%,** which is almost half what was obtained in the SSBN case. The main difference is that only the scenarios (combinations of states) of interest are used in the BN representation of MCSSBN, which makes a downsizing for the results to be within the scenarios of interest taken by the decision maker. It is up to the decision maker to include as much scenarios of interest as possible to study and analyze the system failure. Increasing the number of scenarios of interest will result in more accurate estimates, and approaching the same results of SSBN. The distinction of the MCSSBN over the SSBN is having the ability to predict the system failure with different operation scenarios using transition probability matrices.

5.7 MCSSBN Second Approach for Two Series Reservoirs

In this section, the second approach of MCSSBN, i.e. low level Markov Chains, high level BNs, and higher level Markov Chain, is applied to a system of two series reservoirs of independent inflows shown in Fig.73.

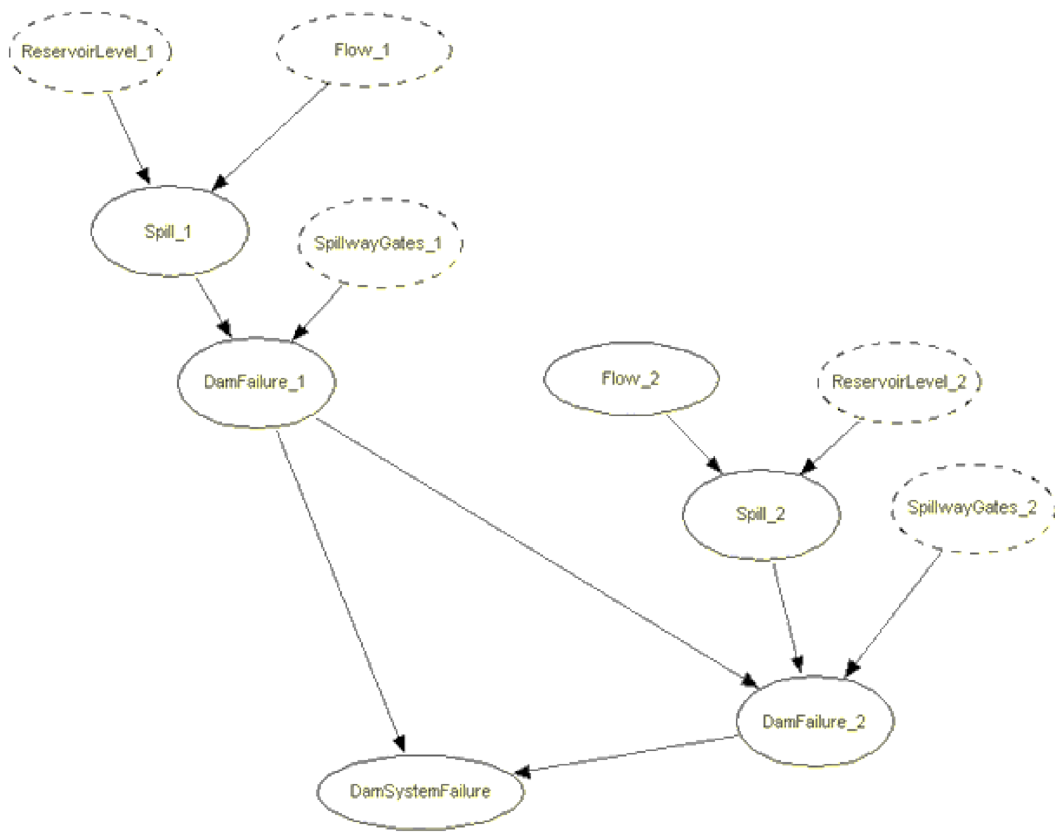


Fig.73: BN of two series reservoirs of independent inflows

In this approach, the following steps are followed to apply the MCSSBN concept:

1- The two reservoir system is decomposed to three sub-systems, the first reservoir sub-system, the second reservoir sub-system, and the system failure sub-system. See Fig.65
2- The system is simulated according to the system constraints (minimum and maximum reservoir capacities) and with randomly generated data for inflows and the states of the spillway gates over a period of 4000 seasons.
3- While simulating each dam, it is obvious that the dam failure may happen at different states of inflows and reservoir levels.
4- In this simulation, inflow of the first dam is supposed to have three different states (low, intermediate, and high), and reservoir level of the first dam also has three different states

(low, intermediate, and high). While for the second dam, the inflow is supposed to have four states (low, intermediate, high, and very high), and its reservoir level is of three states (low, intermediate, and high). The fourth state of the inflow comes from the fact that the inflow of the second dam is affected by the releases of the first dam (because they are connected in series in this case).

5- In this approach, instead of having combinations of states (i.e. scenarios) for each dam like the first approach, the node of every state variable will have its own lower level Markovian states and chain. The state variables in this case are the inflow rate of the first dam, the reservoir level of the first dam, the inflow rate of the second dam, and the reservoir level of the second dam.

6- For every state variable, a Markovian Transition Probability Matrix (TPM) should be constructed. In real world, TPM can be estimated from the operation of the dam, or from its exact simulation. The Markov TPM may also be randomly generated for each of the four state variable nodes. See Fig.74, Fig.75, Fig.76, and Fig.77 for randomly generated Markov Chains for the inflow for the first dam, the inflow of the second dam, reservoir level of the first dam, and reservoir level of the second dam, respectively.

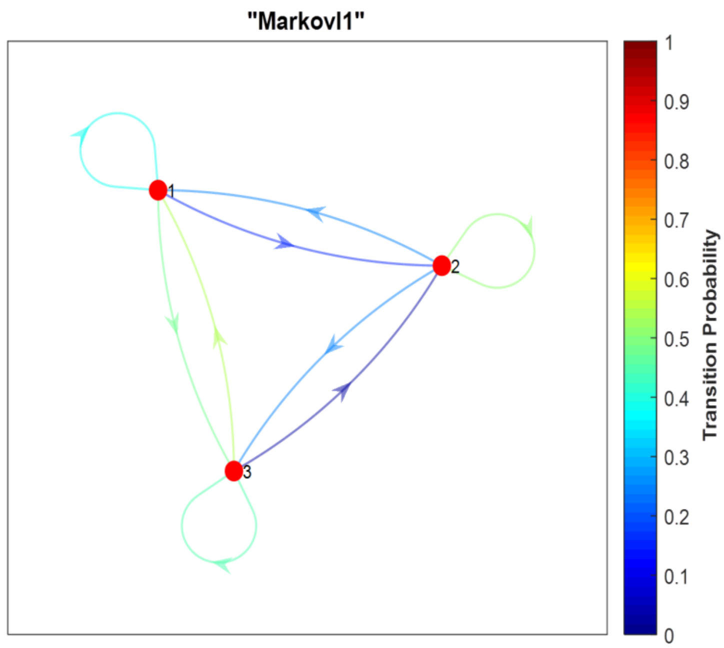


Fig.74: Randomly generated Markov Chain for the three state inflow of the first dam

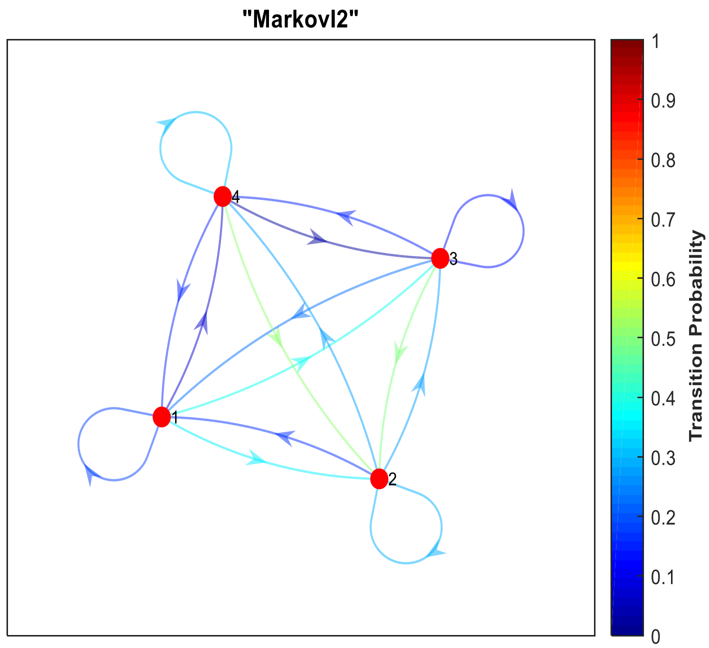


Fig.75: Randomly generated Markov Chain for the four state inflow of the second dam

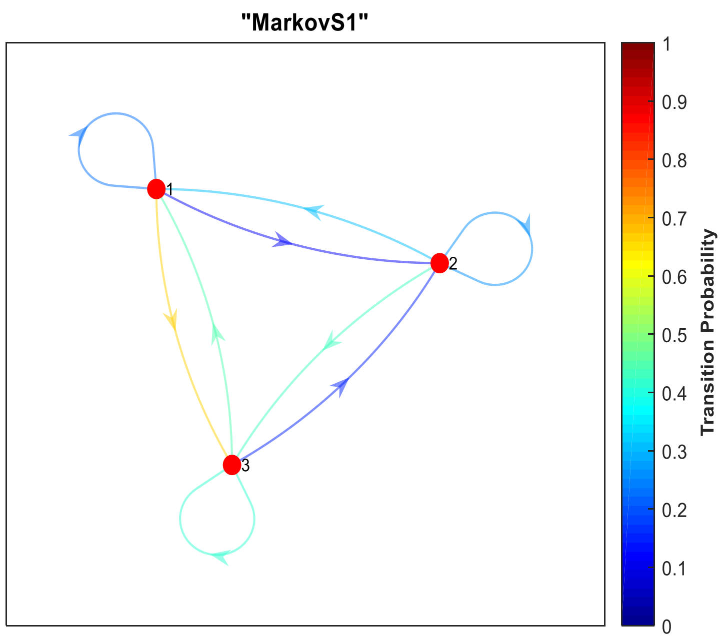


Fig.76: Randomly generated Markov Chain for the three state reservoir level (storage) of the first dam

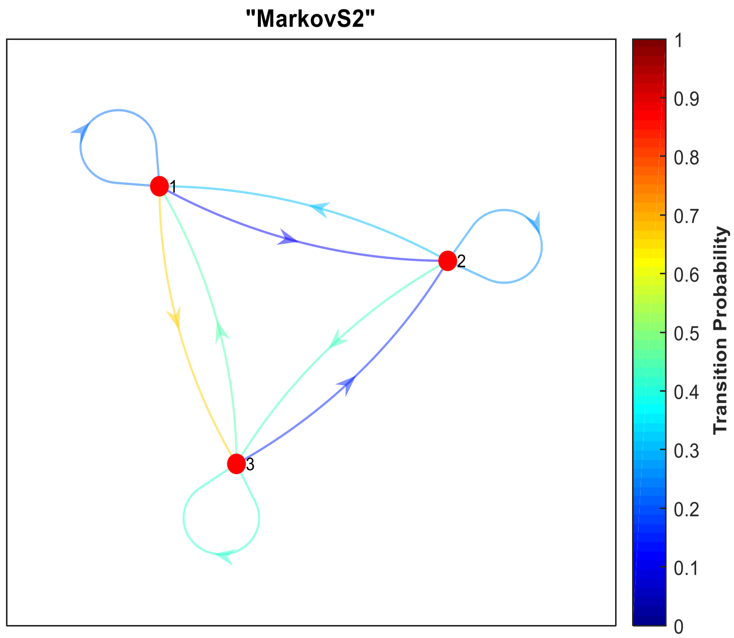


Fig.77: Randomly generated Markov Chain for the three state reservoir level (storage) of the second dam

7- The steady state probability distributions of the different states of the four state variables are estimated from simulation in order to be fed into the BN representation of the two reservoir system. The Markov transition probability matrices may also be obtained for the states of all four state variables.

8- At this point, the simulation results of both dams and the steady state probability distributions of the four state variables in the system are ready to be fed to the BN of the system, shown in Fig.73, to start predicting the system failure.

9- The low level Markov Chains of the state variables (obtained from simulation), along with the simulation results, are the main sources of quantifying the basic and conditional probability tables of the BN of the system shown in Table 15, which is considered a high level BN in this approach (as it contains lower level Markov Chains). Quantification is about determining the probabilities of occurrence of the states at which the first dam fails, the probabilities of occurrence of the states at which the second dam fails, and the probabilities of occurrence of the states at which both dams fail.

10- According to the simulation procedure that was followed, and the **randomly generated Markov Chain Probability Matrices**, the probability of system failure estimated from the high level BN is 0.26% as shown in Fig.78. This probability estimate is different than what was estimated from the SSBN approach because of the use of randomly generated Markov Transition Probability Matrices. These randomly generated data add another source of uncertainty that affects the final results. If more data is available about probability distribution and actual transitions among states, instead of the randomly generated Markov Chains, more accurate results will be obtained from the MCSSBN. The use of randomly generated Markov Chains here mimics the dependence on logic inference and/or expert judgement that may affect the system results by adding sources of uncertainty that may lead to overestimates or underestimates.

ReservoirLevel_2

State1	0.345
State2	0.1556
State3	0.4995

DamFailure_1

SpillwayGates	Open		FailedtoOpen	
Spill_1	Spill	NoSpill	Spill	NoSpill
Failure	0	0	1	0
NoFailure	1	1	0	1

DamSystemFailure

DamFailure_2	Failure		NoFailure	
DamFailure_1	Failure	NoFailure	Failure	NoFailure
Fail	1	1	1	0
NoFail	0	0	0	1

SpillwayGates_1

Open	0.4982
FailedtoOpen	0.5018

ReservoirLevel_1

Satet1	0.345
Satet2	0.1556
State3	0.4995

Spill_1

Flow_1	State1			Satet2			State3		
ReservoirLevel	Satet1	Satet2	State3	Satet1	Satet2	State3	Satet1	Satet2	State3
Spill	0	0	0	0	0	0.0027	0	0.0073	0.0123
NoSpill	1	1	1	1	1	0.9973	1	0.9927	0.9877

Flow_1

State1	0.4284
Satet2	0.1458
State3	0.4258

DamFailure_2

DamFailure_1	Failure				NoFailure			
Spill_2	Spill		NoSpill		Spill		NoSpill	
SpillwayGates	Open	FailedtoOp	Open	FailedtoOp	Open	FailedtoOp	Open	FailedtoOp
Failure	0.5	1	0	0.5	0	1	0	0
NoFailure	0.5	0	1	0.5	1	0	1	1

SpillwayGates_2

Open	0.5052
FailedtoOpen	0.4948

Flow_2

State1	0.1777
State2	0.3937
Satet3	0.2099
State4	0.2187

Spill_2

Flow_2	State1			State2			Satet3			State4		
ReservoirLevel	State1	State2	State3	State1	State2	State3	State1	State2	State3	State1	State2	State3
Spill	0	0	0	0	0	0	0	0	0	0	0.006	0.0155
NoSpill	1	1	1	1	1	1	1	1	1	1	0.994	0.9845

Table 15: BPTs and CPTs of MCSSBN second approach for two series dam reservoirs of independent inflows

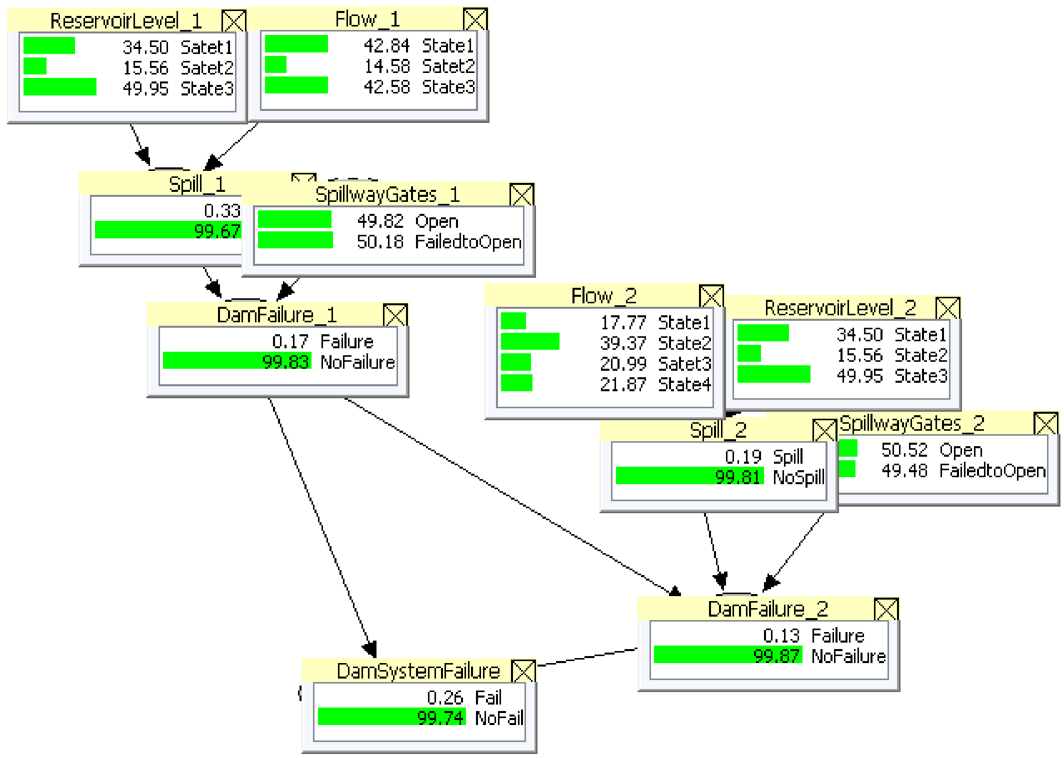


Fig.78: BN with failure probabilities of a system of two series independent reservoirs using MCSSBN second approach

11- Till this point, low level Markov Chains were represented, while a high level BN, which is decomposed to sub-networks shown in Fig.65, is simulated. Having the evidence that system has failed, and by using the Bayesian inference, the main contributors to system failure can be identified. Knowing the main contributors to system failure, and going back to the simulation and state definition stage, will let the decision maker know more information about the contributors to system failure. In Fig.79, it can be seen that, with the evidence of system failure, and according to randomly generated transition probability matrices, the main contributors to system failure are STATE 3 of the inflow of the first dam (high inflow rate), STATE 3 of the reservoir level of the first dam (high reservoir level), STATE 4 of the inflow of the second dam (very high inflow rate), and STATE 3 of the reservoir level of the second dam (high reservoir level).

