DET NORSKE VERITAS™

REPORT

# TECHNOLOGY LEADERSHIP: RISK RELIABILIRT AND HUMAN FACTORS

## Bayesian Networks in DNV

Det Norske Veritas AS

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Task and Objective:

Bayesian Networks (BN) has been proposed as a powerful tool within the field of risk management. While some DNV projects have used them, the use of BNs is still rare in services related to risk, reliability and human factors. This project, initiated by the Technology Leadership group for these services, has attempted to provide answers to some of the questions related to BNs in DNV:

- What is the role of Bayesian Nets in future risk management services?
- Where have we used, or do we currently use them?
- What are the advantages?
- What are the disadvantages?
- What shall our approach be with respect to how, where and when to use BNs in our services. What needs to be in place if/before we are able to widely use BNs in projects?

A search through the organisation has been performed to identify personnel with relevant experience with, and projects related to, BNs. The identified resources were asked to participate in a survey to gather knowledge of how BNs have been applied in projects, how well BNs performed in the projects, and whether BNs should also be used in future projects in DNV. As part of the survey process, a SWOT analysis has been performed attempting to find strengths, weaknesses, opportunities ant threats related to implementation of BNs in DNV.

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# 1 EXECUTIVE SUMMARY

Bayesian Networks (BN) have been proposed as a powerful tool within the field of risk management. Specific proposals include application to:

- QRA
- Modelling of barrier performance
- Integration of MTO perspective in our services
- Failure frequencies
- Operational risk tools

While some DNV projects have used them, the use of BNs is still rare in services related to risk, reliability and human factors. This project, initiated by the Technology Leadership group for these services, has attempted to provide answers to some of the questions related to BNs in DNV:

- What is the role of Bayesian Nets in future risk management services?
- Where have we used, or do we currently use them?
- What are the advantages?
- What are the disadvantages?
- What shall our approach be with respect to how, where and when to use BNs in our services. What needs to be in place if/before we are able to widely use BNs in projects?

A search through the organisation has been performed to identify personnel with relevant experience with, and projects related to, BNs. The identified resources were asked to participate in a survey to gather knowledge of how BNs have been applied in projects, how well BNs performed in the projects, and whether BNs should also be used in future projects in DNV. Projects were identified where BNs have been used for, among other applications: risk analysis of gas pipelines, blowout risk, navigational safety of passenger ships, CO2 pipeline risk, project risk management and climate change effects.

As part of the survey process, a workshop was arranged where the results of the survey were discussed. This workshop was run as a SWOT exercise, attempting to find strengths, weaknesses, opportunities ant threats related to implementation of BNs. They key findings are summarized below.

The general impression is that BNs have significant benefits compared to traditional methods for risk assessment. Key benefits include:

- Capability to express and quantify uncertainty in the models. This, among other benefits, makes BNs suitable for modelling situations which have high levels of inherent uncertainty, e.g. emerging risks, and “soft” factors such as human and organisational factors
- Capability to quickly perform forward and backward inference, to identify both the probable consequences and causes in risk scenarios
- High speed of Bayesian software “engines” can provide near real time decision support
- Modelling of uncertainty and conditional probabilities allows for a higher definition in the outcome space of the risk models
- Transparent and structured modelling of risk influencing factors

As for all other models, there may also be weaknesses associated with BNs. Potential disadvantages include the inability to deal with frequencies, and the propensity to require huge quantification efforts as the number of conditional probabilities required increases exponentially in size as the number of incoming links to nodes increases. In this case, it may also become difficult for customers or other analysts to follow the reasoning behind the quantification, particularly if this is not done in a structured manner.

The benefits and weaknesses of BNs may make them more suitable for specific types of problems. For instance, BNs may be very suitable for modelling complex decision-making problems, and real – or near real – time decision support tools, such as demonstrated in the SOUL and MARV projects. BNs may also be effective for modelling of specific probabilities in the QRA, where suitable historical data is not available. QRA of single process events can also be built using BN. Ship collision modelling using a BN has also been demonstrated. It is therefore likely that a

QRA could be built from a series of BNs representing different process events, plus separate BNs to represent the various types of non-process hazards.

For full QRA implementation, modelling the QRA entirely using a BN, the applicability of BNs is more uncertain than for the type of applications identified in this report. In order to obtain a greater understanding of this, further research will be necessary. This approach could include an extensive research project, which would require a significant investment, and might conclude that the existing QRA methodology is sufficient or that the benefits do not outweigh the added effort. For less complex applications, a bottom-up approach might be suitable where BNs are first applied to a small set of applications where we can already see the advantages of using BNs. One of our major difficulties will be in recognising suitable areas of application. They should be in areas where there is high inherent uncertainty (e.g. emerging risks, human factors) or areas where very rapid reassessment is required. This approach would not require the same level of investment. However, it could be ineffective if the initiative is not coordinated, promoted and supported by investments in training and service development. The two approaches are summarised below:

1. *Gradual development*: Start gradually by developing BNs to calculate probabilities used in QRAs today which are not well defined, and/or for well-defined decision making problems. BNs There are several probabilities used in QRA for which historical data is not available, and no detailed analysis has been performed. These are often defined through very coarse estimations, listed in the assumption register. Development could be done as service development projects, or partly as part of external projects. As more BNs are developed, these can be combined to create larger, generic BNs to apply in risk analyses.
2. *Full QRA approach*: In order to determine how suitable BNs could be in a formal QRA, such as required for offshore applications in Norway in the NORSOK Z-013 standards, a large development project (e.g. a JIP) could be proposed. Here, DNV could invite one or more clients for which we hold the existing QRAs and attempt to remodel these completely or partly using BNs. By remodelling previously completed analyses, the different methods can be carefully examined and compared.

If it is decided that the use of BNs should be encouraged, the following recommendations have been identified:

1. Conduct a coordinated series of BN presentations within DNV (series of lunch meetings, or in competence network groups). This should include:
    - Theory
    - Simple example
    - Applications/Example from the previous DNV projects, with the possibility to 'play' with the models that have been developed, to show the capabilities of BN

    A short training course could be provided to raise awareness and introduce the technology. The short training course could be followed by longer training courses for relevant groups who could be applying the methods in risk management services. The training course should allow attendees to identify projects where BNs might be part of the offered solution. The network of personnel identified in this current project may be available to advise on suitability of BNs to future proposals/projects.
2. Identify key problems in the current risk analyses where BNs might offer significant advantages. This could include applications identified in this project, such as barrier dependability, integration of human factors into QRA, refining leak frequency and factors contributing to leak frequency, blowout frequency and ship collision frequency. It could also include other important issues such as operational risk assessment and cumulative risk, asset management and life extension, competence management, process safety management and the assessment and management of risks arising from MTO issues. In general, issues related to the insufficient data, or industry averages which might bring more value if tailored to the actual situation (in time) or to a certain installation/operator/client, etc.
    - Study the applicability of BN for these problems and develop small BN models. These models have to be general enough to be applicable to other projects, but include also the needed degree of details to help decision making process in that particular problem
    - This activity has to be coordinated by a core group with direct involvement of the TL group.
    - The network of personnel with experience using BNs (including the current project team) could be available to provide advice in the model development projects.

3. An important factor will be to increase awareness of both internal resources and clients regarding the importance of uncertainty in decision making
    - First, to recognize that there is uncertainty
    - Then, show them the ‘power of uncertainty’: the difference between one point estimates and distribution when it comes to take decisions
    - Help the customer deal with uncertainty and take decisions under uncertainty

Reliable 3rd party software tools for building and calculation of BNs are readily available, such as HUGIN and GeNIe. The GeNIe and SMILE software is even provided free of charge by the Decision Systems Laboratory of the University of Pittsburgh. Resources within DNV have significant experience with this tool. DNVRI have been using HUGIN as the preferred tool in several projects. Responses to the BN survey indicate that GeNIe may be more flexible than HUGIN, but a more thorough review of available software should be performed in order to determine the most suitable software for DNV. Defining a common software tool to be made available for relevant DNV employees could facilitate increased use of BNs

# 2 INTRODUCTION

## 2.1 Background

Bayesian Networks (BN) have been proposed as a powerful tool within the field of risk management. Specific proposals include application to:

- QRA
- Modeling of barrier performance
- Integration of MTO perspective in our services
- Failure frequencies
- Operational risk tools

BN are central elements in current DNV projects such as the SOUL and MARV projects. A few years ago, DNV R&I ran a project which concluded that BNs are the future of risk analysis. This program did however not lead to widespread use of BNs in the risk management services. This Technology Leadership (TL) project has been initiated as part of the TL initiative for Risk, Reliability and Human Factors, and aims to identify sources of competence/experience and projects where BNs have been used within the global organisation, and compile and review the results in order to provide recommendations for a strategy for further implementation of BNs in DNV.

## 2.2 Objectives

The objective of this project is to establish a common understanding of the following:

- What is the role of Bayesian Nets in future risk management services?
- Where have we used, or do we currently use them?
- What are the advantages?
- What are the disadvantages?
- What shall our approach be wrt. how, where and when to use BNs in our services. What needs to be in place if/before we are able to widely use BNs in projects?

This project will attempt to survey the competence and experience related to use of BNs in DNV around the globe, and use this knowledge to identify and assess the potential of BNs in the risk management services we provide. Based on this discussion, the project will provide recommendations to the Technology Leadership program regarding the use of BNs.

## 2.3 Limitations

The objective of this project is to gather information about the use of BNs in the organisation, and to provide recommendations for a strategy regarding future use of BNs in the risk management services. Development of tools, or practical use of BNs through case studies, pilot projects etc. is considered service development and is outside the scope of this project.

The project was initiated and commenced before the official closing of the merger between DNV and the GL group, and thus before there could be any interaction between the two companies as partners. The focus of this project does therefore not include the GL group. Hence the title: Bayesian Networks in DNV. However, some information about BNs in GL has come up through the course of the project, after the date of official closing, which could be used to further expand on this study at a later stage.

## 2.4 Stucture of this Report

Section 3 presents a brief introduction to Bayesian networks and the ideas that underpin Bayesian thinking.

Section 4 presents a summary of the survey performed in the DNV organization, providing brief descriptions of DNV projects where BNs have been applied.