12- At every time step, the high level BN is used to predict the system failure during different combinations of states (scenarios) for the entire network, not for every dam like in the first approach, depending on the transition probabilities among states of the state variables. For example, in Fig.80, with the evidence that the first dam has an intermediate inflow, while its reservoir has a high level storage, and this happens when the second dam has a very high inflow, while its reservoir level is at low storage, the posterior probability of system failure, given this combination of evidences, is estimated to be 0.14%.

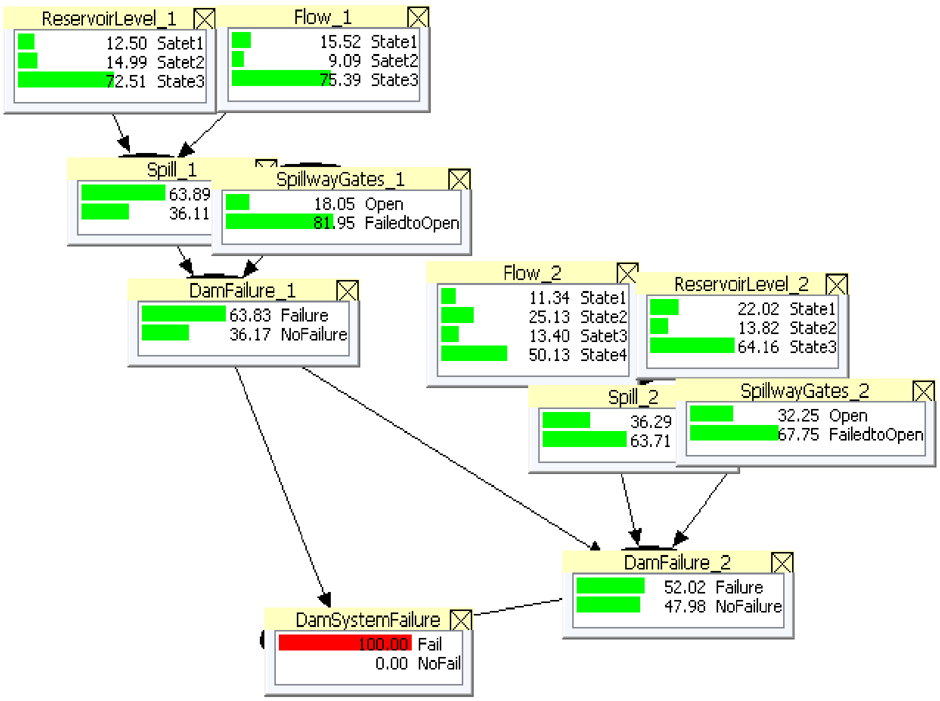


Fig.79: Main contributors to system failure of a system of two series reservoirs using MCSSBN second approach

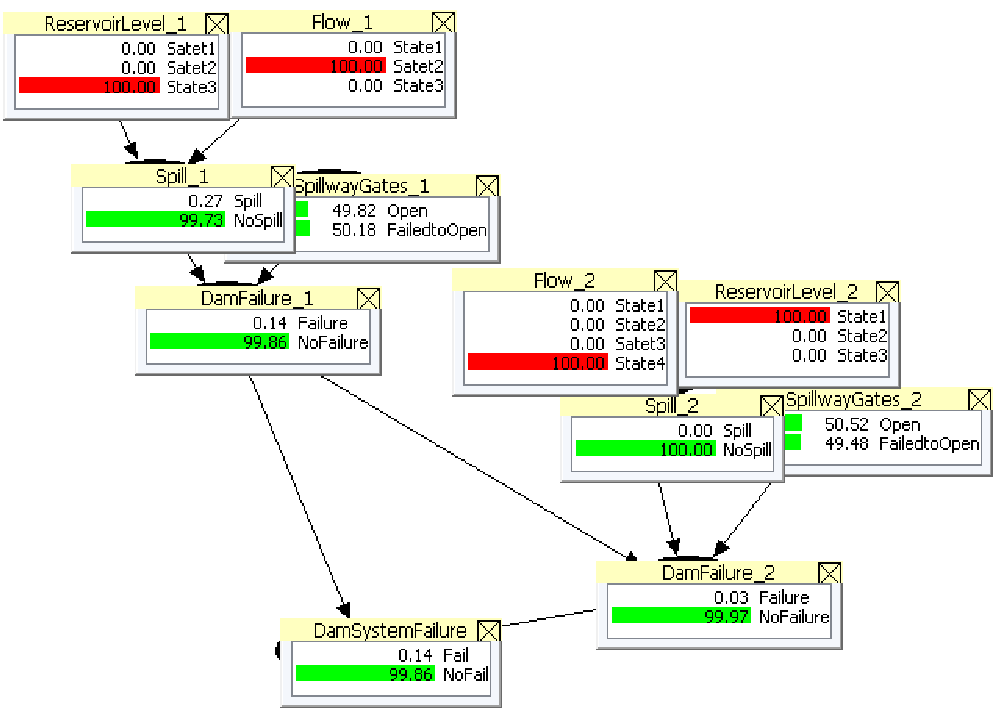


Fig.80: Posterior probability of system failure given some evidences in a system of two series reservoirs using MCSSBN second approach

13- Now, the entire system can be represented with a higher level Markov Chain that shows the dynamic scenarios for different combinations of states for the entire system network in different time steps. Many combinations of states for the four state variables can be defined. These combinations will result in different states of excess water over reservoir capacity (spill or no spill) for both dams, along with the randomly generated states for spillway gates. Thus, the system failure, depending on Dam1 failure and Dam2 failure, will have different probabilities for different combinations of states. Fig.81 shows that the entire network can be represented as one scenario (combinations of states). This means that dynamic scenarios; or combinations of states, for the whole system network can be used to construct a new higher level Markov Chain for different scenarios at different time periods according to the operation of all system components. Fig.82 shows a higher level Markov Chain constructed for the scenarios of the entire network. At every time step, the entire network will experience a scenario (i.e. combination of states or a Markov state). In the next time step, the entire network may remain in the same situation/scenario, or experience a transition to another situation/scenario (i.e. Markov state) through transition probabilities.

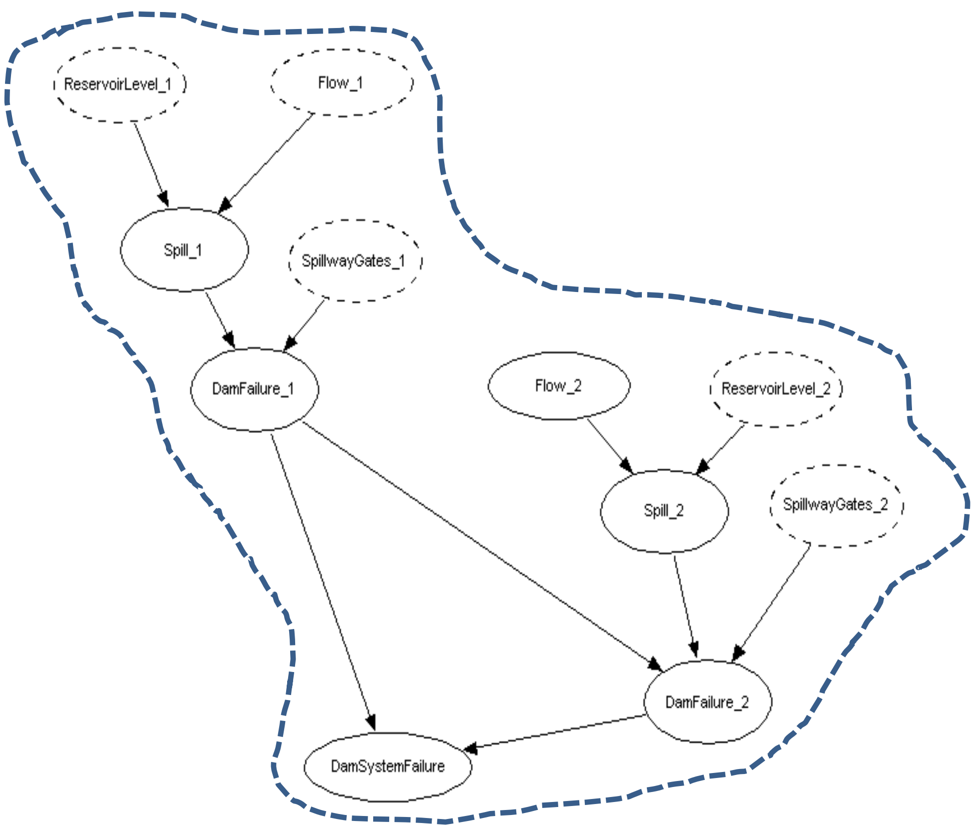


Fig.81: Higher level scenario (combination of states) for the entire network

14- If any new data is available and the system is required to be updated, the sub-network of the dam that was affected by the change will be re-simulated, not the entire network. This will allow for building new TPMs for the state variables that have updated data, along with getting all updated probabilistic results from simulation. Then, the new probabilistic data is fed into the high level BN for updated prediction of system failure. It is up to the decision makers, according to their expertise, to re-simulate the system sub-networks every season, every year, or even every month, to have more updated data and more accurate and reliable prediction results.

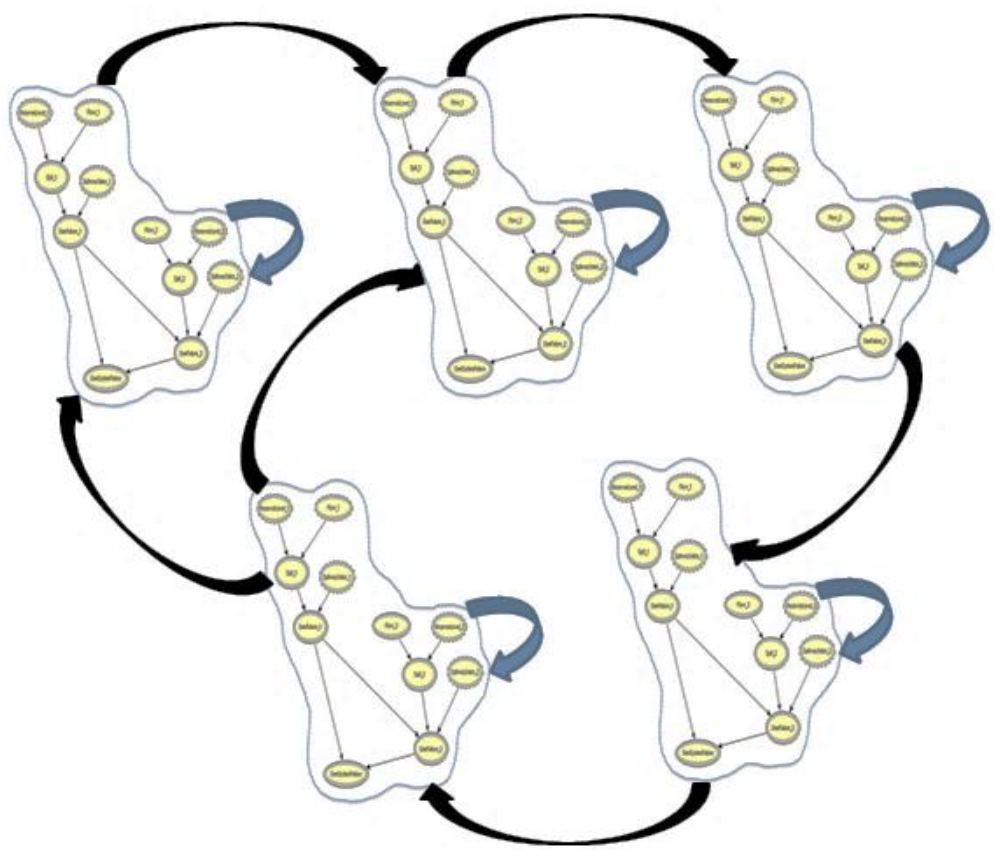


Fig.82: An example of higher level Markov Chain showing dynamic scenarios (combinations of states) for the entire network

15- To compare the MCSSBN and SSBN results while **using probability estimates from exact simulations**, the steady state probability distributions of the different states of the four state variables are estimated from the simulation, and used to quantify the BN probability tables. **It is found that the system failure probability under the same operational conditions is about 2.5%**, which is close or similar to what was obtained in the SSBN stage. The main difference is that the states' discretization used in MCSSBN includes more states for the inflow and the reservoir level nodes for both dams, which makes the results more accurate and converging to the simulation results. The distinction of the MCSSBN over the SSBN is having the ability to predict the system failure with different operation scenarios using transition probability matrices.

5.8 Summary

Cyclic/acyclic representation may facilitate the prediction process for the system during its operation. The transition probabilities among the Markovian states will facilitate the determination of the new state of the system in order to predict the probability of failure – in this research – under the new conditions, which is supposed to save more time and effort. If there is a global change for all - or most of – system variables, re-simulating the entire system will be important to probabilistically update the system. The decompositional approach – decomposing the system into sub-systems – will then be useful for simulation. MCSSBN concept has been explained in details, with possible approaches that can be used to apply the concept to most of the engineering applications. This concept is showing potential in updating the network with different scenarios, which may be taken into consideration for failure prediction. MCSSBN concept was applied, in this chapter, to systems of series dam reservoirs of independent inflows. The first and second approaches of MCSSBN were used to apply the concept, and to compare the probabilistic results with exact simulations and SSBN results, conducted in the previous chapter. The following Table 16 compares the probability of system failure for a system of two dam reservoirs connected in series and having independent inflows using different methods, i.e. simulation, SSBN using only two states per state variable, SSBN with three to four states per variable, and MCSSBN with three to four states per variable in three cases, MCSSBN first approach with scenarios of interest (five for the first dam and seven for the second dam), MCSSBN first approach with all possible scenarios for dam 1 and dam 2, and MCSSBN second approach. It is expected that increasing the number of states per variable in the states' discretization stage will allow for converging to the simulation results.

Method	**Probability of System Failure**
Simulation	2.7%
SSBN (two states/variable)	2.4%
SSBN (3-4 states/variable)	2.5%
MCSSBN 1st approach	1.21% (scenarios of interest)
	2.5% (all scenarios)
MCSSBN 2nd approach	2.5%

Table 16: Comparing probability of system failure using different methods: simulation, SSBN, and MCSSBN

Both MCSSBN approaches are distinctive in representing system dynamics acquiring cyclic representation within the acyclic BN graph. However, the MCSSBN first approach helps the decision makers when certain possible scenarios, of the network sub-systems, are of interest. Experts, according to their experience, may choose to analyze the system with some scenarios of interest that are most probable to happen. The first approach is also distinctive in overcoming the obstacle of BN of being directed graph. If new marginal data is available for any intermediate system node, there is a problem in updating the BN in both directions (bottom-top, and top-bottom). In the MCSSBN first approach, the sub-network, of which the update belongs to, is re-simulated with the new marginal evidence in order to get probabilistic estimates for the combinations of states (scenarios) of the sub-network, not for the system nodes. So, the aggregation of system nodes into sub-networks in the higher level BN representation overcomes this problem. The second approach of MCSSBN is more distinctive in the cases that data for state variables and system components are estimated in the lower levels. However, the MCSSBN second approach is expected to be complicated in very large complex systems in which the Markov Chain representation will be for a huge number of system variables. Moreover, updating the high level BN is challenging in this approach when new marginal data is available for intermediate nodes. Accordingly, this approach may be more efficient for future forecasting and determination of different scenarios, but not for decision making.

It can be concluded that supporting the BN with both simulation and Markov Chains makes the Bayesian analysis more mature for complex engineering networks. MCSSBN is a higher level concept for the decomposition based system analysis.

In the next chapter, a real-world case study of Mountain Chute Dam, operated by Ontario Power Generation (OPG), is represented. As the data available for this dam are limited, it is shown how elicited logic inference and expert judgement can be used to quantify the system's BN for failure analysis purposes.

CHAPTER 6

A Real-World Case Study: Mountain Chute Dam

6.1 Introduction

This chapter deals with a real-world case study of Mountain Chute Dam in Ontario. In this system, a number of system variables, nodes, and interactions among system components is introduced. Such a system is considered to be complex according to the number of components that it includes, and the complex interrelations among these components. Estimating failure probability of this system may be challenging using simulation, especially that this system has very limited data available, which is an obstacle in probabilistic failure analysis of the system. Accordingly, any proposed methodology that relies on simulation like SSBN and MCSSBN methods to simulate system decompositions is challenging when data is scarce. Using logically inferred data and eliciting information from experts may assist in quantifying the BN of the system. This may facilitate the prediction of system failure and identifying the main contributors to system failure that may be taken care of in the future. The results from these two information sources are compared. Using these sources of information may also help in estimating some scenarios of operation for the system under study which may help in identifying the main contributors to system failure in different scenarios/situations.

6.2 BN of Mountain Chute

In section 4.3.2, Mountain Chute Dam and Generating Station are briefly explained. Mountain Chute Dam is a part of Madawaska River System of Dams, and has four main structures: main concrete dam of 55m high having a power generating station, a weir (Mackie creek weir), and two earthen block dams (North dam and White Fish Draw dam). System components were illustrated in order to build the BN for this dam, which is shown is Fig.37a in section 4.3.2. However, the BN of Mountain Chute is modified in this section to give more details on the interdependencies among system components and nodes. The new constructed BN for Mountain Chute dam and generating station is represented as follows in Fig.83 (see Appendix 3 for a larger scale figure). The nodes in this BN represent: rain/precipitation, inflow, flood severity, earthquakes/seismic events, ice loading, efficiency of the weir, water pressure, geology and rock type, spill event, electromechanical equipment including hydropower turbines, head gates, sliding of the main dam, stability of the earthen dams, seepage in the earthen dams, drainage in the main dam, sluice gates of the main dam, overtopping of the main dam, capacity adequacy of the sluice way, generated electric power, vegetation control around the earthen dams, animal burrows control around the earthen dams, main dam failure, and earthen dams failure.

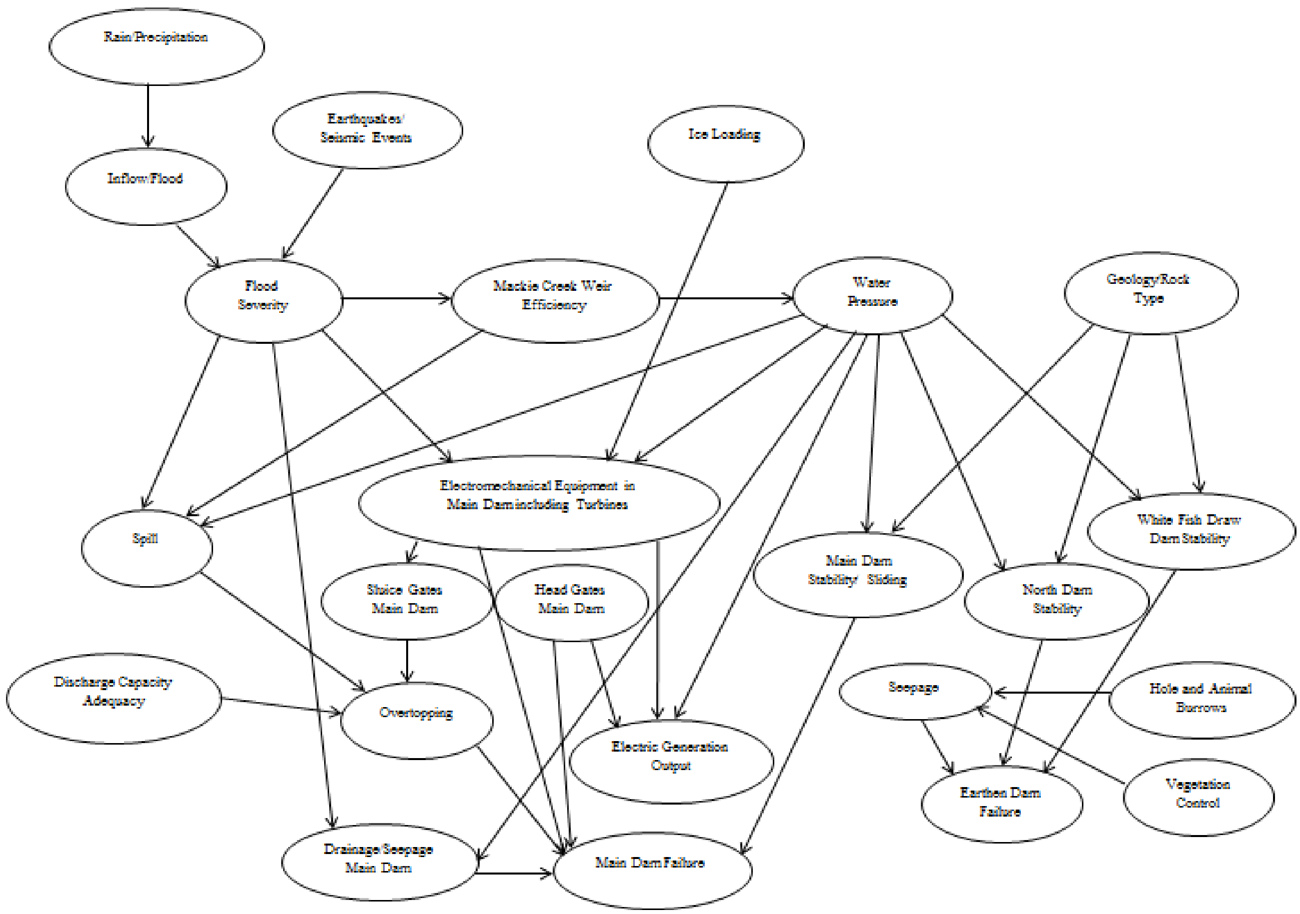


Fig.83: BN of Mountain Chute dam and generating station

To better understand this BN, it can be analysed as follows:

1- This BN consists of 24 nodes (events, components, or variables, explained next), and combining such multiple factors is the major advantage of the proposed BN based method.
2- The main purpose of this BN is predicting the probability of failure of the main dam from overtopping, seepage, or sliding. Moreover, it determines the probability of failure of the earthen block dams, controlling the reservoir of Mountain Chute, resulting from the threats of seepage or sliding. The posterior capability of the BN may also allow for identifying the main contributors to any evidence in the network.
3- The basic events are rain, ice loading limits, earthquakes, geological and rock stability, vegetation control of earthen dams, and control of animal burrows in earthen dams (as the main dam is concrete).
4- The amount of rain affects the inflow to the Mountain Chute Dam. The inflow is considered a flood if it exceeded certain limits. This flood may be severe or of less severity.

5- Flood severity is also affected by the seismic actions and earthquakes.
6- The flood, with certain severity level, is controlled by Mackie Creek Weir. Controlling the inflow is to reduce the river flow rate and prevent severe floods from reaching the dam reservoir. The weir may be efficient or not, depending on the flood severity.
7- After passing the weir, the water is blocked by two earthen block dams, and the main concrete dam with its generating station, and ready to be controlled by the dam head gates. This means there is water pressure behind the dams that may affect their stability.
8- The geological and rock stability for the structure of the three dams should be considered as it affects the sliding of the dams. Sliding is one of the causes of dam breach failure.
9- Ice loading, water pressure, and flood severity are connected to the electromechanical equipment (including turbines). For example, the ice loading is affecting the failure of the mechanical equipment, and with a severe flood and high water pressure, this could result in a failure in operating the mechanical components, which leads to dam operation failure.
10- For the electric power generation, the head gates are opened to let the water flow through the penstock to generate electricity from hydropower turbines. If the head gates failed to open, this is considered a major factor of failure of the main dam, especially, if the water pressure is high in the upstream side of the dam, and this may affect the dam stability. And for sure, this will affect the amount of power generated by the turbines.
11- The flood severity, the weir efficiency in controlling the inflow to the reservoir, and the water pressure, are all affecting the probability to have spill in the main dam. The spill is the amount of water that exceeds the reservoir maximum capacity limit. This amount should be released from the upstream side to the downstream side through the spillway (sluiceway) gates, or an overtopping failure will take place.
12- The amount of water spill is also related to the capacity of sluiceway, which may not be adequate for that amount of water to be discharged, and the condition of the sluice gate (open, or failed to open due to electromechanical failure). If there is a requirement to spill while there is no way for the water to be released from behind the main dam because of the inadequate capacity of the sluiceway, or because the sluice gate failed to open, there is an increasing probability (risk) of overtopping failure.
13- For the main dam, severe floods with increased water pressure increases the possibility to have seepage in the body of the main dam. If the seepage is not controlled and monitored through a drain system with a drain inspection tunnel, this could result in an increasing risk that reduces the remaining life time of the dam. Seepage may also result in dam breaching failure.

14- For the earthen dams in Mountain Chute, seepage may take place because of uncontrolled vegetation and animal burrows and holes in the vicinity of the dams. Seepage is an increasing risk for seepage piping and dam breach failure.

6.3 Quantifying the BN Using Available Data and Logic Inference

In case only limited data are available for nodes/variables of the network, and running simulations is complicated for such networks, the data available along with expert judgement and logic inference may be used for quantifying the basic and conditional probability tables (BPTs and CPTs) of the BN. This section focuses on using the logic inference in quantifying the BN and predicting the probability of failure of Mountain Chute dam. And the next section focuses on improving the results using expert judgement.

According to the data available from Ontario Power Generation (OPG), who are the dam operators for Mountain Chute Dam and Generating Station, the following probabilistic information are estimated:

- Over a range of 84 years in the area of Mountain Chute Dam (even before construction), the rain depth can be classified as low (less than 60 mm), or high (more than 60 mm) with the following probabilities:

  $$P(\text{rain depth} = \text{low} < 60\text{ mm}) = 429/1204$$
  $$P(\text{rain depth} = \text{high} > 60\text{ mm}) = 775/1204$$

  These data are concluded from monthly data over 84 years, and it can be useful in determining the probability of having severe flood, or flood with less severity. It is important to mention that low and high rain depths are assumed discretized states to help quantifying the BN of the system. For more accurate results, more discretized states can be assumed for this node.
- Mountain Chute has two hydro power turbines (units 1 & 2), with capacity (rating) of 75 MVA each. For each turbine, the electric output (in MW) is assumed to be LOW if it is less than 30 MW, INTERMEDIATE if it is less than 60 MW, and HIGH electric output if higher than or equal 60 MW. According to OPG analysis for the relation between different head levels and the electric output from each turbine depending on the discharge in the penstock of each unit, the following probabilistic information were estimated for all different possibilities:

  $$P(\text{low electric output}) = 360/1006$$
  $$P(\text{intermediate electric output}) = 360/1006$$
  $$P(\text{high electric output}) = 286/1006$$
  $$P(\text{low elec. output} \mid \text{low head}) = 120/317$$
  $$P(\text{Intermediate elec. output} \mid \text{low head}) = 120/317$$
  $$P(\text{high elec. output} \mid \text{low head}) = 77/317$$
  $$P(\text{low elec. output} \mid \text{intermediate head}) = 120/335$$

P(intermediate elec. output | intermediate head) = 120 /335
P(High elec. output | intermediate head) = 95 /335
P(Low elec. output | high head) = 120 /354
P(intermediate elec. output | high head) = 120 /354
P(high elec. output | high head) = 114 /354

The maximum discharge per turbine was found to be about 220.8 CMS. This value is the maximum discharge that each penstock can withstand. The three states of electric output and water head levels (i.e. low, intermediate, and high) are assumed discretized states to help quantifying the BN of the system. For more accurate results, more discretized states can be assumed for this node.

- The efficiency of Hydro Power turbines (unit 1 & 2) is 50 %. This means that unit 1 is available for 50% of the time while unit 2 is out (for forced outage, scheduled outage, sudden outage, maintenance, or any other reason), and vice versa. So, it is considered that only one turbine is operating at any time.

6.3.1 BN Input Data and Results

In this section, the BN of Mountain Chute Dam is quantified using the limited data available, logically inferred data, and assumed data. The data available are limited to the data that was provided by OPG and discussed in section 6.3. The logically inferred data are inferred according to the understanding of the system components discussed in section 6.2.
The following Basic Probability Tables (BPTs) and Conditional Probability Tables (CPTs) shown in Table 17 are considered for determining the states of each node of the BN, where the probabilistic quantification depends on the data available, logic inferencing, and assumed data. Probabilistic data in these tables represents an estimated 100 years operation of Mountain Chute Dam.

Geology_and_RockType

Stable	0.7
Unstable	0.3

HeadGatesMainDam

Open	0.5
Closed Failed	0.5

HolesandAnimalBurrows

Controlled	0.3
NotControlled	0.7

Ice_Loading_Limit

Safe	0.583333
NotSafe	0.41667

Inflow_Flood

Rain Precepeta	Low	High
Low	0.9	0.05
Intermediate N	0.1	0.2
High	0	0.75

MackieCreekWeir_Efficiency

FloodSeverity	Severe	Normal
Efficient in cor	0.7	0.7
Not efficient	0.3	0.3

Seepage

HolesandAnima	Controlled		NotControlled	
VegetationCont	Controlled	Uncontrolle	Controlled	Uncontrolle
Exist	0	0.3	0.3	1
NoSeepage	1	0.7	0.7	0

SluiceGatesMainDam

ElectroMechEqu	Fail	NoFail
Open	0	1
Faile to open	1	0

VegetationControl

Controlled	0.3
Uncontrolled	0.7

WaterPressure

MackieCreekW(	Efficient in	Not efficie
High	0.2	0.6
Moderate Norr	0.55	0.35
Low	0.25	0.05

WhiteFishDrawDam_Stability

WaterPressure	High		Moderate Normal		Low	
Geology and F	Stable	Unstable	Stable	Unstable	Stable	Unstable
Stable	0.9	0.75	0.95	0.8	1	0.85
Unstable	0.1	0.25	0.05	0.2	0	0.15

Spill

MackieCreekW(	Efficient in controling inflow						Not efficient			
WaterPressure	High		Moderate Normal		Low		High		Moderate Normal	
FloodSeverity	Severe	Normal	Severe	Normal	Severe	Normal	Severe	Normal	Severe	Normal
Spill	0.5	0.2	0.2	0.1	0.1	0.05	1	0.6	0.7	0.4
NoSpill	0.5	0.8	0.8	0.9	0.9	0.95	0	0.4	0.3	0.6

MackieCreekW(	Not efficient	
WaterPressure	Low	
FloodSeverity	Severe	Normal
Spill	0.55	0.2
NoSpill	0.45	0.8

ElectroMechEquipmentMainDam_Including_turbines

WaterPressure	High				Moderate Normal				Low	
FloodSeverity	Severe		Normal		Severe		Normal		Severe	
Ice Loading Li	Safe	NotSafe	Safe	NotSafe	Safe	NotSafe	Safe	NotSafe	Safe	NotSafe
Fail	0.2	1	0.1	0.75	0.15	0.85	0.05	0.55	0.1	0.6
NoFail	0.8	0	0.9	0.25	0.85	0.15	0.95	0.45	0.9	0.4

WaterPressure	Low	
FloodSeverity	Normal	
Ice Loading Li	Safe	NotSafe
Fail	0	0.2
NoFail	1	0.8

FloodSeverity

Inflow Flood	Low		Intermediate Normal		High	
Earthquakes S(	Severe	Normal	Severe	Normal	Severe	Normal
Severe	0.2	0.05	0.3	0.15	1	0.3
Normal	0.8	0.95	0.7	0.85	0	0.7

MainDamFailure

Overtopping	Failure									
HeadGatesMair	Open								Closed Failed to open	
DrainageMainD	Leakage				NoLeakage				Leakage	
ElectroMechEq	Fail		NoFail		Fail		NoFail		Fail	
MainDam stabi	Stable	Unstable	Stable	Unstable	Stable	Unstable	Stable	Unstable	Stable	Unstable
Fail	1	1	1	1	1	1	1	1	1	1
NoFail	0	0	0	0	0	0	0	0	0	0

Overtopping	Failure						No Failure			
HeadGatesMair	Closed Failed to open						Open			
DrainageMainD	Leakage		NoLeakage				Leakage			
ElectroMechEq	NoFail		Fail		NoFail		Fail		NoFail	
MainDam stabi	Stable	Unstable	Stable	Unstable	Stable	Unstable	Stable	Unstable	Stable	Unstable
Fail	1	1	1	1	1	1	1	1	1	1
NoFail	0	0	0	0	0	0	0	0	0	0