Section 5 contains a discussion of the strengths and weaknesses of BNs related to DNVs risk management services. Finally, recommendations for further work on BNs are presented.

## 2.5 Definitions and abbreviations

| | |
|---|---|
| BBN | Bayesian Belief Network (has same meaning as Bayesian Network) |
| BN | Bayesian Network |
| BORA | Barrier and Operational Risk Analysis (refers to a research project (2003-2006) into modeling and analysis of barriers on offshore production installations) |
| COCATE | Refers to the EU research project studying the potential for capturing CO2 from different industrial facilities and developing a shared infrastructure for the transport and storage of the captured gas |
| CPT | Conditional Probability Table (refers to the table of probability data in each node of a BN which describes the probability of the node's states) |
| ECDIS | Electronic Chart Display and Information System |
| ERM | Environmental Risk Management |
| FAR | Fatal Accident Rate (refers to the average number of fatalities per 100 million man-hours worked) |
| FSA | Formal Safety Assessment |
| GeNIe | Graphical Network Interface (refers to the Graphical Interface for SMILE, developed by Decision Systems Laboratory, University of Pittsburgh) |
| GUI | Graphical User Interface |
| HF | Human Factors |
| HUGIN | Refers to model-based decision support software utilizing Bayesian Network technology as developed by HUGIN Expert AS. |
| IMO | International Maritime Organization |
| IRPA | Individual Risk Per Annum (the annualized risk of death to a representative individual from specific hazards under assessment) |
| MARV | Multi-Analytic Risk Visualization (refers to a DNV tool development in Columbus, Ohio, where a Bayesian Net is being used to aid the interpretation and assessment of pipeline condition monitoring data) |
| MTO | Man, Technology & Organization (refers to factors which affect the likelihood of major accidents in industry) |
| PHAST | DNV's industry hazard analysis software tool. The software examines the progress of a potential incident from the initial release to far-field dispersion including modelling of pool spreading and evaporation, and flammable and toxic effects. |
| PLL | Potential Loss of Life (the average number of fatalities per year from specific hazards under assessment) |
| QRA | Quantified Risk Assessment (or Quantified Risk Analysis) |
| RIF | Risk Influencing Factor (e.g. as used in the BORA methodology and Risk OMT) |
| Risk OMT | Risk modelling – integration of organisational, human and technical factors |
| RRHF | Risk, Reliability and Human Factors (refers to one of the seven Technology Leadership areas) |

| | |
|---|---|
| SINTEF | Norwegian: Stiftelsen for industriell og teknisk forskning |
| SMILE | Structural Modeling, Inference, and Learning Engine (refers to the software for solving Bayesian Networks, performing Bayesian inference etc. as developed by developed by Decision Systems Laboratory, University of Pittsburgh). SMILE is the software 'engine' behind GeNIe. |
| SOUL | Safety Offshore Upstream Landscaping (refers to a DNV project, where a BN is being used to demonstrate risk assessment using data from normally disparate sources). |
| SWOT | Strengths, Weaknesses, Opportunities and Threats (refers to a workshop process to identify such factors) |
| TR | Temporary Refuge (the area on an offshore oil and gas installation designed to provide protection against the effects of a major accident) |

# 3 INTRODUCTION TO BAYESIAN NETWORKS

In order to provide a general understanding of the subject, this section will describe BNs briefly. First, the statistical view that forms the basis for Bayesian modelling will be explained, followed by a description of BNs.

This report will not focus extensively on the statistical or mathematical aspects of BNs, but a basic understanding of statistics is recommended. For interested readers, more detailed information about BNs is readily available in literature on the subject (e.g. ref. /1/ and /9/).

## 3.1 The Bayesian vs. Frequentist Approach to Risk Management

In statistics there are two main philosophical schools or approaches. The first is often referred to as the frequentist or classical approach, and the second is the Bayesian approach. The frequentist approach is typically defined by the belief that parameters are fixed, but unknown constants, ref. /2/. (i.e. that they have a true, underlying value). Probabilities are viewed as long-run relative frequencies. As parameters are understood as fixed values, a probability statement cannot be made about their value (i.e. they cannot be treated as random variables). Samples are taken from a population and a sample statistic is calculated. This sample is compared against a probability distribution for an infinite number of hypothetical repetitions of the same procedure. This probability distribution for all possible random samples from the population is called the sampling distribution. If the sample size is large enough, we often assume that this distribution is approximately normal and use this to calculate the mean and standard deviation. A probability statement is then made about the statistic, which in turn is converted to a confidence statement about the parameter. Typically, this statement can say that we have 95 % confidence that the true mean of the population is within a calculated range. A frequentist can then expect that if we perform the same experiment a large enough number of times, the sample will contain the true mean 95 % of the time.

Note that the probability statement is not related to the sample we started with, but to the entire sampling distribution.

In the Bayesian approach, the parameters themselves are considered random variables, as we are uncertain about their values. Probability is interpreted as a degree of belief. A prior distribution is defined using subjective beliefs about the sample. This will be based on the analyst's personal expectations (informed by available data) of the sample, i.e. how plausible it is considered that the parameter has different values. Using Bayes' theorem we can update the distribution based on observed evidence. This gives a posterior distribution, which is based both on the prior distribution and on observed data.

A Bayesian will argue that this has several advantages. As the parameters are considered random variables, we can make probability statements about them. The Bayesian approach allows us to modify our beliefs based on actual observed data. This contrasts to the frequentist approach, where confidence statements are made based on all possible data sets that could have occurred for the parameter value.

A frequentist will typically argue that the Bayesian approach is not objective enough. Based on the opinion of the analyst, the prior distribution may vary. This means that two analysts, with different opinions, may arrive at different conclusions. A frequentist will be more intent on finding a "true" probability based on data which holds up to scrutiny, not based on the opinion of the analyst.

This report will not attempt to decide which approach is theoretically correct. Statistics is a complex field, and this discussion has gone on since the approaches were first developed. However, some believe that both approaches have different practical advantages. One of the approaches, or a combination, may be suitable for a particular problem. Information about these subjects is readily available in literature.

In risk management, the frequentist approach will argue that risk is an intrinsic, objective property of the physical world and that a true probability can be associated with the risk. These probabilities are obtained from more or less extensive historical data. In a financial risk context, Borison and Hamm (ref. /3/) argues that this view may have significant shortcomings:

"First, it puts excessive reliance on historical data and performs poorly when addressing issues where historical data are lacking or misleading. Second, the frequentist view provides little room – and no formal and rigorous role – for judgment built on experience and expertise. And third, it produces a false sense of security – indeed, sometimes a sense of complacency – because it encourages practitioners to believe that their actions reflect scientific truth."

Remember that the frequentist approach holds true for identical repetitions of the exact same statistical procedure. In complex, real-world situations this may not be the case. This may lead an analyst into applying a historical average in a situation where the average will not be applicable. A Bayesian will see risk as degree of belief informed by this data, rather than a function of the data alone. By looking deeper into the factors which influence risk, a Bayesian may be able to quantify his belief where historical data is not available.

The idea behind the frequentist approach is that uncertainty in a statistical problem arises from collecting data from just a sample of the population. The Bayesian approach recognises that uncertainty is an inherent property of the situation. A Bayesian approach allows the combination of judgment and historical data in situations where there is reason to believe the data is not accurate or if data simply does not exist.

## 3.2 Bayesian Networks

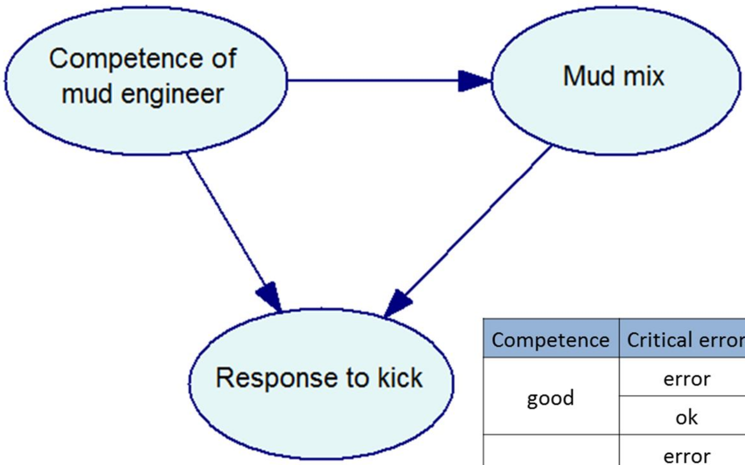
Bayesian networks (BNs), sometimes called Bayesian belief networks (BBN), are used to perform probabilistic analysis of complex systems. A Bayesian network is a directed acyclic graph that illustrates the causal relationships between key factors and one or more final outcomes in a system (ref. /1/).

### 3.2.1 Probability problems

The probability data associated with each node are held in tables (conditional probability tables, or CPT) that are stored inside the nodes. Each node contains a CPT which describes the "state" of the node in terms of the states of other "upstream" nodes. Figure 3-1 Simple Bayesian network shows a simple BN having only three nodes.

| Competence | |
|---|---|
| good | poor |
| 0.8 | 0.2 |

| | Critical error | |
|---|---|---|
| Competence | error | ok |
| good | 0.003 | 0.997 |
| poor | 0.01 | 0.99 |




| | | Failure to respond | |
|---|---|---|---|
| Competence | Critical error | failure | ok |
| good | error | 0.002 | 0.998 |
| | ok | 0.001 | 0.999 |
| poor | error | 0.01 | 0.99 |
| | ok | 0.005 | 0.995 |

**Figure 3-1 Simple Bayesian net**

This simple diagram describes a situation while a drilling a well. In particular, it describes the relations between:

- The competence of the mud engineer
- A critical error in the mud mix, and
- The mud engineer’s appropriate response to a kick

The level of competence of the mud engineer is uncertain as are the probabilities of an error in the mud mix and a failure to respond to a kick in an appropriate manner.

The underlying software contains a “solution engine” which solves the probabilities of the node “states”. In this example each node has only two states:

- The competence of the mud engineer is either ‘good’ or ‘poor’.
- The mud mix activity may be either ‘error’ or ‘ok’
- The response to kick may be either ‘failure’ or ‘ok’

In this particular case, the solution engine tells the user that the probability of an error in the mud mix activity is 0.0044, and probability of failing to make an appropriate response to a kick is 0.0018.

BNs are typically much larger than the mud engineer problem and may contain hundreds of nodes and hundreds of arcs. Practical BN problems may also involve nodes with many more states, so that each node can model a detailed distribution of probabilities. In general, it is considered good practice to limit the number of parent nodes (arcs going into another node) and the number of states to a manageable level, as the CPTs will grow exponentially with the number of parent nodes.

The following paragraphs briefly describe some of the key features of BNs that differentiate them from traditional QRA methods:

- Uncertainty and judgement
- Backward reasoning (causal reasoning)
- Complexity
- Iterative development

### 3.2.2 Uncertainty and judgement

Modelling of uncertainty is an essential feature of BNs where the state of every node in the diagram is modelled as being uncertain. This feature allows users to directly account for uncertainty in each node. For example, the mud engineer's competence is uncertain and could be modelled to account for a wide range of degrees of competence. (The example shows only two states: 80% probability of 'good' competence and 20% probability of 'poor' competence, but the number of states could be much larger if we believe that the range of competences and probabilities can be further refined).

The approach to modelling of uncertainty is fundamentally different to the approach taken in a traditional QRA. A traditional QRA will normally perform probability calculations that are based on single-value best estimates, whereas a BN always models distributions of probabilities. This key difference opens up opportunities for modelling factors that might be omitted from a traditional QRA. Where factors are recognised as being relevant but uncertain they can usually be included by making judgements with probabilities to reflect the confidence in the expert judgements. From a frequentist standpoint, always seeking objectivity, it can be argued that this introduces a new level of uncertainty to the analysis. Clearly, if judgements are to be included, then these judgements should be made by relevant experts. Care should also be taken to account for known biases when assessing probabilities. If experts are not available, then judgements can still be made, but the range of probabilities should be suitably widened.

### 3.2.3 Backward (causal) reasoning

An important feature of BNs is the ability to quickly make inferences between one part of the network and another. Based on evidence associated with one random variable, inferences can be made both forward and backward in the model. A Bayesian network solution engine can recalculate the entire network of probabilities whenever the probability in one node is altered. This means that the BN will recalculate the probabilities in both the 'downstream' nodes and the 'upstream' nodes. The BN therefore calculates the probabilities of both outcomes and causes.

Taking the simple mud engineer problems as an example, the user could set the 'Response to kick' node into the 'failure' state. The BN will then recalculate the probability of an error in the mud mix, and the probability of poor competence. The BN has, in effect, updated the probabilistic beliefs of the causes of the failed kick response. (The revised probabilities of competence will be 'good' probability = 0.443, and 'poor' probability = 0.557).
This feature of BNs is not available in a conventional QRA tool where the calculation is towards outcomes: estimates of IRPA, PLL etc. A conventional QRA is not well suited to identifying the most probable drivers (causes) of accidents, whereas this is an automatic output from a BN.

Medical testing provides further examples of forward and backward inference using Bayesian statistics. For instance, the result of a blood test can be used to infer something about the probability of having a certain illness. This is forward inference. Conversely, knowledge about having this specific illness can be used to infer something about the probability of a blood test being positive for this illness. This is backward or reverse inference. In fact, BNs are solved by propagating these inferences throughout the network.

### 3.2.4 Complexity

BNs are suitable for modelling many complex problems where there are multiple interacting issues. Traditional QRA approaches tend to simplify some of the interacting factors by assuming that some factors are independent. For example, an offshore QRA needs to account for the many different wind speeds and directions that can occur. A conventional approach might be forced to consider a small number of wind directions and speeds, and also have difficulty in accounting for these values are common factors in different parts of the assessment. For example, the wind speed and direction will affect:

- Dispersion of gas
- Ignition (affected by gas cloud size, and direction of dispersion)
- Explosion overpressure (affected by gas cloud size)
- Dispersion of smoke
- Impairment of TR (affected by gas/smoke concentration and direction of dispersion)
- Impairment of lifeboat stations
- Drift of lifeboats / people in water (affected by wind direction)

BNs can take account of the way that wind speed and direction act as common factors throughout the assessment and also take account of the complex interdependencies between the bullet-point factors. A conventional QRA may assume that many of these factors are independent of each other. Besides the independence between factors, traditional QRA also mainly assumes a linear logical-deterministic causation between factors. However, the interactions between factors are often more complex. For example, if the competence of the mud engineer is poor and the mud mix has a critical error, it does not necessarily mean that there is failure to respond (probability 1), as a traditional fault tree analysis might imply. However, there will be a higher chance of failure to respond (probability 0.99 in the CPT for 'Response to kick'). BNs can also account for the complexity in the causation between different factors contributing to the overall risk.

### 3.2.5 Iterative development

The design of a Bayesian network is typically an iterative process. The BN may start small and simple and grow as the designers and stakeholders identify additional factors that should be included in the model. The model can be tested as the model is developed. This approach contrasts with a typical QRA build process where the final results are usually not available until all parts of the QRA are in place. In a conventional QRA the iterations are usually driven by the need to correct errors, whereas in a BN the iterations are used to ensure that the model includes all relevant factors to an appropriate level of detail. In general a BN designer should aim to build a network that has breadth to cover the types of influencing factor where it may be possible to implement control measures. The model should include details to a depth that allows decisions to be made; there is little benefit in modelling to a depth where risk decisions will have no effect.

# 4 SURVEY RESULTS

In order to identify where Bayesian networks have been used in DNV (or are currently in use), a research process was initiated as part of this project. A preliminary identification of personnel in the organisation with knowledge of BNs had been performed in association with the SOUL project, and this was used as a basis for further research. A search through the organisation was performed using the intranet and contact with the resources identified in the preliminary list. A questionnaire was developed and sent to all personnel identified in the process. The questionnaire contains questions regarding the use of BNs, and is included in Appendix 2 of this report.

In this process, a total of around 20 people were identified who have been exposed to BNs in their work. Of these, 12 people kindly either responded to the BN questionnaire and/or participated in brief meetings with the project team. The respondents are listed in Table 4-1. The project team would like to acknowledge their invaluable contribution to this study.

**Table 4-1 Participants in BN survey**

| Name | Location | Current Role in DNV | BN Application |
|---|---|---|---|
| Peter Friis-Hansen | Oslo | DNV Research & Innovation - Programme Director, Energy Programme | Vast academic experience from DTU, and several projects in DNVRI |
| Daniela Hanea* | Bergen | DNV MOG – Senior Consultant, Safety & Risk Assessment | Academic experience from TU Delft. |
| Rolf Skjong | Oslo | DNV MOG - Director / Chief Scientist, International regulatory affairs | FSA: Navigation of Large Passenger Ships, FSA: ECDIS as risk control measure for the world fleet |
| Linn Kathrin Fjæreide | Oslo | GGD – Senior Project Manager, Project Managers and Facilitators | FSA: Navigation of Large Passenger Ships, FSA: ECDIS as risk control measure for the world fleet |
| Anders Mikkelsen | Oslo | DNV MOG - Business Development Leader, Maritime Advisory Resources | FSA of ECDIS as risk control measure for the world fleet |
| Magnus Strandmyr Eide | Oslo | DNV MOG - Principal Consultant, Environment and Energy Efficiency | FSA of ECDIS as risk control measure for the world fleet |

| | | | |
|---|---|---|---|
| Lars Harald Hauge | Oslo | DNV MOG - Service Responsible Asset & Enterprise Risk Management, Business Risk Management | Several project risk analyses using influence diagrams (ca. 2005) |
| Todd Flach | Oslo | DNV KEMA – Principal Consultant, Gas Consulting and Services | COCATE, ECO2. |
| Narasi Sridhar | Columbus | DNV Research & Innovation - Program Director - Materials and sensors program | MARV |
| Andy Bolsover* | Aberdeen | DNV MOG – Principal Consultant, SHE Risk | SOUL, Decision support QRA |
| Bill Nelson | Houston | DNV MOG – Principal Consultant, Risk Management Solutions | N/A – Proposed the use of BNs for a cutting edge project |
| Luiz Fernando Oliveira | Rio de Janeiro | DNV MOG - Regional Manager, Brazil | N/A – academic experience, and experience within the field of Bayesian updating of probability distributions |

*Also members of the project team

Geographically, the resources are located mostly in Norway, Aberdeen and in the USA (Columbus, Ohio). No resources in Asia were identified during the course of this project. While many of the respondents have recent experience or are currently using BNs, it is interesting to note that there appears to have been an increase in activity in the early to mid 2000s. This increase in use appears to have faded out somewhat towards the late 2000s, before new projects such as SOUL and MARV were initiated recently.

The following section will briefly describe the projects identified in the survey.

## 4.1 MARV

The primary objective of the Multi-Analytic Risk Visualization (MARV™) project is to develop a flexible but rigorous methodology for risk assessment and deliver the results on a dynamic, visual platform. Pipelines in the oil and gas industry are an ideal test case for the MARV™ methodology, mainly because pipeline failures are often unexpected and have severe consequences on life, property and the environment (ref. /4/). Risk is often location and time dependent. Therefore, geographic information must be connected to an understanding of failure processes. The prediction of future risk of pipeline failure requires the ability to connect causative factors in a quantitative manner to the failure process. The MARV™ process involves three separate steps:

1. *Data Acquisition and Management:* In order to develop a truly comprehensive risk assessment method, it is critical to use 'all' available information. Many types and sources of information exist. The types of information regarding a pipeline can be grouped into three main categories: incident databases, time based data, and geographic based information. The MARV™ tool box can integrate a wide variety of data sources. (The MARV project is expected to develop a capability for collection of "real-time" data from remote sensors, e.g. pipeline inspectors working in the field).

2. *Modeling of Probability and Consequences:* Bayesian network models rely on the idea that the probability of an event depends on the probabilities of its causes and that, in the absence of existing statistical information, initial guesses can be updated using a variety of observations. A Bayesian network model is especially useful for complex systems, such as pipelines, where hundreds of factors can be linked together in a complex network. In MARV™, a variety of methods is used to develop the initial probability distributions of causative events and the cause-consequence connections.