Overtopping	No Failure									
HeadGatesMair	Open				Closed Failed to open					
DrainageMainD	NoLeakage				Leakage				NoLeakage	
ElectroMechEq	Fail		NoFail		Fail		NoFail		Fail	
MainDam stabi	Stable	Unstable	Stable	Unstable	Stable	Unstable	Stable	Unstable	Stable	Unstable
Fail	1	1	0	1	1	1	1	1	1	1
NoFail	0	0	1	0	0	0	0	0	0	0

MainDamFailure

Overtopping	No Failure	
HeadGatesMair	Closed Failed to open	
DrainageMainD	NoLeakage	
ElectroMechEq	NoFail	
MainDam stabi	Stable	Unstable
Fail	1	1
NoFail	0	0

MainDam_stability_Sliding

WaterPressure	High		Moderate Normal		Low	
Geology and F	Stable	Unstable	Stable	Unstable	Stable	Unstable
Stable	0.9	0.75	0.95	0.8	1	0.85
Unstable	0.1	0.25	0.05	0.2	0	0.15

NorthDam_Stability

WaterPressure	High		Moderate Normal		Low	
Geology and F	Stable	Unstable	Stable	Unstable	Stable	Unstable
Stable	0.9	0.75	0.95	0.8	1	0.85
Unstable	0.1	0.25	0.05	0.2	0	0.15

Overtopping

Spill	Spill				NoSpill			
DischargeCapa	Adequate		NotAdequate		Adequate		NotAdequate	
SluiceGatesMai	Open	Faile to op	Open	Faile to op	Open	Faile to op	Open	Faile to op
Failure	0	1	1	1	0	0	0	0
No Failure	1	0	0	0	1	1	1	1

Rain_Precepetation

Low	0.36
High	0.64

DischargeCapacityAdequacy

Adequate	0.2
NotAdequate	0.8

DrainageMainDam_Seepage

WaterPressure	High		Moderate Normal		Low	
FloodSeverity	Severe	Normal	Severe	Normal	Severe	Normal
Leakage	0.2	0.15	0.15	0.1	0.1	0.05
NoLeakage	0.8	0.85	0.85	0.9	0.9	0.95

EarthenDamsFailure

NorthDam Stal	Stable				Unstable			
WhiteFishDraw	Stable		Unstable		Stable		Unstable	
Seepage	Exist	NoSeepage	Exist	NoSeepage	Exist	NoSeepage	Exist	NoSeepage
Fail	1	0	1	1	1	1	1	1
NoFail	0	1	0	0	0	0	0	0

Earthquakes_SeismicEvents

Severe	0.1
Normal	0.9

Elec_Gen_Output

WaterPressure	High				Moderate Normal				Low			
ElectroMechEq	Fail		NoFail		Fail		NoFail		Fail		NoFail	
HeadGatesMair	Open	Closed Fai	Open	Closed Fai	Open	Closed Fai	Open	Closed Fai	Open	Closed Fai	Open	Closed Fai
Low or no ge	1	1	0	1	1	1	0.25	1	1	1	0.7	1
High	0	0	1	0	0	0	0.75	0	0	0	0.3	0

Table 17: BPTs and CPTs of the BN of Mountain Chute dam

Quantification of the above tables, according to available data, and logic inference, is explained as follows:

- Rain/Precipitation is either LOW or HIGH state. According to the available data of rain depth, LOW is about 0.36 probability, while HIGH is about 0.64 probability.
- For earthquakes/seismic events, it is supposed that the dam is built in an area with limited seismic activity. So, the probability to have severe earthquakes is limited.
- Ice loading could be considered as NOT SAFE only during the winter season, which counts for about 5 months per year. For the rest of the year, ice loading is not taken into consideration.

- Inflow states may be high, intermediate, or low depending on the rain/precipitation. Depending on logic inference, if the rain depth is low, the inflow is assumed to be low with 0.9 probability, and intermediate by 0.1, while if the rain depth is high, the inflow is assumed to be 0.75 probable to be high, 0.2 probable to be intermediate, and 0.05 low.
- Mackie Creek Weir is assumed to be efficient for 70% of the time in controlling the flood flow rate (logically inferred).
- If Mackie Creek Weir is not efficient in controlling the flood, there is an increased probability to have higher water pressure.
- For Geology and rock type stability, it is logically inferred that the dam is already constructed in a geologically stable area. Thus, the probability of having stable geological formation is assumed to be 0.7.
- The probability of having excess water more than the reservoir capacity (i.e. spill) increases with severe floods and lack of efficiency of the weir to control the flood flow rate, which will also affect the water pressure (low, normal, or high). If the weir is not efficient during a severe flood, resulting in an increased water pressure, the probability to have excess water would be 100%. The spill probability decreases with less severe floods, increased efficiency of the weir, and less water pressure.
- Failure of electromechanical equipment of the main concrete dam is affected by the non-safe ice loading limits, severe floods, and high water pressures.
- The head gates are assumed to operate for 50% of the time it is required to operate, and fail to operate for the other 50% of the time. Thus, the probability of failure (failed to open) of the head gates is taken to be 0.5 (this is an assumption because the data of maintenance/outage schedules is not available).
- Water pressure and stability of geological and rock formations affect the stability of the three dams (main concrete dam, and the two block dams).
- It is concluded from the dam's data that the sluiceway capacity is not adequate for the peak outflow of the maximum design flood (Probable Maximum Flood, PMF). Thus, the probability to have inadequate sluiceway capacity (i.e. discharge capacity adequacy node) is assumed to be 0.8 (logically inferred).
- The state of the sluice gates to be opened or closed (failed to open) depends on the state of the electromechanical equipment. If the electromechanical equipment has failure, it means that the sluice gates fail.
- The electric power generation depends on the state of the penstock head gates (open or failed to open). The hydropower turbines may also experience outage for different reasons during that time, which means that no electric output from the turbines can be generated. So, there is low or no electric power generation if the head gates of the penstock failed to open, or the turbines – which are electromechanical equipment – experience failure to operate because of forced or scheduled outages.

- The overtopping failure is assumed to take place in two events: 1- If there is excess water more than the reservoir capacity and the sluice gates failed to open (closed), even if the sluiceway discharge capacity is adequate for releasing the spill, 2- If there is excess water more than the reservoir capacity and the sluiceway discharge capacity is not adequate for releasing the spill, even if the sluice gates are opened.
- Seepage/leakage in the main dam depends on the water pressure and the flood severity. It is logically inferred that the dam is under a monitoring and inspection system that ensures no more than 0.2 probability to have leakage in the dam body with the highest water pressure and the most severe flood. Seepage/leakage is considered to be a risk of failure as it reduces the remaining service life of the dam.
- Main dam failure considers the failure of any part of the main dam sub-system. Thus, overtopping failure, instability/sliding of the main dam, leakage/seepage in the main dam body, failure in operating head gates, or any failure in electromechanical equipment, are considered cases for main dam failure. This means that any failure which makes the main dam unable to operate properly as designed, or fail to do one of its operations, is considered a failure.
- For the two earthen block dams, the vegetation and animal burrows are assumed not to be efficiently controlled by a 0.7 probability (0.3 probability of being controlled), which is an assumption because data about monitoring and maintenance schedules are not available. Inefficient control of vegetation and animal burrows/holes in the vicinity of the block dams may increase the probability of seepage piping in both of them.
- Earthen dams' failure considers the instability of any of the two dams, or existence of seepage piping in any of the dams.
- System failure happens if the main dam fails, or earthen dams fail, or both fail.

When the network is compiled using Bayesian inference on Hugin Lite software, while using the limited data available and logic inference to quantify the probability tables of the BN, it can be seen in Fig.84 that, in the life time of 100 years, the probability of the main dam failure is about 77%, and the earthen dams fail with a probability of about 68%. These probabilities are considered very high, which means that quantifying the network with logically inferred data may not be accurate for prediction results that should help the decision maker while taking decisions. It is obvious that logically inferred data is considered a source of uncertainty in predicting the system failure, as it contains limited knowledge which needs to be improved by other data sources, i.e. expert engineering judgement.

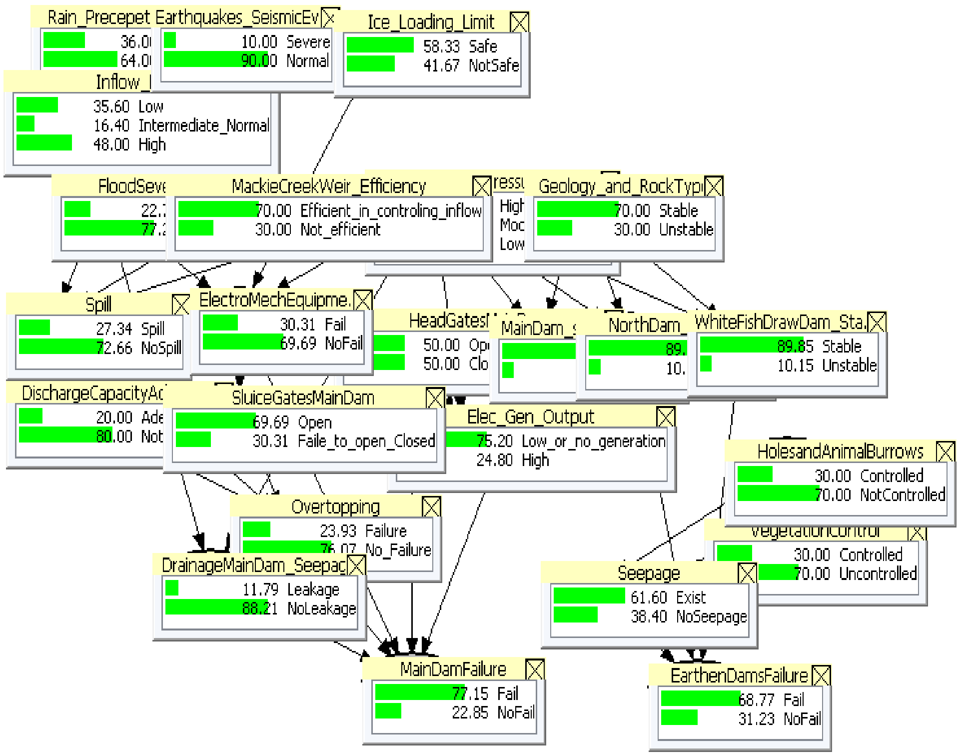


Fig.84: BN of Mountain Chute dam after compilation on Hugin Lite

From another perspective, it can be seen from the BN in Fig.85 that – given the evidence that the main dam has failed - the main contributors to the Main Dam Failure are: inadequate discharge capacity of the sluiceway of 81% probability, electromechanical equipment failure of 39% probability, head gates failure of about 65% probability, non-safe ice loading of 46.6% probability, 48.9% probability of high inflow, 64.7% probability of high rain/precipitation, about 39% probability of sluice gate failure, and 36% probability of high water pressure.

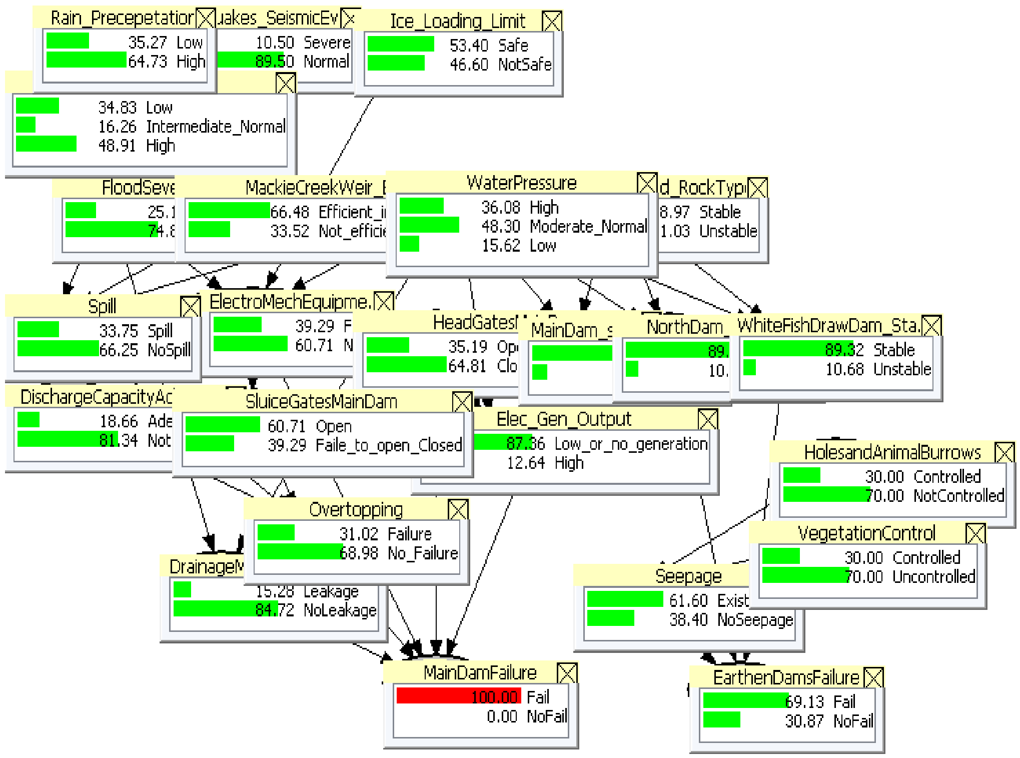


Fig.85: BN of Mountain Chute given the evidence that main dam failed

If these main contributors to the main dam failure are controlled to be within normal/safe operating conditions, the evidence can be set in the Bayesian equations to calculate the updated posterior probability for the main dam failure given these evidences. The same procedure can also be applied to the earthen dams. In Fig.86, it is shown that while setting the evidence to have most of the network nodes operating at normal/safe operating conditions, the probability of failure of the main dam falls to 5.7% probability of failure, and zero probability of failure of the earthen block dams with the efficient inspection, monitoring, and control of both of them.

This means that with the proper inspection, monitoring, control, and maintenance of the dam system, the probability of failure can be kept at lower limits (i.e. 5.7 % and 0%), even if the whole dam system is at risk (i.e. 77%, and 68%).

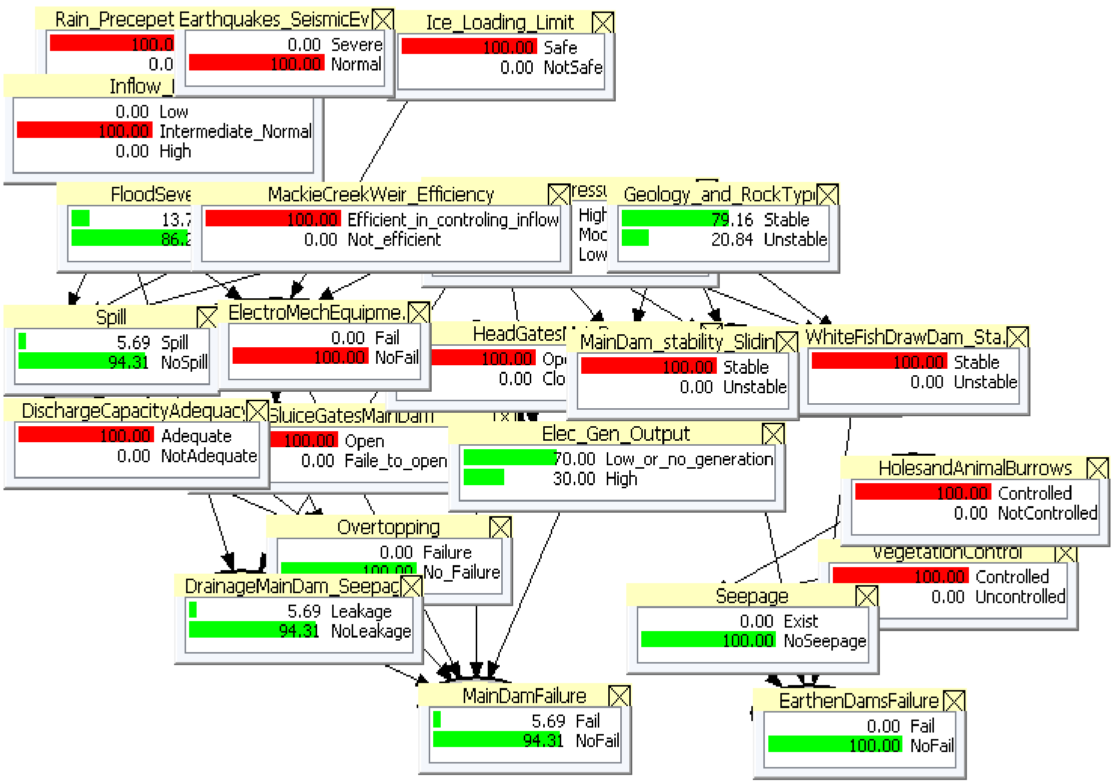


Fig.86: BN of Mountain Chute given the evidence of normal/safe operating conditions

6.4 Expert Judgement for Quantifying the BN of Mountain Chute Dam

On October 11th, 2018, a site visit was made to Mountain Chute Dam and Generating Station to meet Dr. Dehai Zhao, Technical (Civil) Production Supervisor, Plant Engineering Services - Eastern Operations, Ontario Power Generation. Andrea Verzobio, an International Visiting Graduate Student to University of Waterloo, and PhD student in the Department of Civil and Environmental Engineering at University of Strathclyde, Glasgow, Scotland, was also helping in defining a methodology for elicitation of required data for such complex networks through engineering expert judgement. Dr. Zhao was the expert who provided some information regarding dam operation. This information was beneficial in updating basic and conditional probabilities of the BN. It is important to note that all the expert judgement data used to quantify the BN, in this section, are assumed to be for 100 years of operation of Mountain Chute dam. Fig.87 and Fig.88 are site pictures to show Mountain Chute main dam and its sluice way, respectively, while Fig.89, Fig.90, and Fig.91 show a drainage collecting point in the main dam, vegetation control around the main dam, and one of the earthen block dams, respectively.