3. *Visualization and Communication:* A good visualization tool is essential in a risk management program. The MARV™ tool shows the results of the risk assessment in a location and time specific manner. The tool is designed to obtain an overview of the system and to drill down and discover more detailed information. All numbers and calculations used to assess the risk can be made available, thus providing complete

transparency. Technological developments have enabled us to receive the information electronically via touch screen interfaces anywhere we go.

### 4.1.1 Projects

The MARV team has completed a project with Kuwait Oil Company (KOC). Modelling results were right on target. KOC engineers want to publish results in a joint paper DNV-KOC to a forthcoming NACE conference.

The MARV team has also completed a project with Zakum Development Company (ZADCO). Modelling results were validated by ILI data. Discussions on how to proceed with future collaboration are going on at the time of issue of this report.

### 4.1.2 MARV Team

The MARV project is located in DNV Columbus, Ohio. Participants include Narasi Sridhar (section manager), François Ayello (project manager) and Vinod Khare (software development).

## 4.2 SOUL

The SOUL project addresses the problems in applying the risk assessment decision methods to practical operational decisions making (ref. /5/). The limitations include:

- Long turn-around times for QRA studies
- Use of industry generic data
- No account of plant status
- No account of safety management performance
- Omission of human factors, experience and competence

In 2012, the SOUL development project developed a pilot system (demonstration tool) that illustrates how risks can be monitored and enabling safer decision making.

In the initial development, the tool was aimed at offshore operations personnel who need to understand the risks that they face on a day-to-day basis given the current condition of their safety critical plant, tasks, procedures and personnel competence. During development it has become apparent that the methods used in the SOUL project will also be relevant to a wider range of persons involved in risk assessment. The tool uses a Bayesian net in order to bring together information from normally disparate sources in order to provide a broad view of the factors that affect major accident risk.

The methodology is applicable to risk assessment in different types of major hazard industries. An early project decision was that the demonstration tool should use a blowout scenario as an example application in line with the next generation drilling theme.

The SOUL tool addresses the limitations of commonly available risk assessment techniques through:

- Use of location-specific data for plant status
- Inclusion of human factors issues including competence and training
- Inclusion of findings from safety management system audits
- Inclusion of findings from verification of safety critical elements

After entering new data, users of the SOUL tool obtain an immediate update of the risk status. The work in 2013 is proceeding to demonstrate that the tool can take live data from a remote source. The report from the SOUL project has demonstrated how various aspects of risk assessment can be addressed using a Bayesian Network.

The SOUL model was initially implemented using Visual Basic to provide buttons and scrollbars to adjust the probabilities in the BN nodes (Figure 4-1). The full graphical form of the Bayesian network was not visible to users in this initial implementation (The SOUL demonstration model contains about 150 nodes and 150 connecting arcs).

In 2013, the SOUL model GUI was changed to MARV which allows users to view parts of the BN and interact directly with the nodes (Figure 4-2).

Figure 4-1 Screenshot of SOUL model GUI (2012)

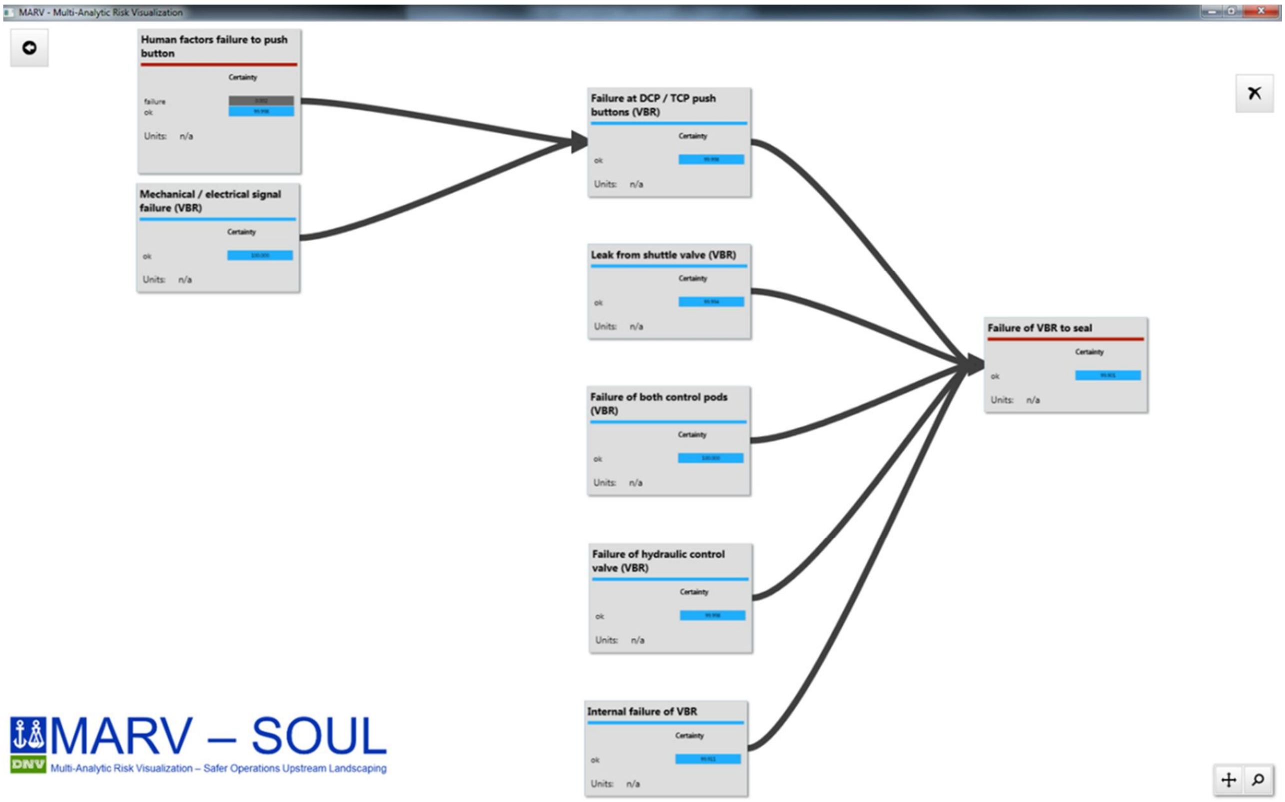



Figure 4-2 Screenshot of SOUL blowout model implemented in MARV (2013)

### 4.2.1 Note of the underlying Bayesian Nets in SOUL and MARV

The SOUL and MARV tools are both based on the use of Bayesian Nets to solve complex risk assessment problems. The projects have used two BN modelling tools: HUGIN and GeNIe / SMILE. The SOUL project made a rapid review of available tools and identified GeNIe / SMILE as its preferred tool. MARV started with HUGIN and then moved across to GeNIe to provide the SMILE “solution engine”. The SOUL project has now adopted the MARV interface as a means of interrogating the BN nodes. The network structures and initial data for these BNs are defined in simple text files. These text files use the HUGIN format, which is readable by the SMILE solution engine.

### 4.2.2 SOUL Team

The SOUL project is being delivered from DNV Aberdeen. The team includes: Andy Bolsover (project manager) and Sohaib Tahseen (software development).

## 4.3 QRA with Decision Support

This report is primarily concerned with Bayesian Nets, but there is a simple extension to the basic BN which adds decision support to the basic BN functionality. BNs that include this extension are termed ‘Influence Diagrams’. Influence Diagrams introduce two further types of node, termed ‘Decision’ nodes and ‘Value’ nodes. (The basic node in a BN is termed a ‘Chance’ node when it appears in an Influence Diagram in order to distinguish it from the other node types). Figure 4-3 shows an Influence Diagram with nodes shown as:

- Chance nodes – ellipses (white, green and yellow)
- Decision nodes – rectangles (blue)
- Value nodes – hexagons (red)

The Influence Diagram shown in Figure 4-3 was developed in 1999 for the Elf Company to study a variety of blast risk reduction options that were being considered for a North Sea production platform (confidential name). The work was reported at a conference in the same year, ref. /14/. The model shown in the Figure 4-3 is slightly simplified from the original study model.

The client had needed to assess several risk reduction options in a situation characterised by complexity, uncertainty, and multiple objectives. The decision making was complex because of the number of interacting issues involved. Many of the decision parameters were uncertain, but a robust practical solution was required that achieved safety at an affordable cost.

The Influence Diagram was used to model an ignited hydrocarbon release and explosion event on the offshore installation. The model is a coarse QRA for a single event, plus a number of decision options for risk reduction. The QRA modelled: the leak event, the dispersion of gas, ignition, explosion overpressure, blast wall failure, impairment of escape routes and primary muster areas by blast and smoke, evacuation by lifeboat, and fatalities. (These factors are modelled in 61 ‘chance’ nodes coloured white or green in the Figure). The probability data in the nodes were taken from various sources: the wind speed and direction nodes used historical data for the platform location, while the module ventilation rates and explosion overpressures were based on CFD modelling. Wall failure probabilities were based on discussions with the client’s structural engineers under a range of blast loading scenarios and resulted from a combination of calculation and professional engineering judgement. The ‘fatality nodes’ used probabilities of bands of fatality numbers. Much of the modelling was simplistic (for example, jet fire modelling was omitted), but the model clearly demonstrated the feasibility of doing a process QRA using a Bayesian Network.

Some of the Chance nodes QRA had up to 13 different states to model the full range of wind speeds and blast overpressures etc.

There was considerable uncertainty about how the ignition should be modelled. The BN therefore included this uncertainty by modelling more than one approach and assigning probabilities to the different approaches. These model uncertainty probabilities were obtained by expert judgement and are held in the yellow Chance nodes.
Prior to developing the Influence Diagram, an initial ALARP workshop and supporting studies had identified a very large number of options for reducing risks. Steps were taken for immediate implementation of some risk reduction options while other options were rejected. The remaining options were then studied using the QRA Influence Diagram.

The risk reduction options assessed in the model included:

- Option to upgrade the gas detection system
- Several options to upgrade or modify the module ventilation arrangements
- Several options to strengthen blast walls

Taken in combination, these risk reduction options gave 40 different options.

In addition to the four decision nodes (shown in Figure 4-3) there were up to 8 value nodes (the Figure shows 4 of these nodes) to assign costs to the risk reduction modifications and assign costs to the fatalities.
The completed model provided information on the risks associated with the blast event and the factors that could be controlled to reduce this risk. The model also identified the combinations of risk reduction options that were most cost-effective in achieving tolerable levels of risk.

Using a modern (2013) laptop computer, the run time for the model shown in the Figure is less than 1 second. Original model development occurred over a period of several weeks during which time the CFD studies for ventilation and blast overpressure were also being performed.

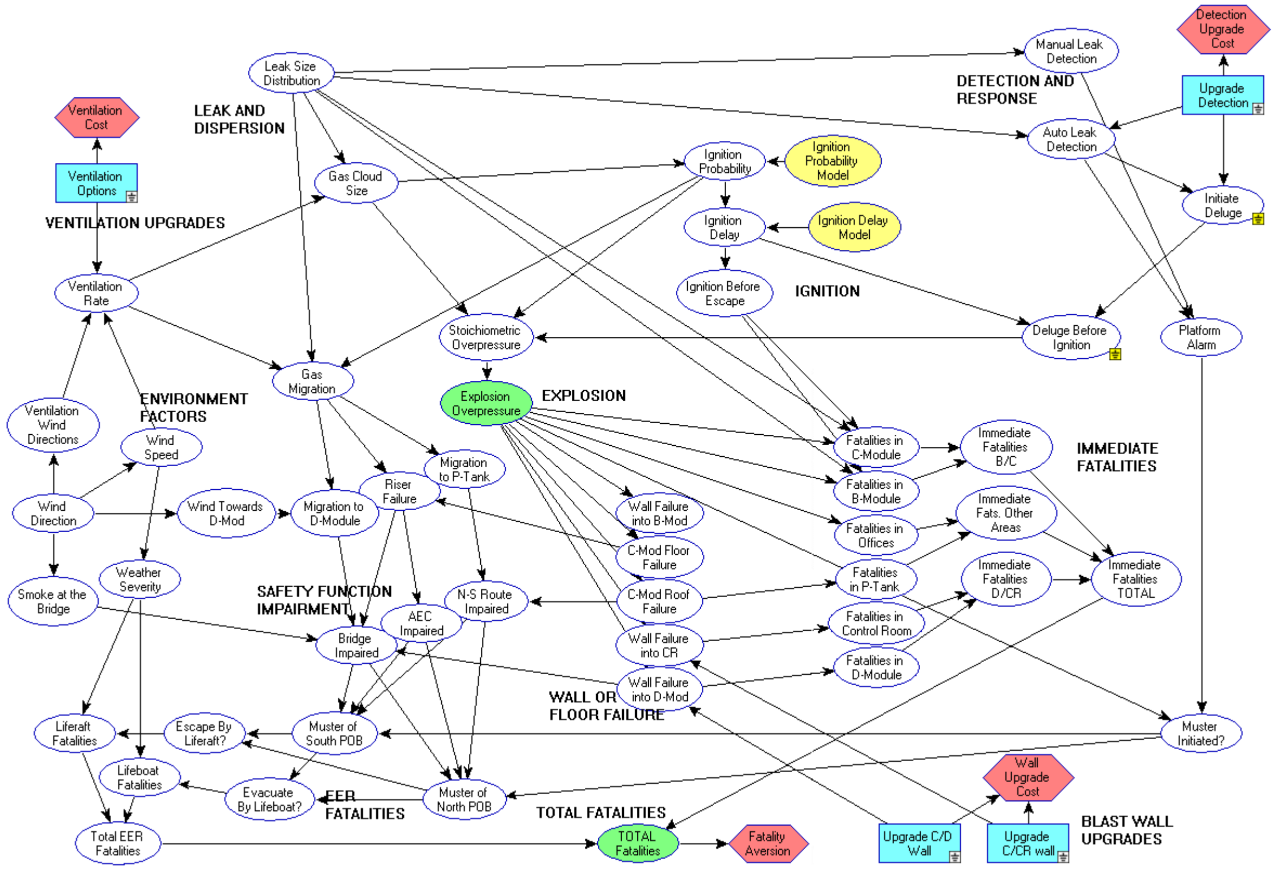



**Figure 4-3 Influence Diagram for offshore process QRA (gas release and blast)**

## 4.4 Navigational Safety

In the 2000s DNV performed a series of assessments of navigational safety, using BNs. The first project, initiated in 2002, was SPIN-HSV. SPIN-HSV was a research project co-funded by the European Commission under the 5th Framework Programme for Research and Development. The objective of this project was to identify concepts and recommendations for coordinated euro-national policies on integration of safer high-speed maritime transport in the logistics chain. A BN was used to model risk of high-speed navigation.

A BN was also used in a series of Formal Safety Assessments (FSAs) of navigational safety, resulting in submissions to the International Maritime Organization (IMO). The first project, “Formal Safety Assessment – Large Passenger Ship – Navigation” (ref. /6/) was a Joint Industry Project with partners the Norwegian Maritime Authority (NMA), the Norwegian Ship owners Association, and Kongsberg Maritime Ship Systems – Norway in addition to DNV – Norway. The objective of the project was to identify risk control options to be implemented for large passenger ships by IMO, based on FSA.

The project consisted of a risk and cost effectiveness assessment of risk reducing measures for navigational risk. Bayesian networks were selected to perform the risk modelling as, historically, few accidents have occurred with cruise vessels. Statistics were used to coarsely calibrate the results from the modelling, but statistics were however not considered to be the correct answer. The report argues that the observation that there is no record of a certain type of accidents in a database does not necessarily mean that the type of event cannot happen.

A team of risk analysts developed the models, and the result was reviewed by navigational experts.

A follow-up project was initiated for an FSA, including cost effectiveness assessment of Electronic Chart Display and Information System (ECDIS) for relevant ship types (excluding High Speed Crafts) (ref. /7/). This FSA used a Bayesian network model based on that in ref. /6/, developed further to be valid for other vessel types as well as cruise ships.

## 4.5 COCATE

DNV Norway participated in the European Union 7th Frame Programme project COCATE. The objective of COCATE is to analyse the conditions for transporting the flue gases emitted from several CO2-emitting industrial facilities with a view to pooling the capture process, and for exporting large quantities of captured CO2 to storage areas. Led by IFP (France), the project brings together eight other research and industrial partners: the Le Havre Region Development Agency (France), Geogreen (France), Accoat (Denmark), SINTEF Energy Research (Norway), DNV (Norway), TNO (Netherlands), Port of Rotterdam NV (Netherlands) and SANERI (South Africa) (ref. /10/).

As part of the COCATE project, a risk analysis model has been developed by DNV, in partnership mainly with TNO, in order to quantify and analyse safety risks related to loss-of-containment scenarios in the pipeline transport of CO2. The risk model integrates the identified failure modes, consequence estimates and emergency response, producing consistent risk profiles based on complete outcome spaces and for different system design choices. The method involves integration in a BN of analytical equations for gas dispersion combined with statistics and expert estimates of particularly uncertain variables (ref. /8/).

The project involved producing consequence (Probit) results in the PHAST software for a wide outcome space for different conditions and failure modes, transporting these into Matlab and producing huge correlation tables. These tables were imported into the HUGIN BN model. The main, top-level BN model is shown in Figure 4-4.

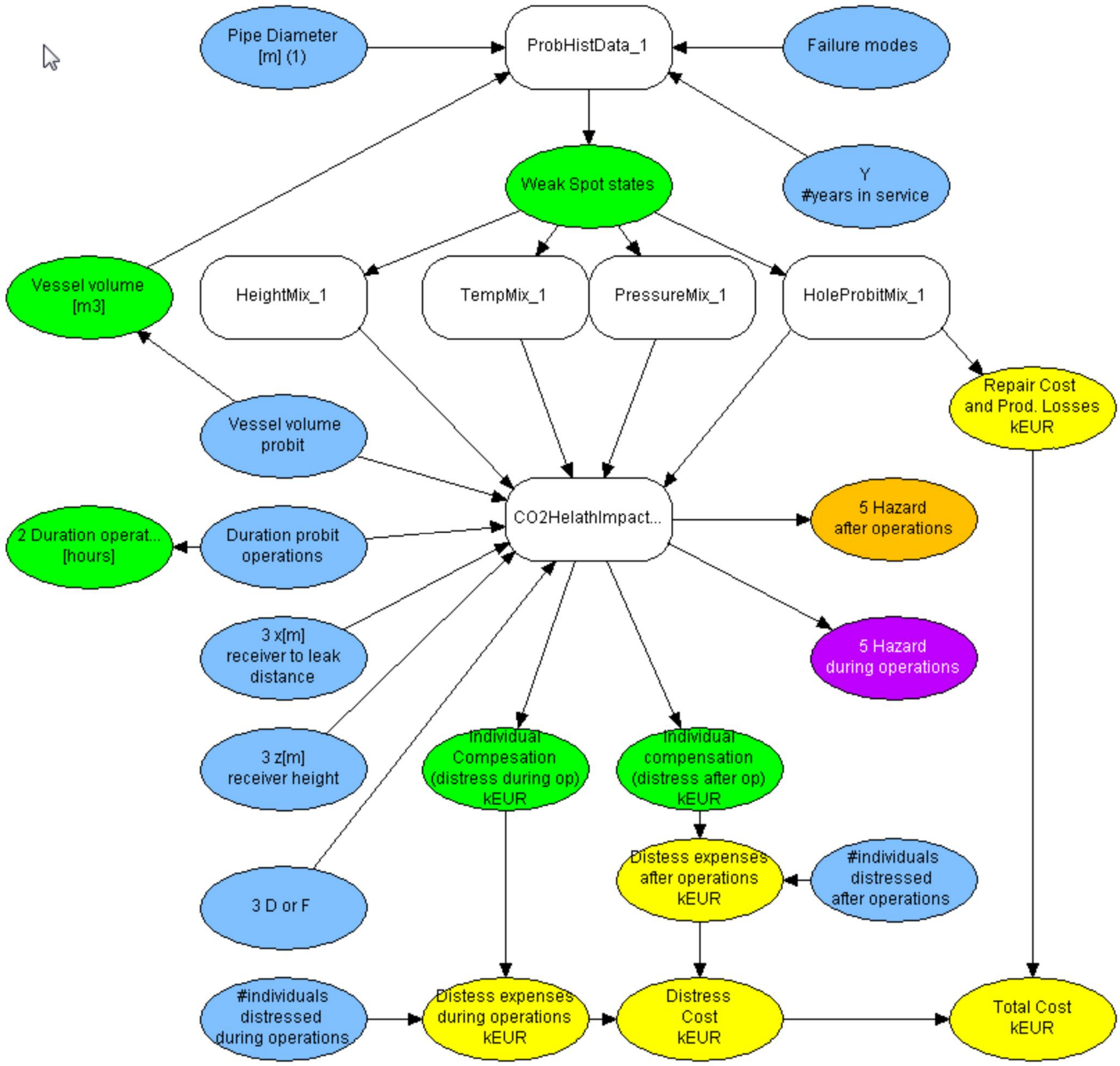



**Figure 4-4 Screen capture of the main, top-level BN model showing input nodes (blue), main output nodes (yellow) and intermediate results (green, orange, purple) and imbedded sub-models (white), ref. /8/.**

The DNV team involved in the COCATE project are currently developing a BN evaluating the propensity to leak from underground geological CO2 storage sites as part of another EU 7th Frame Programme project, ECO2.