Fig.87: Mountain Chute Dam and Generating Station (sluiceway and sluice gates to the left)


Fig.88: Side view of the sluiceway and sluice gates of Mountain Chute dam

Fig.89: Collecting point of drainage in the main dam body

Fig.90: Controlled vegetation around the main concrete dam

Fig.91: One of the earthen block dams (behind the trees)

The aim is to propose a methodology for populating BNs in the case where the topology of the BN has already been defined, i.e. starting from a graphical model with all the variables described. In this case, the elicitation process is then required to extract and quantify the subjective judgments about the uncertain quantities, which are mainly the conditional probabilities that represent the interrelationships among connected nodes. In the literature, there are various protocols for probability elicitation; the methodology used here is based mainly on the one that seems the most suitable, i.e. the SRI (Stanford Research Institute) model, [108], [109], and [110].

The process for eliciting expert judgment is composed by seven stages: motivating the experts with the aim of the elicitation process, structuring the uncertain quantities in an unambiguous way, conditioning the expert's judgement to avoid cognitive biases, encoding the probability distributions, verifying the consistency of the elicited distributions, aggregating probabilities from different experts, and discretizing continuous probability distributions. To conduct an elicitation process, at least two characters are necessary: a subject, i.e. the expert, and an analyst, i.e. the interviewer. The first one provides expertise, i.e. "a person who has substantive knowledge about the events whose uncertainty is to be assessed" [108], while the second one is who take responsibility for designing and developing the process and the evaluation procedures. Starting from this protocol and according to the specific requirements of a BN, a four-stage structured methodology was developed to support the elicitation meaningfully. Each stage is presented in details by defining each phase of the process and presenting the roles of the key personnel along with highlighting all the potential biases, as follows:

- **Stage 1**: To start, the analysts have to study carefully the project and the proposed BN, to understand which kind of expertise is required. It is fundamental to ensure coverage of all the different perspectives of the problem, so more than one expert is usually necessary. So, the analysts should identify the essential and desired characteristics of experts and build up profiles of experts who may be able to answer these questions. For the number of required experts, it is variable and depends on the variability of expertise per domain. From a theoretical perspective, adding as many experts as possible would seem beneficial; however, too many experts can be problematic too, depending on the type of elicitation process chosen.

- **Stage 2**: Individual interviews between the analysts and the selected experts are conducted. The initial part of the interview has two purposes; to introduce the expert to the encoding task as well as identifying and addressing motivational biases, such as management and expert bias. Management bias is where an expert provides goals rather than judgments (e.g. the dam will not fail), and expert bias is where an expert becomes overly confident. During this initial part of the interview, the BN should be explained, indicating the uncertain variables that will be elicited and explaining how this process can be useful towards the resolution of the overall problem. The second part of this stage focuses on structuring the variables. Each quantity of interest that will be quantified needs to be specified so that a measurement scale can be determined. Even if the topology of the BN has already been defined, it is fundamental to review with the experts the definitions of the variables and their states, in order to structure the uncertain quantities in an unambiguous and meaningful way, before starting the encoding phase. Each variable must have a clear definition that will be understood without any possibility of misunderstanding by the expert. Depending on the experience of the expert, it may be appropriate to disaggregate the variable into more elemental variables. This can be very useful in the case of the BN, because each node might depend on several aspects and it can be easier for the expert to evaluate these secondary probabilities. This technique also allows the analyst to combat motivational biases and to reduce some cognitive biases by increasing the level of details.
- **Stage 3**: Information which is relevant to estimating uncertainties is discussed in this stage to minimize cognitive biases by conditioning the expert's judgments [111]. In particular, biases such as anchoring, i.e. when the evaluation is conditioned by an initial assessment, and availability, i.e. when the evaluation is based on the ease of which relevant instances come to mind, have to be investigated. Thus, the interviewers should ask some specific questions to test the experts. In addition, probability training should be provided to calibrate the experts, where a brief review of basic probability concepts may be helpful, beside some training questions which can help the experts to become familiar with the elicitation process itself. Experts should be trained on problems relevant to the questions on which they will be providing judgement. Different training questions are necessary for instance in the cases of a frequent event or a very rare event. When the training is completed, the encoding stage commences. During the interview, the same question can be asked in various ways, to find potential inconsistencies.
- **Stage 4**: This final stage starts by verifying the consistency of the elicited probabilities. First of all, the analysts should verify that each expert has provided a reflection of their true beliefs. If the results are not satisfactory, the previous stage should be repeated. In the case that the same conditional probabilities have been elicited from different experts, the analysts

should then develop an aggregation technique to obtain one final result; see [112] for a performance-based approach or [113] for a behavioral based approach. Once each elicited probability has been verified and aggregated, the analysts should solve the overall BN to achieve the conclusive results.

Following the above mentioned stages, the following data and information have been provided by the expert of Mountain Chute Dam:

- Vegetation is controlled and monitored around the main dam, and both of the earthen block dams. Trees are cut regularly according to a designed schedule. See Fig.90.
- Animal holes and burrows, of the earthen dams, are also monitored and maintained regularly.
- Both earthen dams have elevation more than the main concrete dam; thus, there is no high risk of overtopping in both of them. Overtopping is considered a risk for only the main concrete dam.
- There are collecting points for the drainage water in the main dam body. All the drainage is discharged to the drainage inspection tunnel in order to monitor the amount of water drainage before being released to the tail race of the main dam. See Fig.89.
- Water pressure on the main concrete dam is also monitored, and if exceeded certain limits, the gates (head gates and sluice gates) are used to release water to get the water pressure back to its acceptable limits.
- The ice loading affecting the hoists of sluice gates and head gates is controlled by using heaters. If the heaters failed for any reason, there is another mechanism called “water bubbler” that prevents ice from accumulating on the mechanical parts of the gates.
- The sluiceway capacity was also a matter that has been discussed with the expert. However the sluiceway capacity is inadequate for the maximum design flood, there is a weather monitoring plan that allows the dam operators to take decisions within 48 hours before any flood hits the dam. This plan depends on releasing the water by operating all the gates (sluice gates, head gates, and all service gates). So, there is a limited risk of overtopping.
- For the stability of the main dam, horizontal and vertical movements are also monitored in all dams of the Madawaska river system, including Mountain Chute. No movements were reported since the beginning of operation of the dam.
- Since dams are considered to be Water Mountains, constructing any dam may change the seismic activity in the area around the dam. While performing an experiment for ice accumulation in the reservoir and its effect on the main dam, Mountain Chute dam operators made sure that the dam is designed to withstand up to 1.45 Ib/ft of earthquake effect. Since the dam didn’t experience any destructive or severe earthquake, this value is not representable for such seismic actions. So, there is still limited probability of facing a destructive earthquake that the dam can’t withstand.

BPTs and CPTs of the proposed BN of Mountain Chute dam are updated using data elicited from expert engineering judgement, which are 18 probability estimates. This judgement considers minimum risks to take place and claims that all dam components are working properly and within the safe and normal operating conditions. Accordingly, it can be seen from the BN in Fig.92 that the failure probability of the main dam falls to 1.33%, and the failure probability of the earthen dams falls to 1.28% over 100 years of operation.

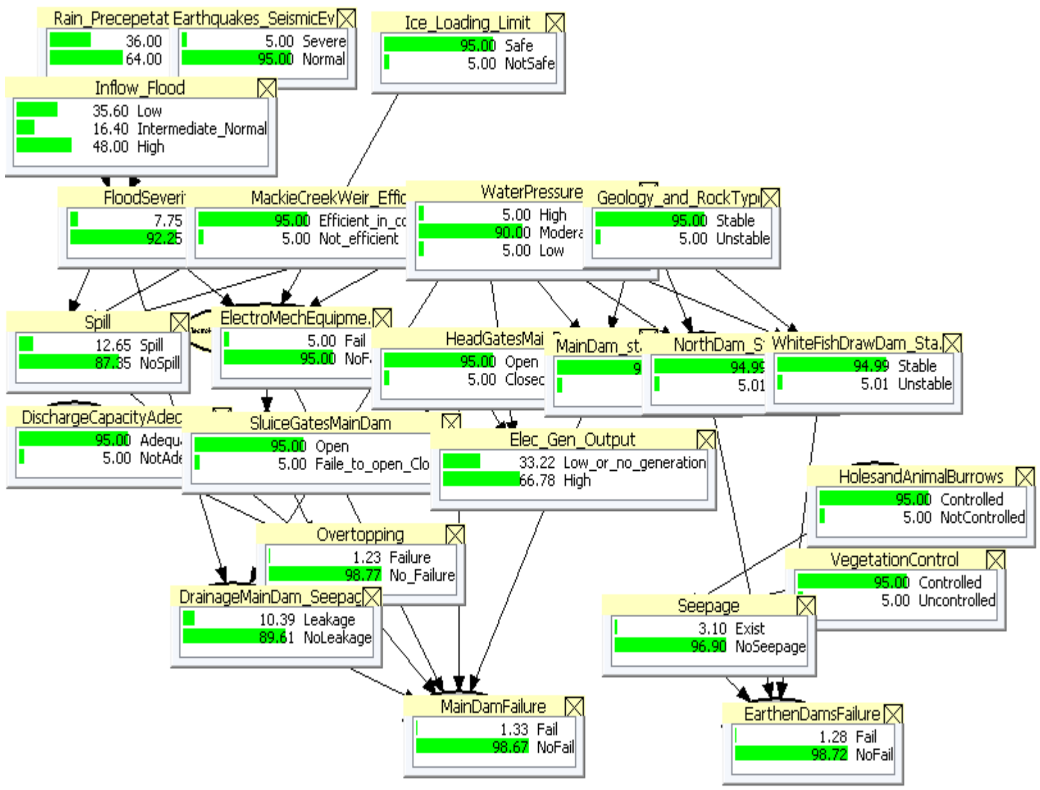


Fig.92: BN of Mountain Chute dam using expert engineering judgement for quantification

By setting the evidence that the main dam failure is 100%, the main contributors to main dam failure can be identified from Fig.93 as high rain/precipitation, high inflow, sluice gate failure, and leakage of water in the main dam body.

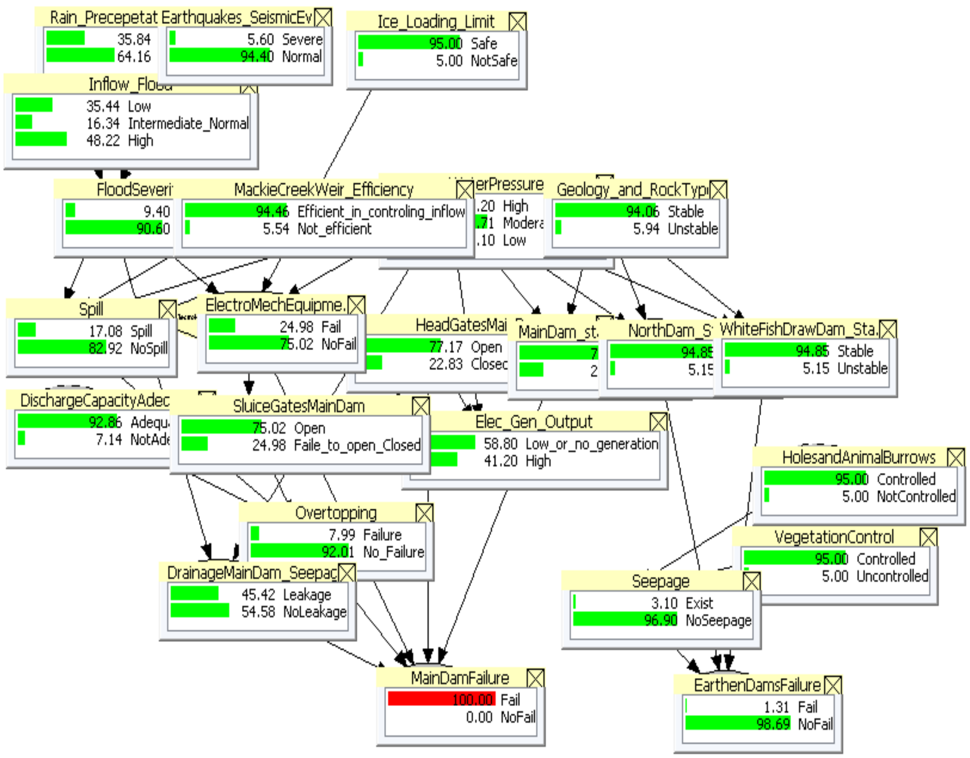


Fig.93: Contribution in main dam failure of Mountain Chute dam when using expert judgement

If sluice gate failure, for example, is considered one of the main contributors in the failure with almost 25% probability, it is required to do more causal analysis in the sluice gate component. Sluice gate itself can be represented as a sub-BN having sub-components as shown in Fig.94. This means that every component in the BN can be represented with a lower level sub-BN that can be analyzed, according to available data, logic inference, and expert judgement, and may be with simulation, in order to find the probability of failure of the higher level component, which is the sluice gate failure in this case. If the sluice gate component/node is decomposed/disaggregated to its sub-BN and sub-components, it can be seen in Fig.94 that if a tornado took place in the area of Mountain Chute dam, it may affect the generation of electricity coming from turbines by affecting the transmission lines. Any disturbance in the electricity generation will affect the operation of the sluice gates, which are electrically supplied by this source. As a backup, there is a diesel generator that is placed near the sluice gates to supply heaters and the on-site control board of the sluice gates with electricity in the case of any emergency. If tornado took place, there is a higher risk that this diesel generator is blown away, and thus, sluice gates may lose all kinds of electric supply to allow their operation. In the meanwhile, the remote operation of the sluice gates by the control station may have trouble in connectivity that blocks the control station from operating the gates remotely. If any mechanical problem happens at this time, there is a higher probability of failure of the gates, and they may not operate/open at the required time in order to release certain amounts of water in case any flood took place. BPTs and CPTs of this new sub-BN of the sluice gates can be built and quantified with available data, expert judgement, logic inference, or from simulation, in order to predict the probability of failure of the sluice gates. Once the predicted probability is available, this probability can be used to quantify the sluice gate node in the higher level BN, i.e. in Fig.83.

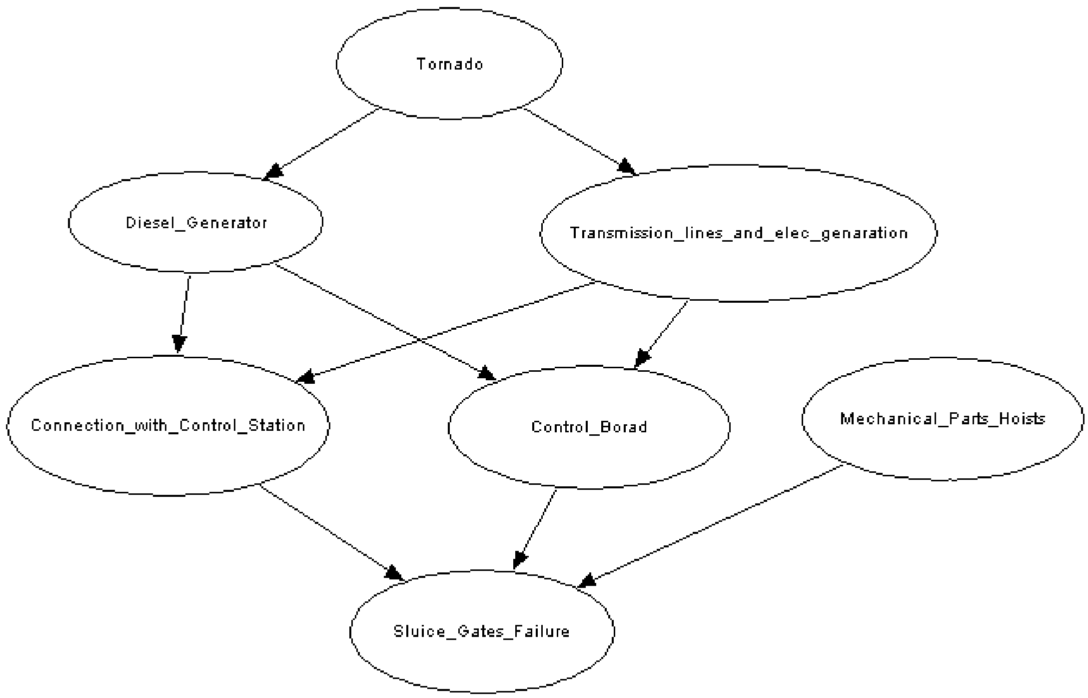


Fig.94: Sluice Gate node decomposed to its sub-BN and sub-components

6.5 Summary, Comments, and Recommendations

In this chapter, it can be shown that there is a significant difference in the failure probabilities when the BN is quantified by expert judgement than the case that uses logic inference in quantifying the BN; once again showing the importance of adequate data collection and their availability for analysis. Adding expert engineering judgement resulted in more specific estimates for the safe operation of the dam. The two cases of using logic inference (in section 6.3) and using expert judgement (in section 6.4) can be considered as two different scenarios that may be helpful for the decision maker. The worst case scenario may be the one that uses logically inferred data, and the safe operating scenario is the one that uses data from expert judgment.