## 4.6 Enterprise Risk Management

In the Business Risk Management (BRM) unit in Norway, influence diagrams were used in several projects related to project risk in a period approximately between 1995 and 2005. Influence diagrams are a generalized form of BNs, including decision and value nodes in addition to probability/uncertainty nodes. The use was however discontinued in favour of more traditional project management methods. Reasons cited for opting to use traditional methods include lack of familiarity with BNs for both analysts and customers. This lack of familiarity could lead to a reluctance of customers to understand and accept the models.

## 4.7 Other Applications

DNVRI have used BNs in several other research projects. Championed among others by programme director of the energy programme, Peter Friis Hansen, BNs have been used for risk modeling of health effects of nano particles, human error modeling, ship-ship collisions among other applications. BNs are currently applied in a model of climate change effects on systems.

## 4.8 External Use

The research in the area of BN has been growing considerably in the last decade mainly due to the need to model more complex systems and the higher simulation capabilities of computers. The scientific literature database shows an increasing trend in the occurrence of papers on BNs in the last 20 years (see Figure 4-5). A summary of BN applications in academia and other industries are presented in Section 4.8.1.

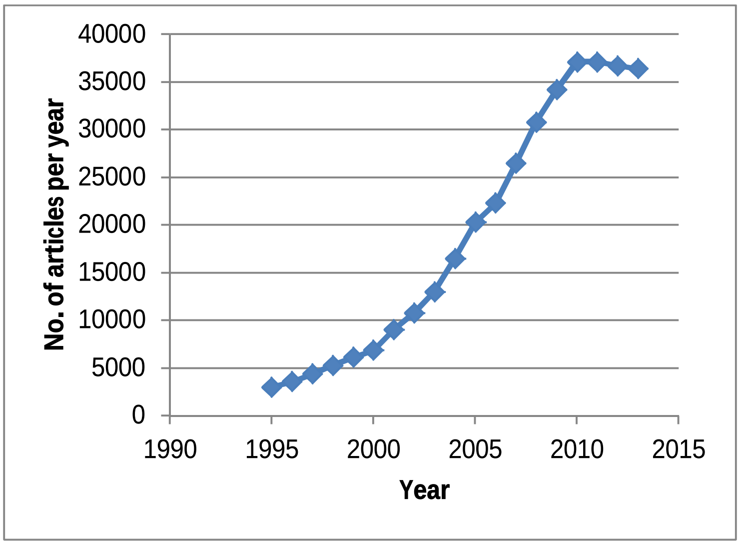



Figure 4-5: Articles on "Bayesian networks" in Google Scholar

Through the course of this project, it has not been possible to identify whether BNs are widely used in services by any of DNV's direct competitors in the risk management field. However, a new methodology for calculation of hydrocarbon release frequencies has been developed by competitors to DNV in Norway. This methodology is introduced in Section 4.8.2

### 4.8.1 BN applications in academia and other industries

As it can be seen in Figure 4-5, there have been a large number of scientific publications on BN in the last several years. An overview of applications of Bayesian networks to dependability, risk analysis and maintenance (ref. /13/) shows also an increase trend in the literature related to these domains in the last decade. The authors explain this trend by the benefits of BNs compared to the classical methods of dependability analysis, as Markov Chains, Fault Trees and Petri Nets. "Some of these benefits are the capability to model complex systems, to make predictions as well as diagnostics, to compute exactly the occurrence probability of an event, to update the calculations according to evidence, to represent multi-modal variables and to help modeling user-friendly by graphical and compact approach." (ref. /13/) Figure 4-6 shows the main steps of the evolution of BN literature and its application in risk analysis based on the most relevant papers. Some of the aspects covered by these publications are modeling the dependencies between events and quantitatively estimating the risk with barriers' impact on the system. In 2001, one of the first applications of BN in the oil and gas industry proposed a framework to integrate organizational risk indicators for assessing the risk impact.
Other areas with most of the BN applications are:

- Nuclear industry: for human reliability analysis and integration of human factors for evaluation of several risk scenarios
- Maritime transportation: for quantification of human and organizational factors in the risk analysis carried out in the design phase of High Speed Craft
- Offshore operations: integration of organizational risk indicators for assessing the risk impact
- Energy industry: for cost benefit analysis of operational and maintenance of offshore wind turbines; risk modeling of hydrogen refueling stations

- Transportation safety: for probabilistic assessment of excavation performance of tunnel projects which consider the quality of the design and construction process
- Infrastructures: for assessing structural reliability of bridges with updating observed information from measurements, monitoring and visual inspection; risk assessment of urban drainage industry
- Aviation safety: for integration of human and organizational factors into a risk based decision model for flying into the ground frequency
- Natural hazards: earthquake risk management; application to rock-fall hazard risks on roads; incorporation of uncertainties in an avalanche risk assessment
- Medical field: for cardiograph, clinical diagnosis of diseases, gene expression, interpretation of electromyography data
- Finance: for prediction of operational risk in a banking organization

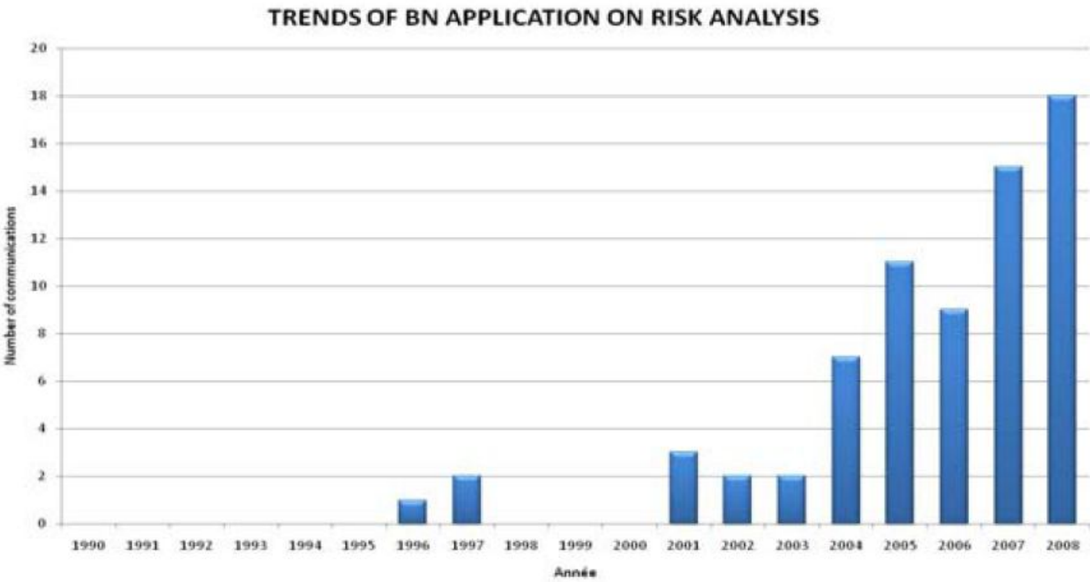



**Figure 4-6: Publication number related to Bayesian Networks applications on risk analysis (taken from ref. /13/)**

### 4.8.2 Risk OMT

A new methodology for estimation of hydrocarbon release frequencies has been developed in recent years, mainly by risk consultancy company Safetec Nordic AS and the University of Stavanger, called Risk OMT. The model, based on the previous BORA methodology and the Statoil Operational Condition Safety (OTS) project, attempts to reconcile MTO (man, technology, and organisation) factors with historical leak frequencies. The premise of the model is that almost 2/3 hydrocarbon releases in the Norwegian offshore industry have resulted from manual operations and interventions, according to data from the Petroleum Safety Authority (PSA) Norway from 2001-2005. The Risk OMT methodology therefore attempts to model hydrocarbon releases as a function of manual operations and interventions. The model consists of generic scenarios, and considers the operational barriers in event trees and fault trees, as well as risk influencing factors (RIFs) that determine the basic event probabilities in the fault trees. BNs are applied for the modelling of RIFs. Risk OMT provides a generic framework, using a pre-defined set of scenarios and generic BNs for the basic events in the fault trees. Each basic event is associated with an average human error probability, and the BNs are used to adjust this probability based on the states of the RIFs.

The BNs contain RIFs for which a score from A to F can be assigned. Here, A corresponds to best industry practice, C corresponds to the average probability, and F corresponds to an unacceptable state. RIFs are organised in two levels, where Level 1 RIFs directly influence the basic event. Level 2 RIFs are factors which influence the RIFs on level 1. Generic CPTs were created for the different RIFs, by assigning triangular probability distributions for the RIFs and relative weights between nodes. The weights were assigned on a three point scale (high-medium-low influence), corresponding to a quantitative weight of 5-3-1. If no relation was identified, the weight was set to zero. A detailed description of the Risk OMT methodology can be found in ref. /12/.

The Norwegian oil company Statoil has showed interest in this methodology, and DNV is currently involved in discussions with Statoil and other QRA providers regarding the possibility of implementation of Risk OMT in QRA.

As this is a separate, on-going process, this report will not attempt to make any statements regarding the validity, suitability or quality of the Risk OMT methodology. While a discussion of the application of BNs in Risk OMT would certainly be interesting, it would require a much more detailed review than what has been possible within the scope of this study.

However, it is an important observation for this study that BNs are being used in methods developed by our competitors and key clients.

# 5 SWOT

In order to review the experiences made by personnel involved in the use of BNs, either in the projects described in section 4 or otherwise (e.g. academic experience), the questionnaire used in the survey included question related to the success of applying BNs for the given application. Respondents were asked to identify advantages and disadvantages of BNs, suggestions for other areas where BNs could be applied and perceived reasons why BNs are not more widely applied in DNV services related to risk management. Finally, respondents were asked to explain whether they thought BNs should be considered a tool for the future, and what DNV could do to pursue further use of BNs.

A workshop was arranged in Oslo on 25 September 2013 where the results of the questionnaire were reviewed and discussed. The workshop was carried out as a SWOT-type exercise, where strengths, weaknesses, opportunities and threats associated with BNs were identified. The exercise was carried out using relevant services and focus areas defined in the TL Position Paper for Risk, Reliability and Human Factors (RRHF) (ref. /11/) in addition to other internal and external factors as guidewords:

- Quantitative Risk Analysis (QRA)
- Safety Barrier Management (SBM)
- Human Factors (HF)
- Technical issues (e.g. software)
- Organisational issues (e.g. competence, management)
- Market issues (e.g. customer demand or willingness, market opportunities)

The identification process involved both review of the responses to the BN questionnaire and roundtable discussions. The participants in the workshop are listed in Table 5-1.

**Table 5-1 BN workshop participants**

| Name | Role | DNV Unit |
|---|---|---|
| Andy Bolsover | Project team member, BN experience | Aberdeen SHE Risk |
| Daniela Hanea | Project team member, BN experience | Safety & Asset Risk Management, Bergen |
| Geir Korneliussen | Workshop participant | Integrity Management Development, DNV Software, Oslo |
| Kjetil Holter Næss | Project manager, facilitator | Safety Risk Assessment, Oslo |

A further review of the questionnaires was performed as a desktop exercise after the workshop. A comparison of the features of BNs and trends in the safety/risk management field was also performed.

## 5.1 SWOT Findings

The results from the SWOT analysis are contained in Appendix 1.

Key findings are summarised as follows:

Strengths

- Bayesian nets are well-suited to modelling decision problems which have a high level of inherent uncertainty. For example, they are likely to be useful in modelling of "emerging" risks where the relevant factors have not been fully identified or evaluated.
- Bayesian net are able to explicitly quantify the uncertainty in the major relevant factors in a decision problem.
- The Bayesian network approach allows for both forward and backward inference, which is not possible in a traditional QRA. For example, the backward inference capability means that the risk drivers for a major accident scenario can be readily identified
- The Bayesian network approach can improve the bow-tie analysis, but providing a more detailed modelling of the left hand side of the bow-tie, as well as by identifying and displaying the causal relations between barriers and their relative criticality
- One of the benefits of the BN approach is the capability to model and incorporate soft factors such as human and organizational factors into a risk model. These factors are usually characterized by high uncertainty. One source of uncertainty comes from the fact that there is sparse data regarding these factors and therefore, expert opinion has to be used for quantification. Moreover, there is also inherent variation in these factors, for example in the level of competence of people performing a certain task at a particular platform. BNs can model these uncertainties and propagate them through the risk model, providing in this way a higher resolution in the outcome space.

Weaknesses

- Bayesian nets are tools for modelling probability, not consequence. Any necessary consequence modelling must be done outside the Bayesian net.
- The output from a BN is a probability, not risk, or a frequency. This means that post-processing is required to obtain FAR, PLL, IRPA, impairment frequencies etc.
- Using BNs to model large, complex systems such as those used in QRA leads to a large number of causal relations and states, which increases exponentially the quantification effort.
- Rewriting a bow-tie as BN might lead to a loss of visibility in the path from threat to top event and consequence, due to the cross-linking of causal factors which may appear in several branches of the bow-tie.
- There are scattered resources in DNV regarding the use of BNs, with little or no formalised contact. Very few people have been trained in using BNs or Bayesian statistics

Opportunities

- Bayesian networks are most likely to find applications in areas of emerging risks. In areas of high uncertainty, such as the Arctic oil and gas development, where historical industry data may not apply, the Bayesian approach might be a useful decision tool. In fact, BN potentially have a role in any risk assessment where the likelihoods (of hazardous events, protection/mitigation failure etc) are inherently uncertain.
- Many organisations are trying to find a way of addressing MTO issues as a source of risk. BNs seem to be a useful tool for addressing this issue.
- Small and easy validated networks can be built up for parameters in QRA for which good and trustworthy data is not available. This might reduce the number of assumptions that are made in a QRA and lead to a more detailed assessment. In the same time, smaller BN models can prove the applicability of this method.
- Already existing operational risk tools, can be used together with BN approach to visualize the barrier conditions and to establish the connection between the actual barrier condition and the risk level.
- The development of in-house software in DNV can be a great strength to include BNs in future risk assessment tools, but it could also be a hindrance if BNs are viewed as competitors to existing software.

Threats

- DNV may fail to recognise appropriate opportunities for effective application of Bayesian nets; BNs are not straightforward replacements for existing tools.

- Customers and consultants who are used to traditional methods may not immediately accept a sudden change in approach.
- Increased use of BNs across regions may require a significant investment. This could include providing sufficient / suitable training (both for both own employees and clients) in the use of Bayesian nets, development of BNs for use in risk models, specialised software etc. If a coordinated implementation of BNs is wanted, a clear sense of direction, and explicit support, from the TL initiative may also be required.

## 5.2 Relevance of BNs for Trends in Risk Management

The TL Position Paper for RRHF (ref. /11/) contains a list of trends in the technology development and market needs. Relevant features of BNs for these trends are presented in Table 5-2.

**Table 5-2 Trends in technology development and market need, and comments related to BNs.**

| | Trend | Characteristic | Comment on Bayesian networks |
|---|---|---|---|
| General Trends | From risk assessment to risk management to risk governance | The traditional assessment process is replaced by a management process whereby risks are continuously managed. Risk management is increasingly integrated into the governance system of the companies. | - |
| | Emerging risks | Non-traditional risks are supplemented by emerging risks where the industry perceive this to be potentially significant but where they have little knowledge and thereby not fully understood. | BNs are expected to be a particularly powerful tool for assessment of emerging risks where uncertainties are an important consideration. |
| | Resilience engineering | Resilience Engineering looks for ways to enhance the ability of organisations to create processes that are robust yet flexible, such that they maintain or regain a dynamically stable state when responding to upset and stress. | - |
| | Newer risk methods | Traditional risk methods are now being supplemented by newer approaches using Bayesian Networks and integrating Computational Fluid Dynamics (CFD) and MTO issues. | BNs directly address this issue. |
| | From compliance to value creation | The traditional domain of risk assessment as a tool to evaluate compliance is extended to a broader focus on risk assessment as part of value creation. | - |
| | From risk reduction to risk optimization | Risk reduction shifting towards risk optimisation across multiple sources of risk, where there is a balance between risk and reward. | Influence diagrams (an extension of BNs) model decision options and the costs of decisions. If costs are modelled uniformly (e.g. a $ value is assigned to loss of life, as well as cost of implementation) running the influence diagram will identify the optimal risk reduction solution. |
| | From methods to frameworks | Traditional risk assessment methods are extended to complete frameworks containing description of methods risk strategy, - appetite, -structure, reporting | - |
| | Safety Barrier | There is a shift toward focus on safety barrier management both with respect to operational decision making, maintenance and design and including effect of safety barriers in the risk assessments. | Safety Barrier diagrams are used to present different types of barrier (plant, people and procedure) on the same picture. BNs allow the probabilities of barrier states to be modelled, thus generating a risk evaluation. |

| | Trend | Characteristic | Comment on Bayesian networks |
|---|---|---|---|
| | Operational risk | Operators are moving to more systematic approaches for managing operational risks. | The SOUL project has demonstrated how BNs solve many of the problems in modelling operational risk. |
| | Focus on human and organizational factors | The scope of risk assessments is also extended to reflect the effects of organizational behaviour, human factors, safety/organisational culture and leadership/-involvement. And dealing with competing objectives. | The implications of these factors on risk are highly uncertain. This makes BNs an ideal tool for evaluating risk associated with HF and organisational factors. |
| | Focus on Safety Culture | Extend the current focus on safety management systems and human factors to address the overall safety culture of an organization and how this might reduce major accidents. | The implications of issues related to safety culture risk are highly uncertain. This makes BNs an ideal tool for evaluating risk associated with safety culture. |
| | From technical risk management to Enterprise risk management | Traditional risk assessment focusing on technical risk assessment of a physical asset is extended into integrated risk assessments covering both technical objectives and all important governing objectives for the enterprise (strategic, financial, operational, HSE, brand, etc.) | The implications of some issues related to ERM are highly uncertain (other issues may be readily quantified). This makes BNs a useful tool for evaluating some ERM risks. |
| Stochastic risk processes | Real options/flexibility | Future uncertainty can be mitigated by inclusion of flexibility and options that allow for future changes. The value of real options on investments and projects is becoming increasingly important. | BNs are well suited to evaluating some types of stochastic risk processes. |
| | Stochastic processes | To calculate risks related to assets with a changing uncertainty and risk profile, a stochastic process needs to be employed. Stochastic processes are not new to DNV of course, but here we refer to dynamic stochastic processes. | |
| | Value and control of information | During risk management processes, there is often the possibility of acquiring more information to reduce uncertainty. Ensuring the optimal level of information becomes an important part of the risk management process itself. | |
| Earlier Involvement through decision support | Earlier involvement of risk assessment | Risk assessments are shifted from serving as a compliance assessment to a decision support exercise, being brought in much earlier in the companies' value chain, typically at a "Business case" or "Feasibility" stage. | BNs / Influence Diagrams provide support of decision-making under uncertainty. |
| | Risk assessments used more for comparison between decision | Traditionally risk assessments are used as a compliance exercise towards (safety) criteria. More and more risk assessments are often used as a comparison exercise to support the actual decisions between several options. | |
| Cost Utility Risk management | Taking the right risks | Risk is part of every business. No risk – no business. With the expansion into enterprise risk management the risk strategy is related to safely and responsibly improving the business results. | BNs can potentially aid the evaluation of risks and risk drivers in many different aspects of business. The usefulness of BNs must be traded against the time that it takes to develop the BN model and the necessary speed of response. In situations where development time and speed of response are not critical, BNs may be well-suited. |
| | A portfolio approach to cost/utility assessments | With the extension of risk assessments into enterprise risk management, companies can to a greater extent use their risk mitigation resources from a portfolio perspective. Traditionally risk resources (cost, people, systems, etc.) have been allocated to each discipline individually for reducing the risk exposure (financial risk, safety risk, security risk, etc.) | Traditional methods might be better suited when evaluating risks across a very diverse and dynamic portfolio where new unexpected risks (unknown unknowns) are being identified at a high rate. |