It is obvious that there is a need for a Dam Safety Program that defines different scenarios of dam operation in order to help decision makers and dam operators. The dam safety program should define all the interrelationships and mathematical models that relate different dam components, which will be helpful to monitor, inspect, operate, and predict the states of these components. It will also be helpful in designing maintenance schedules and maintenance actions until the end-of-life of the dam, and defines the need of rehabilitation or decommissioning of the dam.

In conclusion, there is a need to quantify the Bayesian Network more accurately with reducing the uncertainty measures arising from limited knowledge and/or any false data. Detailed simulation may be the solution. Simulation Supported Bayesian Network (SSBN) and Markov Chain Simulation Supported Bayesian Network (MCSSBN) may be two more accurate ways of quantifying the BN that enables entering available data from one side, and randomly generating data within certain ranges from the other side. MCSSBN allows for updating the network with new available data more smoothly, especially when having cyclic nature in the network. If simulation is to be performed for Mountain Chute Dam, the decompositional approach, i.e. decomposing the system to smaller sub-networks, should be applied to the system's BN as shown in Fig.95. The same procedures for SSBN and MCSSBN that were followed in the two reservoir system may also be applied to this network. However, this network is more complex as there are many variables to be included in the network, and the relational (conditional) mathematical equations and models are not easy to obtain.

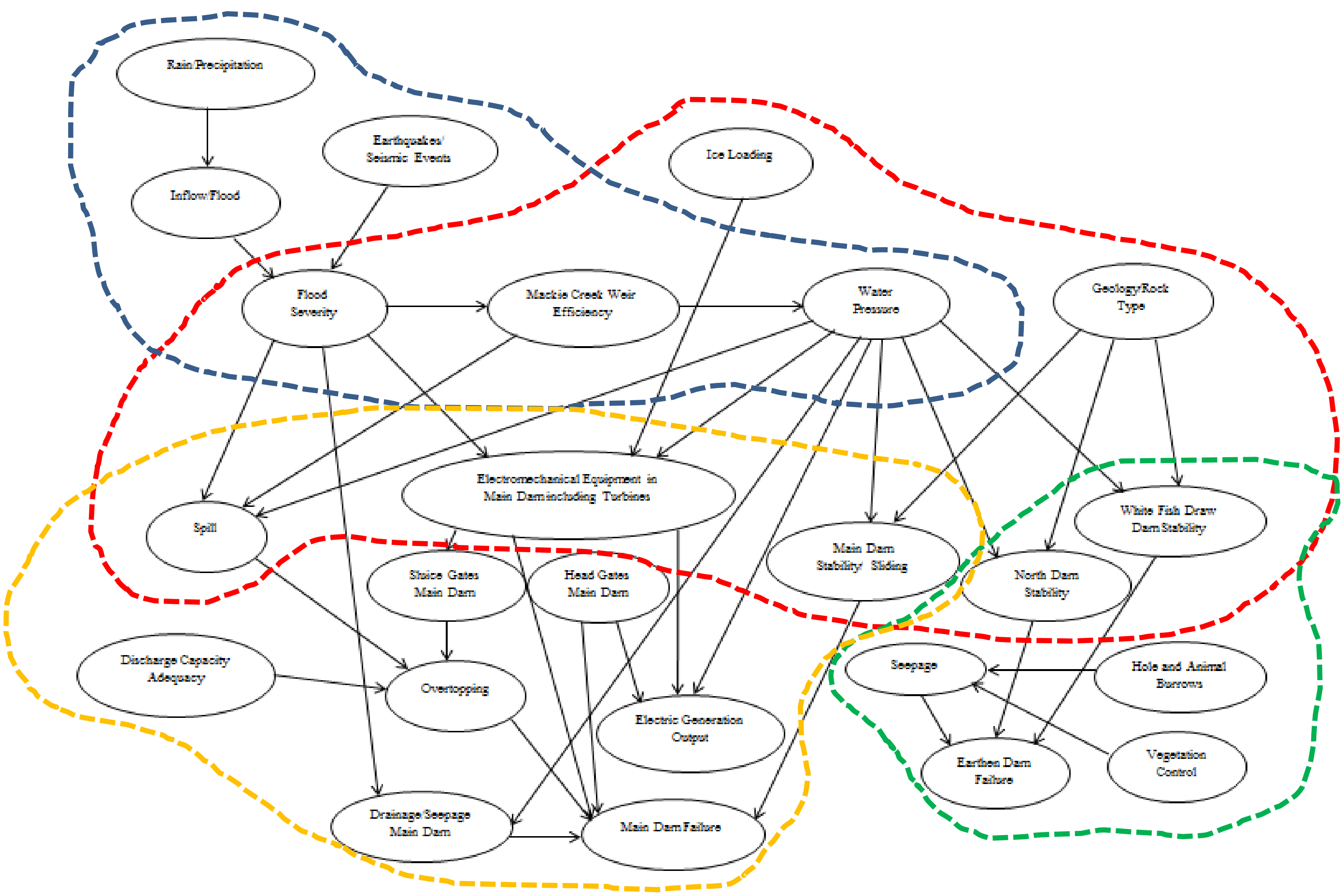


Fig.95: BN of Mountain Chute decomposed to four sub-networks

CHAPTER 7

Conclusions, Recommendations, and Future Work

7.1 Conclusions

Failure analysis of complex systems having a huge number of interacting system components is challenging, especially while having probabilistic events that affect the systems performance. A probabilistic multifactor representation that represents different types of factors (i.e. technical and non-technical) and events may be helpful in performing failure analysis of complex systems. In this thesis, it can be concluded that the engineering complex systems have many ways to be represented, however, BNs have shown advantages in representing such systems in terms of defining the interrelationships among system components. The quantification of BNs depends on different sources of data like logic inference, expert engineering judgement, empirical mathematical models, historical and operational data, and/or detailed simulation. The aim of this thesis is to facilitate the process of predicting the probability of failure of complex systems, like Nuclear Waste Management (NWM), or Safety of Hydropower Dams (SHPD), using BN probabilistic representation. The posterior capability of the BN may also be helpful in identifying the main contributing components to system failure. This may be useful in the design, operation, or decision making stages.

In this thesis, the different factors affecting the failures of NWM and SHPD systems are reviewed. The BN of NWM problem is then represented and quantified according to available data and logically inferred data. The diagnostic capability of the BN has been used to know the main contributors to system failure. As the NWM is still a blue print and not yet a real-world application, any new data when available during design and site selection processes will be helpful in updating the probabilistic estimates of failure. On the contrary, hydropower dams are pre-existing structures operating for decades, and they are prone to failure according to large number of different factors and system variables.

For the SHPD problem, a real-world case study of Mountain Chute dam is explained, and the system is represented by a BN while using different ways of quantification, i.e. logic inference, and expert judgement. In this case study, data are limited and not fully available for this complex engineering system. The importance of finding a new procedure to easily quantify the BN representation using simulation became obvious to overcome the uncertain data sources (i.e. logic inference, or expert judgement).

Two BN based methodologies, i.e. SSBN and MCSSBN, are developed for that purpose. Both methodologies rely on the decompositional approach of decomposing the complex network, represented by BN, into less complex sub-networks to be simulated separately. This decomposition helps in avoiding the complications that may arise when dealing with exhaustive simulation of large complex networks.

A simple two dam reservoir system was used to demonstrate the SSBN and MCSSBN methods.

For SSBN, simulating decomposed sub-systems of the entire system is used as a quantification source for the BN. Using the two dam reservoir system of different configurations, the SSBN results are shown to be close to the simulation results. However, there is a difference between the results in both cases because of the states' discretization that was defined for the different BN states. It is also shown that increasing the number of states for every BN node lead to convergence to the simulation results. The steady state estimates of the SSBN can be used to predict the probability of system failure and diagnose the main contributors to system failure by using the posterior capabilities of BN.

For MCSSBN, Markov Chains are integrated with both simulation and BNs to acquire cyclic property for the BN that is limited to only acyclic representation. Markov Chains are used to define combinations of states (i.e. scenarios) for the sub-systems or for the entire system that helps the decision maker in predicting the probability of system failure. Moreover, the system can be updated more easily if any updated data becomes available for any system node. The system analysis is proposed to be more dynamic while integrating the SSBN with Markov Chains. MCSSBN method has been demonstrated using two different approaches on the two dam reservoir system. Each of the two approaches has some potential and some limitations.

For considering the feedbacks, in simulation, feedback is introduced and simulation deals with continuous variables. When the probability estimates are obtained from simulation and fed into the BN, the variables lose their time stamp, as there is no time stamp in probability, and the BN is a probabilistic representation. So, in BN, there is no time stamp and feedback can't be introduced as normally considered in detailed simulations of systems. In order to overcome that limitation, MCSSBN that uses SSBN and Markov Chain integration is proposed to use Markov transition probabilities to reflect any feedback from different situations, scenarios, or operational conditions to the system failure analysis that is required to be considered. From another point of view, in SSBN and MCSSBN, the BN is supported by simulation which inherits the feedbacks among system components. The simulation is the main source for probability estimates in SSBN and MCSSBN. So, when the probabilities are estimated from simulation, they already have the effect of feedbacks while being fed into the BN representation. This means that BN encapsulates most of the features of the simulation including feedback in the case of SSBN and MCSSBN methods. In addition, BN facilitates representing systems scenarios according to different evidences.

7.2 Recommendations

This thesis gives the following recommendations for operators and decision makers of complex engineering systems:

- A simplified probabilistic representation using BN is very competitive when dealing with complex networks. BN has many advantages over the other probabilistic representation techniques, i.e. sequence diagrams and dependability analysis techniques.
- In order for the BN to be mature for such complex networks, a safety program for any complex network should be available. Safety programs define the interrelationships among system components, the mathematical models that relate different variables and the different operational scenarios for the system at different times within the life time

period of the system. The safety program will be useful in setting criteria for all variables in the system, their lower and upper bounds, and their risk situations. This will be useful in updating the BN of the system when any new data becomes available, but with certain limitations.

- SSBN methodology is recommended to be used for probabilistic analysis of complex systems in which acyclic nature of BN representation is not an obstacle. In other words, if the system is static and minimal changes and updates in data take place, SSBN is expected to have a huge contribution in probabilistic analysis. If any change or update took place in the system, simulation should be re-performed for the sub-network having the change, if the change is local, or for the entire network, if the change is global. This will take more time and effort to estimate results during any risky situation.
- MCSSBN methodology is recommended to be used for dynamic system analysis. In such cases, transitions among system components may be cyclic and not acyclic. Different scenarios, i.e. combination of states, are defined for the sub-networks or for the entire network. The probability estimates from simulation are the corner stone in this concept. System simulations can be performed for updating the system states/scenarios according to different events or situations, e.g. climate change and change in weather conditions. Markov Chains can then be used to predict the most probable events to happen in the next time period through the transition probability matrices.

7.3 Limitations

The following limitations are associated with the proposed methodologies:

- Like any other approach, data availability is a challenge for quantifying the BN representation of systems
- Acyclic limitation of the BN. Although BNs are restricted to account for just acyclic dependencies, this feature could be an advantage from another point of view making them much faster to solve class of problems in which cyclic relationships are not important, especially when such relationships have been included in probabilistic information.
- BN representation of systems is problem-dependent and there is no generic representation applicable in different systems as every system has its own influential factors and cause and effect relationships.
- In the SSBN approach, there is no unique way of system decomposition, and the number of decomposed sub-systems and their boundary conditions depend on the interrelationships among system components, data availability and computational resources.

7.4 Future Work

Depending on the methodologies explained in this thesis, there is potential to do the following tasks in the near future:

- Optimization of different scenarios in case of MCSSBN,
- Using fuzzy logic in BN states' definition,
- Using expert judgement to have a global mathematical modelling for conditional relations among different system variables,
- Setting criteria for a Dam Safety Program that can be used for dams in Madawaska River System.

References

References

[1] Y. Bar-Yam, "General Features of Complex Systems," *Encyclopedia of Life Support Systems* (EOLSS), vol. 1, 2002.

[2] J. Berk, "Systems Failure Analysis," *ASM International*, pp.1-9, 2009.

[3] Office of the Gene Technology Regulator, Department of Health and Aging, Australian Government, "Risk Analysis Framework," January 2005.

[4] D. C. Cox and P. Baybutt, "Methods for Uncertainty Analysis: A Comparative Survey," *Society for Risk Analysis*, vol. 1, no. 4, pp. 251-258, 1981.

[5] M. Peng and L. M. Zhang, "Analysis of human risks due to dam-break floods—part 1: a new model based on Bayesian networks," *Nat Hazards, Springer,* vol. 64, p. 903–933, 2012.

[6] M. Peng and L. M. Zhang, "Analysis of human risks due to dam break floods—part 2: application to Tangjiashan landslide dam failure," *Nat Hazards, Springer,* vol. 64, p. 1899–1923, 2012.

[7] L.M. Zhang, Y. Xu, J.S. Jia, and C. Zhao, "Diagnosis of embankment dam distresses using Bayesian networks. Part I. Global-level characteristics based on a dam distress database," *Can. Geotech., NRC Research Press,* vol. 48, p. 1630–1644, 2011.

[8] V. Kumar, P. K. Wattal, S. Banerjee, and S. Majumdar, "Disposal of Radioactive wastes," in *Nuclear Fuel Cycle*, Mumbai, India, BARC Highlights, pp. 104-109, 2006-2007.

[9] C.J. Lee and K. J. Lee, "Application of Bayesian network to the probabilistic risk assessment of nuclear waste disposal," *Reliability Engineering and System Safety, Elsevier Ltd.,* vol. 91, pp. 515-532, 2005.

[10] STUK (Radiation and Nuclear Safety Authority), "Disposal of Nuclear Waste, Guide YVL D.5," Helsinki, Finland, 15 November 2013.

[11] U.S Department of Energy, "Strategy for the Management and Disposal of Used Nuclear Fuel and High-Level Radioactive Waste," January 2013.

[12] T. Standish, J. Chen, R. Jacklin, P. Jakupi, S. Ramamurthy, D. Zagidulin, P. Keech, and D. Shoesmith, "Corrosion of Copper-Coated Steel High Level Nuclear Waste Containers Under Permanent Disposal Conditions," *Electrochimica Acta, Elsevier Ltd.,* vol. 211, p. 331–342, 2016.

[13] IRSN (The French Institute for Radiological Protection and Nuclear Safety), "Radioactive Waste Management," 2013.

[14] V. Ryhänen, "Management of Spent Fuel and Other Nuclear Waste in Finland - Progress of the Programme since the 1970s," in *IAEA Workshop on Building Partnership in Waste Disposal Programme*, Kuala Lumpur, 2011.

[15] L. Thiele, "Radioactive Waste Management in Canada," in *14th Regional Conference of the German Branch of the International Nuclear Law Association*, Nürnberg, Germany, September 29, 2015.

[16] Nuclear Waste Management Division, Ontario Power Generation Inc., "Nuclear Waste Management, Technical Support Document, New Nuclear - Darlington Environmental Assessment," August 2009.

[17] IAEA (International Atomic Energy Agency), "Disposal of Radioactive Waste, IAEA Safety Standards for protecting people and the environment," Vienna, Austria, 2011.

[18] Y. Onishi, "Fukushima and Chernobyl nuclear accidents' environmental assessments and U.S. Hanford Site's waste management," *23rd International Congress of Theoretical and Applied Mechanics, Elsevier Ltd.*, p. 372 – 381, 2013.

[19] A. Triguero, C. Alvarez-Aledo, and M.C. Cuerva, "Factors influencing willingness to accept different waste management policies: empirical evidence from the European Union," *Journal of Cleaner Production, Elsevier Ltd.*, vol. 138, pp. 38-46, 2016.

[20] U.S. NRC (Nuclear Regulatory Commission), Technical Training Center, "Reactor Concepts Manual," 2012.

[21] E. Sartori, "Nuclear data for radioactive waste management," *Annals of Nuclear Energy, Elsevier Ltd.*, vol. 62, p. 579–589, 2013.

[22] V. F. N. Torres and R. N. Singh, "Thermal State and Human Comfort in Underground Mining," in *Developments in Heat Transfer*, InTech, pp. 589-610, 2011.

[23] "https://www.currentresults.com/Weather/Canada/Cities/temperature-annual-average.php," Feb 3, 2017, 10:34 PM.

[24] J. Forrest, E. Marcucci, and P. Scott, "Geothermal Gradients and Subsurface Temperatures in the Northern Gulf of Mexico," *Adapted from article prepared for presentation at GCAGS Convention, New Orleans, September, 2005, which was canceled due to Hurricane Katrina. Article is published in GCAGS Transactions, 2005, v. 55, p. 233-248,* February 2007.

[25] Environment and Natural Resources, Northwest Territories, "Geothermal Favourability Map, Northwest Territories," April 2010.

[26] "http://climate.weather.gc.ca/historical_data/search_historic_data_e.html," Feb 3, 2017, 10:53 PM.

[27] S.E. Grasby, J. Majorowicz, and M. Ko, "Geothermal Maps of Canada," Geological Survey of Canada, Natural Resources Canada, 2009.

[28] "http://www.thecanadianencyclopedia.ca/en/article/geological-regions/ & http://www.thecanadianencyclopedia.ca/en/article/physiographic-regions/," Feb 3,2017, 11:10 PM.

[29] R. A. Gibb, "The densities of Precambrian rocks from northern Manitoba," *Canadian Journal of Earth Sciences*, vol. 5, pp. 433-438, 1968.

[30] The Expert Panel on Groundwater, "The Sustainable Management of Groundwater in Canada," *Council of Canadian Academies*, Ottawa, Canada, June 2009.

[31] L. Werme, P. Sellin, and N. Kjellbert, "Copper canisters for nuclear high level waste disposal. Corrosion aspects," *Swedish Nuclear Fuel and Waste Management Co.*, Stockholm, Sweden, October 1992.

[32] J. R. Davis, "Basic Understanding of Weld Corrosion," in Corrosion of Weldments, *ASM International*, pp. 1-10, 2006.

[33] C. Hatton and A. Murchison, "Nuclear Waste Management Organization," in *Presentation to DOUG group at University of Waterloo*, Waterloo, ON, Canada, December 2016.

[34] Q. Wang, A. M. Tang, Y.J. Cui, P. Delage, and B. Gatmiri, "Experimental study on the swelling behaviour of bentonite/claystone mixture," *Engineering Geology, Elsevier,* vol. 124, pp. 59-66, 2012.

[35] G. Yilmaz, "The effects of temperature on the characteristics of kaolinite and bentonite," *Scientific Research and Essays, Academic Journals,* vol. 6, no. 9, pp. 1928-1939, 2011.

[36] H. E. Tveit, Evaluation of Bentonite as an Alternative Sealing Material in Oil and Gas Wells, M.Sc. Thesis, Norwegian University of Science and Technology, Department of Petroleum Engineering and Applied Geophysics, June 2012.

[37] J.O. Lee, W.J. Cho, C.H. Kang, and K.S. Chun, "Swelling and hydraulic properties of Ca-bentonite for the buffer of a waste repository," in *The International Symposium on Technologies for the Management of Radioactive Waste from Nuclear Power Plants and Back End Nuclear Fuel Cycle Activities (http://www.pub.iaea.org/MTCD/publications/PDF/csp_006c/PDF…/paper-68.pdf)*, September 1999.

[38] G. B. Baecher, M. E. Pate, and R. D. Neufville, "Risk of Dam Failure in Benefit-Cost Analysis," *Water Resources Research, American Geophysical Union,* vol. 16, pp. 449-456, 1980.

[39] T. C. MacDonald and J. Langridge-Monopolis, "Breaching Characteristics of Dam Failures," *Hydraulic Engineering, ASCE,* vol. 110, no. 5, pp. 567-586, 1984.

[40] V. P. Singh and P. D. Scarlatos, "Analysis of Gradual earth-Dam Failure," *Hydraulic Engineering, ASCE,* vol. 114, no. 1, pp. 21-42, 1988.

[41] M. Foster, R. Fell, and M. Spannagle, "The statistics of embankment dam failures and accidents," *Can. Geotech, NRC Canada,* vol. 37, p. 1000–1024, 2000.

[42] T. L. Wahl, G. J. Hanson, J. R. Courivaud, M. W. Morris, R. Kahawita, J. T. McClenathan, and D. M. Gee, "Development of Next-Generation Embankment Dam Breach Models," in *Embankment Dam Breach Models, The Sustainability of Experience — Investing in the Human Factor*, 2008.

[43] T. L. Wahl, "Prediction of Embankment Dam Breach Parameters, A Literature Review and Needs Assessmnet," DSO (Dam Safety Office), Bureau of Reclamation, U.S. Department of the Interior, July 1998.

[44] G. Hanson and D. Temple, "The National Dam Safety Program, Final Report on Coordination and Cooperation with the European Union on Embankment Failure Analysis," FEMA (Federal Emergency Management Agency), National Dam Safety Program, August 2007.

[45] J. E. Evans, S. D. Mackey, J. F. Gottgens, and W. M. Gill, "Lessons from a Dam Failure," *The Ohio Journal of Science, Ohio Academy of Science,* vol. 100, no. 5, pp. 121-131, 2000.

[46] Y. Xu and L. M. Zhang, "Breaching Parameters for Earth and Rockfill Dams," *Journal of Geotechnical and Geoenvironmental Engineering, ASCE,* vol. 135, no. 12, pp. 1957-1970, 2009.

[47] M. L. DeKay and G. H. McClelland, "Predicting Loss of Life in Cases of Dam Failure and Flash Flood," *Risk Analysi, Society for Risk Analysis,* vol. 13, no. 2, pp. 193-205, 1993.

[48] D. Bocchiola and R. Rosso, "Safety of Italian dams in the face of flood hazard," *Advances in Water Resources, Elsevier Ltd.,* vol. 71, pp. 23-31, 2014.

[49] H. H. Chernet, K. Alfredsen, and G. H. Midttømme, "Safety of Hydropower Dams in a Changing Climate," *Journal of Hydrologic Engineering, ASCE,* vol. 19, no. 3, pp. 569-582, 2014.

[50] J. Kirchherr and K. J. Charles, "The social impacts of dams: A new framework for scholarly analysis," *Environmental Impact Assessment Review, Elsevier Inc.*, vol. 60, p. 99–114, 2016.

[51] X. L. Chang, X. Liu, and W. Zhou, "Hydropower in China at present and its further development," *Energy, Elsevier Ltd.*, vol. 35, p. 4400–4406, 2010.

[52] A. Bartle, "Hydropower potential and development activities," *Energy Policy, Elsevier Science Ltd.*, vol. 30, p. 1231–1239, 2002.

[53] K. McDonald, P. Bosshard, and N. Brewer, "Exporting dams: China's hydropower industry goes global," *Journal of Environmental Management, Elsevier Ltd.*, vol. 90, p. S294–S302, 2009.

[54] G. F. Sowers, "Human Factors in Civil and Geotechnical Engineering Failures," *Journal of Geotechnical Engineering, ASCE*, vol. 119, no. 2, pp. 238-256, 1993.

[55] D. Kumar and S.S.Katoch, "Dams turning devils: An insight into the public safety aspects in operational run of the river hydropower projects in western Himalayas," *Renewable and Sustainable Energy Reviews, Elsevier Ltd.*, vol. 67, p. 173–183, 2017.

[56] L. You, C. Li, X. Min, and T. Xiaolei, "Review of Dam-break Research of Earth-rock Dam Combining with Dam Safety Management," *Procedia Engineering, International Conference on Modern Hydraulic Engineering, Elsevier Ltd.*, vol. 28, p. 382 – 388, 2012.

[57] Y. Xu, L. Zhang, and J. Jia, "Lessons from Catastrophic Dam Failures in August 1975 in Zhumadian, China," *GeoCongress on Geosustainability and Geohazard Mitigation, ASCE*, pp. 162-169, 2008.

[58] J. D. Pisaniello, T. T. Dam, and J. L. Tingey-Holyoak, "International small dam safety assurance policy benchmarks to avoid dam failure flood disasters in developing countries," *Journal of Hydrology, Elsevier B.V.*, vol. 531, p. 1141–1153, 2015.

[59] J. E. Costa and R. L. Schuster, "The formation and failure of natural dams," *Geological Society of America Bulletin*, vol. 100, pp. 1054-1068, 1988.

[60] H. Su, J. Hu, and Z. Wen, "Service Life Predicting of Dam Systems with Correlated Failure Modes," *Journal of Performance of Constructed Facilities, ASCE*, vol. 27, no. 3, pp. 252-269, 2013.

[61] S. Bernardi et al., "Dependability Analysis Techniques," in *Model-Driven Dependability Assessment of Software Systems*, Springer-Verlag, pp. 73-90, 2013.

[62] K. Ponnambalam and A. Seifi, "Using Bayesian Network for Reliability Assessment of a Dam system", *a talk presented at Ontario Power Generation*, Kipling, Toronto, 2015.

[63] S. Cao, K. Ponnambalam, A. Seifi, and P.A. Zielinski, "Identifying Multidisciplinary Factors Affecting Dam Safety," *ICWRER 2016 Conference*, Kyoto, Japan, June 2016.

[64] H. P. Berg, "Risk Management: Procedures, Methods and Experiences," *RT&A #2*, vol. 1, no. 17, pp. 79-95, June 2010.

[65] I. Häring, "Introduction to Risk Analysis and Risk Management Processes," in Risk Analysis and Management: Engineering Resilience, *Springer Science+Business Media* , pp. 9-26, Singapore, 2015.

[66] C. Rodger and J. Petch, "Uncertainty & Risk Analysis, A practical guide from Business Dynamics," *Pricewaterhouse Coopers, MCS, Business Dynamics*, United Kingdom, April 1999.

[67] G.L. S. Babu and A. Srivastava, "Risk and Reliability Analysis of Stability of Earthen Dams," in *IGC* , Guntur, India, 2009.

[68] FAO (Food and Agricultureorganization), "Introduction to Risk Analysis – Basic principles of Risk Assessment, Risk Management and Risk Communication," Yerevan, Armenia, October 2010.

[69] U.S. Army Corps of Engineers & U.S. Department of the Interior, Bureau of Reclamation, "Best Practices in Dam and Levee Safety Risk Analysis," July 2015.

[70] U.S. Army Corps of Engineers & U.S. Department of the Interior, Bureau of Reclamation, "Best Practices in Dam and Levee Safety Risk Analysis," 26 February 2015.

[71] L. King, "Reliability of Flow- Control Systems," *BC Hydro for Generations*, May 12, 2014.

[72] D. N.D. Hartford and G. B. Beacher , "Risk and Uncertainty in Dam Safety, " *Thomas Telford Ltd.*, 2004.

[73] N. G. Leveson, Engineering a Safer World, Systems Thinking Applied to Safety, *The MIT Press*, 2011.

[74] U.S. Army Corps of Engineers & U.S. Department of the Interior, Bureau of Reclamation, "Probabilistic Stability Analysis (Reliability Analysis)," March 2015.

[75] S.J. Kline, "The Purposes of Uncertainty Analysis," *Journal of Fluids Engineering, ASME*, vol. 107, pp. 153-160, June 1985.

[76] I. BEN-GAL, "Bayesian Networks," in *Encyclopedia of Statistics in Quality & Reliability*, Wiley & Sons, pp. 1-6, 2007.

[77] K. B. Korb and A. E. Nicholson, "Introducing Bayesian Networks," in *Bayesian Artificial Intelligence, Second Edition*, Chapman & Hall/CRC Press LLC, pp. 29-54, 2004.

[78] S. Hosseini and K. Barker, "Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports," *Computers & Industrial Engineering,Elsevier Ltd.*, vol. 93, p. 252–266, 2016.

[79] F. Nadim and Z.Q. Liu, "Quantitative risk assessment for earthquake-triggered landslides using Bayesian network," in *Proceedings of the 18th International Conference on Soil Mechanics and Geotechnical Engineering*, Paris , 2013.

[80] P. Li and C. Liang, "Risk Analysis for Cascade Reservoirs Collapse Based on Bayesian Networks under the Combined Action of Flood and Landslide Surge," *Mathematical Problems in Engineering, Hindawi Publishing Corporation*, pp. 1-13, 2016.

[81] M. Smith, "Dam Risk Analysis Using Bayesian Networks," in *Engineering Conferences International, Geohazards*, Lillehammer, Norway, 2006.

[82] X. Zheng, Y. Wei, K. L. Xu, and H. M. An, "Risk Assessment of Tailings Dam Break Due to Overtopping," *EJGE*, vol. 21, no. 7, pp. 1641-1649, 2016.

[83] T. Daemi , A. Ebrahimi , and M. Fotuhi-Firuzabad, "Constructing the Bayesian Network for components reliability importance ranking in composite power systems," *Electrical Power and Energy Systems, Elsevier Ltd.*, vol. 43, no. 1, pp. 474-480, 2012.

[84] F. Garisto, "Fifth Case Study: Features, Events and Processes," *Nuclear Waste Management Organization*

(NWMO), December 2013.

[85] Nuclear Waste Management Organization (NWMO), "Postclosure Safety Assessment of a Used Fuel Repository in Crystalline Rock," December 2017.

[86] M. Garamszeghy, "Nuclear Fuel Waste Projections in Canada – 2017 Update," *Nuclear Waste Management Organization (NWMO)*, December 2017.

[87] Dr. Jorge Andres Garcia Hernandez, Ph.D. UWaterloo, ja4garciahernandez@uwaterloo.ca

[88] D. N. D. Hartford, G. B. Baecher, P. A. Zielinski, R. C. Patev, R. Ascila, and K. Rytters, "Operational Safety of Dams and Reservoirs, Understanding the reliability of flow-control systems," *Institution of Civil Engineering (ICE) Publishing*, 2016.

[89] L. M. King, S. P. Simonovic, and D. N. D. Hartford, "Using System Dynamics Simulation for Assessment of Hydropower System Safety," *Water Resources Research, American Geophysical Union*, no. 53, pp. 7148-7174, 2017.

[90] S. P. Simonovic, "From Risk Management to Quantitative Disaster Resilience – A Paradigm Shift," *Internatioanl Journal of Safety and Security Eng.*, vol. 6, no. 2, pp. 85-95, 2016.

[91] A. Schardong, S. P. Simonovic, and H. Tong, "Use of Quantitative Resilience in Managing Urban Infrastructure Response to Natural Hazards," *Internatioanl Journal of Safety and Security Eng.*, vol. 9, no. 1, pp. 13-25, 2019.

[92] Y. Xu, L.M. Zhang, and J.S. Jia, "Diagnosis of embankment dam distresses using Bayesian networks. Part II. Diagnosis of a specific distressed dam," *Can. Geotech. J., NRC Research Press*, vol. 48, p. 1645–1657, 2011.

[93] R. G. Bea, and T. Johnson, "Root Causes Analyses of the Oroville Dam Gated Spillway Failures and Other Developments," *University of California, Berkeley, Center for Catastrophic Risk Management*, July 2017.

[94] R. G. Ingalls, "Introduction to Simulation," *Proceedings of the 2008 Winter Simulation Conference, IEEE*, pp. 17-26, 2008.

[95] H. Perros, "Computer Simulation Techniques: The definitive introduction!," *NC State University* Raleigh, NC, 2009.

[96] A. Lakehal and F. Laouacheria, "Reliability based rehabilitation of water distribution networks by means of Bayesian networks," *Journal of Water and Land Development*, no. 34, pp. 163-172, 2017.

[97] Z. Q. Liu, F. Nadim, U. K. Eidsvig, and S. Lacasse, "Reassessment of Dam Safety Using Bayesian Network," *Geo-Risk, ASCE*, pp. 168 - 177, 2017.

[98] N. Carter, D. Young, and J. Ferryman, "A Combined Bayesian Markovian Approach for Behaviour Recognition," in *Proceedings of the 18th International Conference on Pattern Recognition (ICPR'06), IEEE Computer Society*, 2006.

[99] A. L. Tulupyev, and S. I. Nikolenko, "Directed Cycles in Bayesian Belief Networks: Probabilistic Semantics and Consistency Checking Complexity," in *4th Mexican International Conference on Artificial Intelligence, MICAI 2005, Advances in Artificial Intelligence*, Monterrey, Mexico, 2005.

[100] S. Sharma, "Markov Chain Monte Carlo Methods for Bayesian Data Analysis in Astronomy," *Annual Review of Astronomy and Astrophysics*, vol. 55, pp. 213 - 259, 2017.

[101] Z. Ghahramani, "An Introduction to Hidden Markov Models and Bayesian Networks," *Journal of Pattern Recognition and Artificial Intelligence,* vol. 15, no. 1, pp. 9 - 42, 2001.

[102] G. Meeden and S. Vardeman, "A Simple Hidden Markov Model for Bayesian Modeling with Time Dependent Data," *Communications in Statistics - Theory and Methods,* vol. 29, no. 8, pp. 1801-1826, 2000.

[103] L. Bouillaut, O. Francois, and S. Dubois, "A Bayesian network to evaluate underground rails maintenance strategies in an automation context," *Journal of Risk and Reilabiility, Institution of Mechanical Engineers,* vol. 227, no. 4, pp. 411-424, 2013.

[104] F. Wang and Q. L. Zhang, "Systemic Estimation of Dam Overtopping Probability: Bayesian Networks Approach," *Journal of Infrastructure Systems, ASCE,* vol. 23, no. 2, pp. 1-12, 2016.

[105] C. G. Jong, and S. S. Leu, "Bayesian-Network-Based Hydro-Power Fault DIagnosis System Development by Fault Tree Transformation," *Journal of Marine Science and Technology,* vol. 21, no. 4, pp. 367-379, 2013.

[106] T. B. Jones, M. C. Darling, K. M. Groth, M. R. Denman, and G. F. Luger, "A Dynamic Bayesian Network for Diagnosing Nuclear Power Plant Accidents," in *Proceedings of the Twenty-Ninth International Florida Artificial Intelligence Research Society Conference*, 2016.

[107] D. J. Delgado-Hernández, O. Morales-Nápoles, D. De-León-Escobedo, and J. C. Arteaga-Arcos, "A Continuous Bayesian Network for Earth Dams' Risk Assessment: An Application," *Structure and Infrastructure Engineering,* vol. 10, no. 2, pp. 225-238, 2014.

[108] W. Ferrell, "Combining individual judgements," in G. Wright (ed.), Behaviour decision making, *New York: Plenum Press,* 1985.

[109] C. Spetzler and C.A. Stael Von Holstein, "Probability Encoding in Decision Analysis," *TIMS,* no. 22, pp. 340-358, 1985.

[110] M. Merkhofer, "Quantifying Judgemental Uncertainty: Methodology, Experiences, and Insights," *IEEE Trans Syst, Man Cybernet,* vol. 17, no. 5, pp. 741-752, 1987.

[111] A. Tversky and D. Kahneman, "Judgment under Uncertainty: Heuristics and Biases," *Science, New Series*, pp. 1124-1131, 1974.

[112] J. Quigley, A. Colson, W. Aspinall, and R. Cooke, "Elicitation in the Classical Model," in M. Q. Dias (ed.), Elicitation: The Science and Art of Structuring Judgement, *New York: Springer,* 2018.

[113] J.P. Gosling, "SHELF: the Sheffield Elicitation Framework," in M. Q. Dias (ed.), Elicitation: The Science and Art of Structuring Judgment, *New York: Springer,* 2018.

Appendices

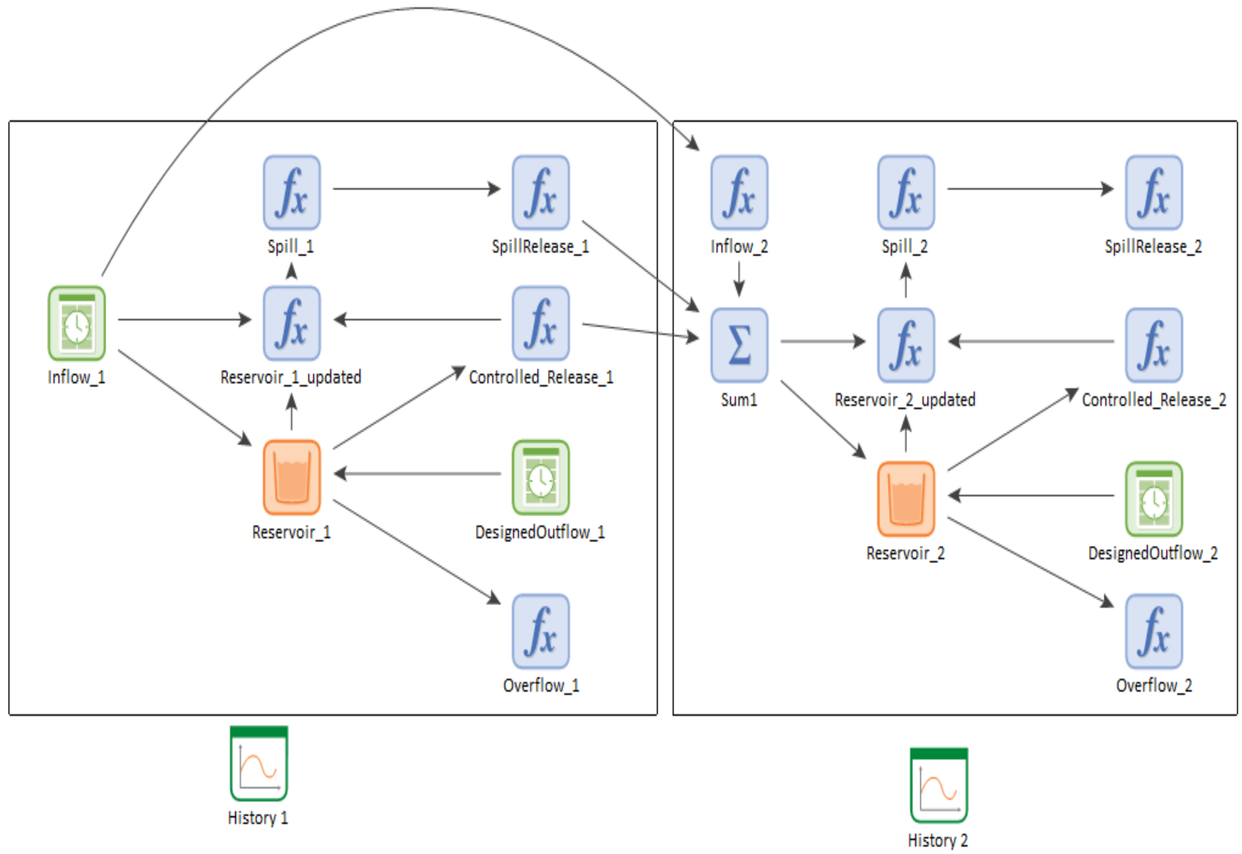
Appendix 1:

Input data for the two reservoir case study used in this thesis:

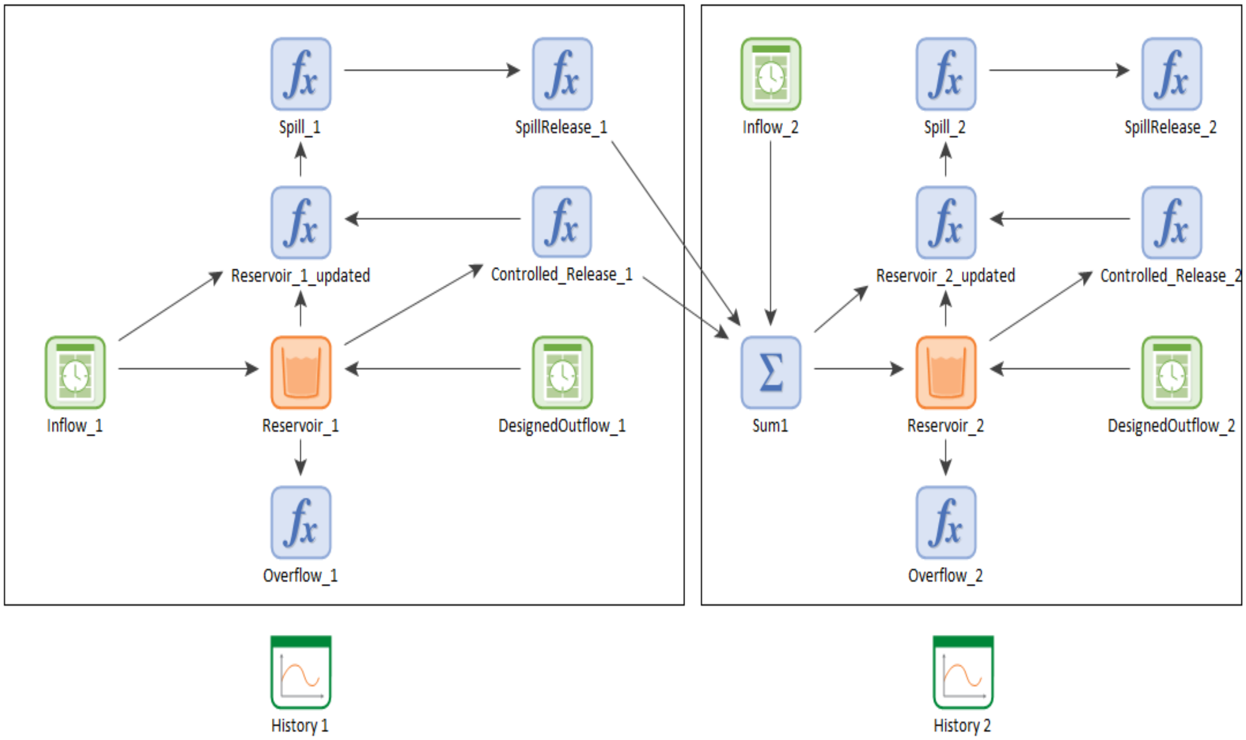
Minimum storage capacity of each reservoir	2 m^3
Maximum storage capacity of each reservoir	3 m^3
Average inflow	0.5 – 1.5 m^3/season, uniformly distributed
Designed outflow	Mean of the inflow in each year (over 4 seasons)
Spillway gate failure	Randomly generated value of 0 (failure) or 1 (success) according to certain gate operation management. For the results presented in this thesis, the gates are managed to operate for 50% of time it is required to operate, and fail for 50% of time it is required to operate. Other gate management policies will result in different estimates and numerical results.

Appendix 2:

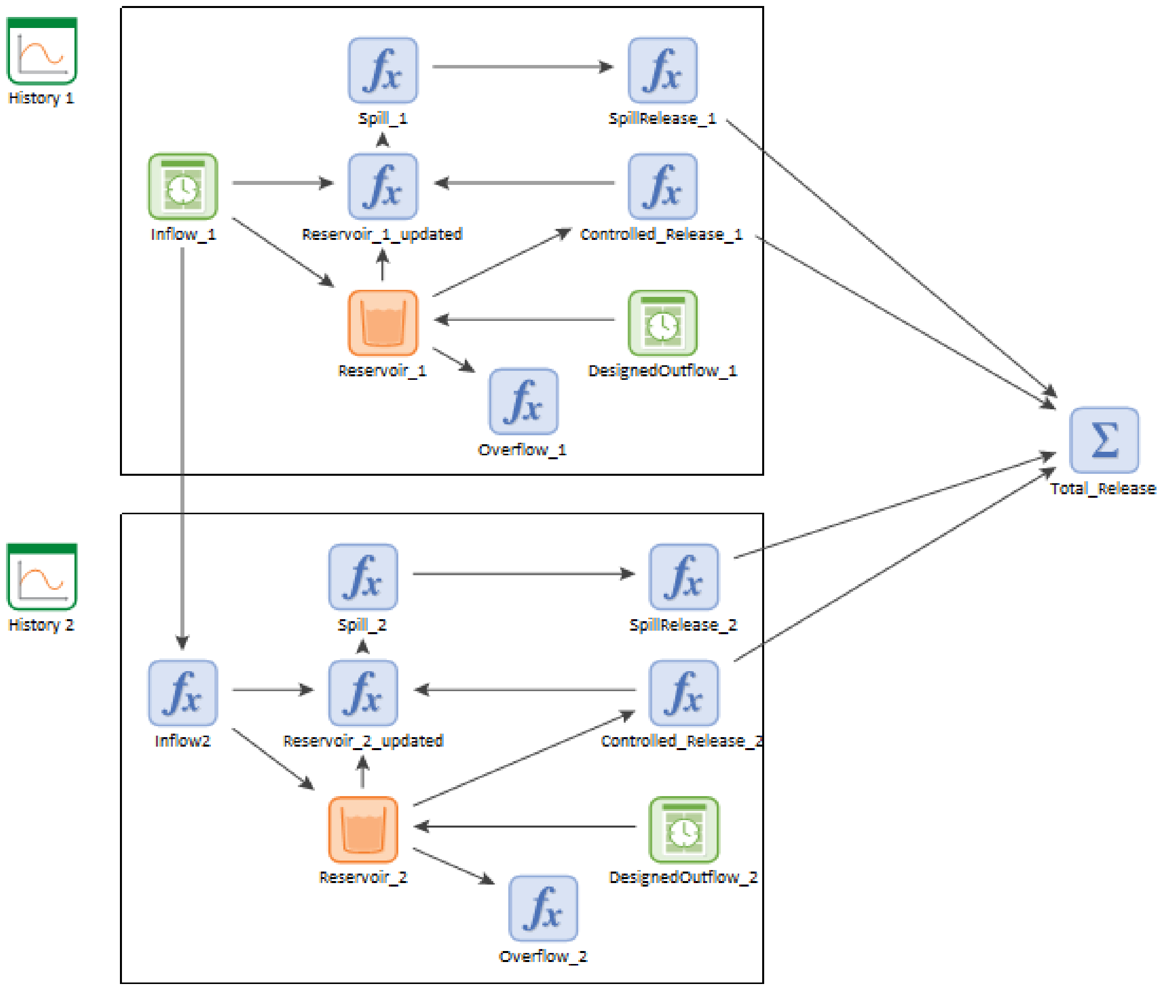
GoldSim simulation for a system of two dam reservoirs



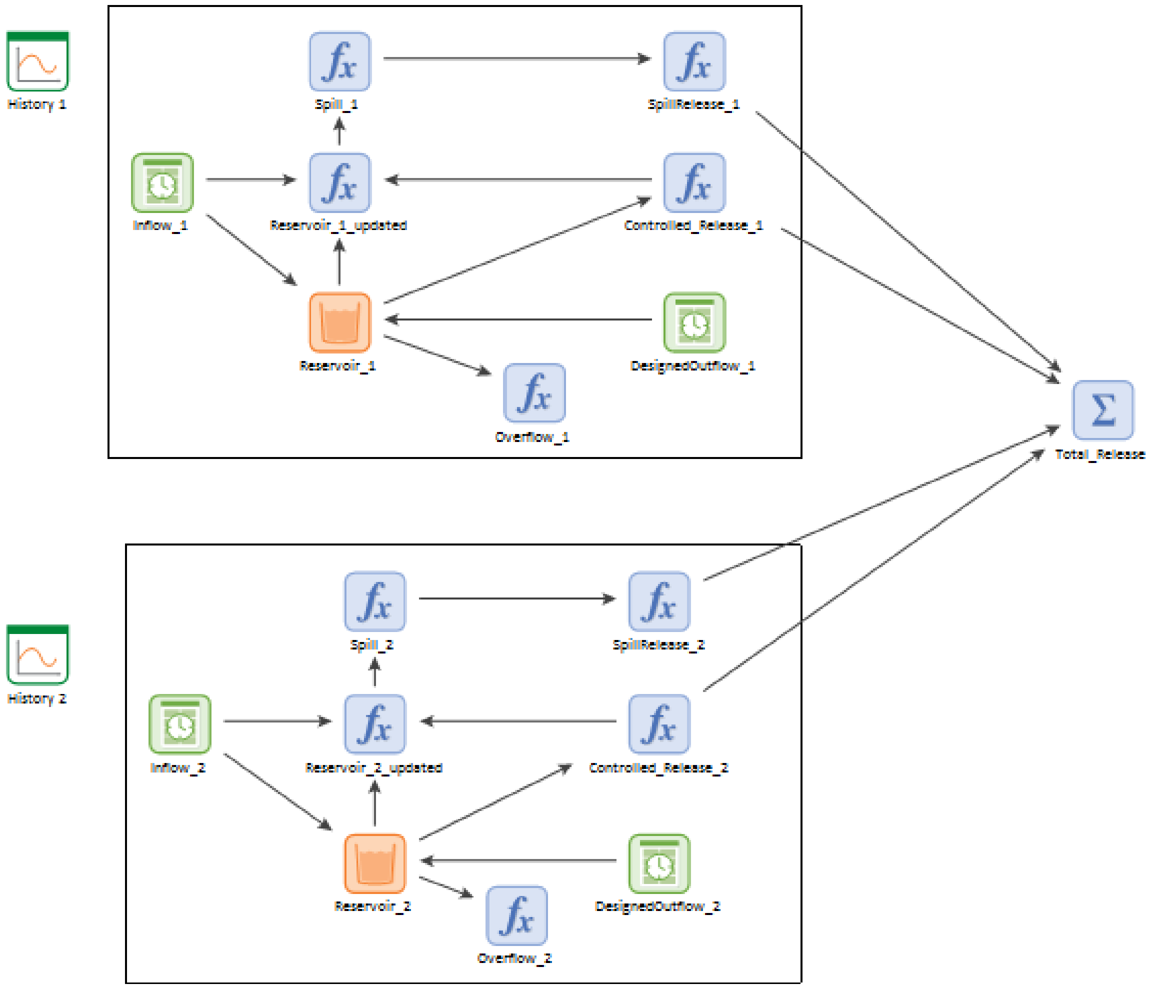
Two dams in series having dependent inflows



Two dams in series having independent inflows



Two dams in parallel having dependent inflows



Two dams in parallel having independent inflows

Appendix 3:

BN of Mountain Chute dam and generating station