| | Trend | Characteristic | Comment on Bayesian networks |
|---|---|---|---|
| Decision making | Real-time risk management | Risk management is more and more integrated into real-time decision making. Integrated operations in the oil & gas industry are an example where control systems, safety barriers and risk management systems are integrated into a real-time decision support system. | The SOUL project (and also MARV project) has directly addressed this issue. |
| | Leading risk indicators | The increase of real-time risk management has brought with it an increased focus on *leading* risk indicators and key performance indicators. Traditionally risk indicators have been centred around measurements of consequences, such as numbers of incidents/near misses, etc. Recent focus has been shifted towards more leading indicators such as number of people, complexity of operation, activity type, operational windows, etc. Leading indicators have been agreed in industry (API754) that link directly (e.g. safety barrier failures) and indirectly (e.g. procedures not followed) to major accidents. | BN's provide a potential means to synthesize an overall risk "temperature" which takes account of multiple risk indicators. The BN can be used to infer the main risk drivers. |
| | Influence diagrams | Bayesian networks / influence diagrams as a tool for decision support | BNs directly address this topic. |

# 6 SUMMARY AND CONCLUSIONS

This report has presented the findings of the TL project Bayesian Networks in DNV. The main objective of the project has been to identify personnel who have worked with BNs and projects where BNs have been applied within DNV, to discuss the potential of BNs in DNVs services related to risk, reliability and human factors, and to provide suggestions for future work related to BNs.

Several projects where BNs have been applied were identified, some of which are currently on-going. A small group of experienced resources were identified in Norway, the UK, and in America. These resources were asked to answer a questionnaire and/or participate in talks with the project team about their experience with BNs. After this, a workshop was carried out where the findings of the survey were discussed.

The general impression is that BNs have significant benefits compared to traditional methods for risk assessment. Key benefits include:

- Capability to express and quantify uncertainty in the models. This, among other benefits, makes BNs suitable for modelling situations which have high levels of inherent uncertainty, e.g. emerging risks, and “soft” factors such as human and organisational factors
- Capability to quickly perform forward and backward inference, to identify both the probable consequences and causes in risk scenarios
- High speed of Bayesian software “engines” can provide near real time decision support
- Modelling of uncertainty and conditional probabilities allows for a higher definition in the outcome space of the risk models
- Transparent and structured modelling of risk influencing factors

As for all other models, there are also weaknesses associated with BNs. Limitations include the inability to deal with frequencies, and the propensity to require huge quantification efforts as the CPTs increase exponentially in size as the number of incoming links to nodes increases. In this case, it may also become difficult for customers or other analysts to follow the reasoning behind the quantification, particularly if this is not done in a structured manner.

The benefits and weaknesses of BNs may make them more suitable for specific types of problems. For instance, BNs may be very suitable for modelling complex decision-making problems, and real – or near real – time decision support tools, such as demonstrated in the SOUL and MARV projects. BNs may also be effective for modelling of specific probabilities in the QRA, where suitable historical data is not available. QRA of a single process event can certainly be built in a BN, and ship collision modelling using a BN has also been demonstrated. It is therefore likely that a QRA could be built from a series of BNs representing different process events, plus separate BNs to represent the various types of non-process hazards.

For full QRA implementation, that is modelling the QRA entirely using BNs, the applicability of BNs is more uncertain than for the type of applications identified in this report. In order to obtain an understanding, further research will be necessary. This approach would be an extensive research project, which would require a significant investment, and might conclude that the existing QRA methodology is sufficient or that the benefits do not outweigh the added effort. For less complex applications, a bottom-up approach might be suitable where BNs are first applied to a small set of applications where we can already see the advantages of using BNs. One of our major difficulties will be in recognising suitable areas of application. They should be in areas where there is high inherent uncertainty (e.g. emerging risks, human factors) or areas where very rapid reassessment is required. This approach would not require the same level of investment. However, it could be ineffective if the initiative is not coordinated, promoted and supported by investments in training and service development. The two approaches are summarised below:

1. *Gradual development*: Start gradually by developing BNs to calculate probabilities used in QRAs today which are not well defined, and/or for well-defined decision making problems. BNs There are several probabilities used in QRA for which historical data is not available, and no detailed analysis has been performed. These are often defined through very coarse estimations, listed in the assumption register. Development could be done as service development projects, or partly as part of external projects. As more BNs are developed, these can be combined to create larger, generic BNs to apply in risk analyses.
2. *Full QRA approach*: In order to determine how suitable BNs could be in a formal QRA, such as required for offshore applications in Norway in the NORSOK Z-013 standards, a large development project (e.g. a JIP) could be proposed. Here, DNV could invite one or more clients for which we hold the existing QRAs and attempt to remodel these completely or partly using BNs. By remodelling previously completed analyses, the different methods can be carefully examined and compared.

Reliable 3rd party software tools for building and calculation of BNs are readily available, such as HUGIN and GeNIe. The GeNIe and SMILE software is even provided free of charge by the Decision Systems Laboratory of the University of Pittsburgh. Resources within DNV have significant experience with this tool. DNVRI have been using HUGIN as the preferred tool in several projects. Responses to the BN survey indicate that GeNIe may be more flexible than HUGIN, but a more thorough review of available software should be performed in order to determine the most suitable software for DNV. Defining a common software tool to be made available for relevant DNV employees could facilitate increased use of BNs.

## 6.1 Recommendations

If, based on the discussions in this report, it is decided that DNV should encourage the use of BNs in suitable projects, the following recommendations have been identified to facilitate this:

1. Conduct a coordinated series of BN presentations within DNV (series of lunch meetings, or in competence network groups). This should include:
   - Theory
   - Simple example
   - Applications/Example from the previous DNV projects, with the possibility to ‘play’ with the models that have been developed, to show the capabilities of BN

   A short training course could be provided to raise awareness and introduce the technology. The short training course could be followed by longer training courses for relevant groups who could be applying the methods in risk management services. The training course should allow attendees to identify projects where BNs might be part of the offered solution. The network of personnel identified in this current project may be available to advise on suitability of BNs to future proposals/projects.
2. Identify key problems in the current risk analyses where BNs might offer significant advantages. This could include applications identified in this project, such as barrier dependability, integration of human factors into QRA, refining leak frequency and factors contributing to leak frequency, blowout frequency and ship collision frequency. It could also include other important issues such as operational risk

assessment and cumulative risk, asset management and life extension, competence management, process safety management and the assessment and management of risks arising from MTO issues. In general, issues related to the insufficient data, or industry averages which might bring more value if tailored to the actual situation (in time) or to a certain installation/operator/client, etc.

- Study the applicability of BN for these problems and develop small BN models. These models have to be general enough to be applicable to other projects, but include also the needed degree of details to help decision making process in that particular problem
- This activity has to be coordinated by a core group with direct involvement of the TL group.
- The network of personnel with experience using BNs (including the current project team) could be available to provide advice in the model development projects.

3. An important factor will be to increase awareness of both internal resources and clients regarding the importance of uncertainty in decision making
   - First, to recognize that there is uncertainty
   - Then, show them the 'power of uncertainty': the difference between one point estimates and distribution when it comes to take decisions
   - Help the customer deal with uncertainty and take decisions under uncertainty

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# *Appendix 1*
# *SWOT table*

| | **Strengths** | **Weaknesses** | **Opportunities** | **Threats** |
|---|---|---|---|---|
| **QRA** | -Ability to explicitly quantify uncertainty both in the parameters and the relationships between nodes.<br>-Bayesian approach allows for backward inference, which is not possible in a traditional QRA. This means that the risk drivers are readily identified.<br>-Provides a structured, transparent probabilistic model for the QRA. All factors, and the relations between them, can be accounted for in the same model.<br>-BNs provide a transparent visualization of the risk model compared to traditional QRA.<br>- Assists more detailed modelling of the left hand side of the bow tie.<br>-Allows a structured, transparent method for supplementation of historical data by judgmental values, which often disappear in the QRA assumption register.<br>-More suitable for gradually refining the analysis (i.e. by creating relatively simple BNs and gradually building detail where necessary)<br>-For an analyst it may require less effort to apply a range of uncertainty than being forced to provide a point estimate, where data is not available.<br>-BNs provide higher resolution in the outcome space, i.e. for specific combinations of parameters.<br>- It can provide a light version of QRA for decisions at different phases of a project, when a detailed QRA is not possible (due to high uncertainty) or not needed. | - Maybe not as useful for dynamic modelling of time-dependencies? It can only be modelled as Markov chains. Safeti Offshore relies heavily on physical modelling in time steps.<br>-Detailed consequence modelling must be done separately. In a BN the outcome space may be large, and require a vast amount of iterations of the consequence modelling.<br>-The output of a BN is always a probability, not frequencies (This can theoretically be circumvented by introducing very small frequencies (e.g. in reducing the time steps) and use rare event approximation). This makes BNs somewhat less suitable for consequence assessments and means some post-processing is required to obtain FAR, PLL, IRPA, impairment frequencies etc.<br>-Not necessarily suitable for structural reliability assessments, as the correlation structure and formulation of the limit state function is generally too complex. FORM/SORM and simulation models are probably more useful.<br>- Building complex systems (such as an entire QRA) as BNs, with large numbers of causal relationships and states, can yield enormous networks. | -Some areas of the QRA today are associated with considerable uncertainty and often end up as an assumption in the assumption register in lack of a more detailed assessment. As a starting point input parameters to QRA could be modelled in BNs where good, trustworthy data is not readily available. Smaller, easily validated networks. As these are built, they can eventually be linked together. This will also demonstrate the applicability of the tool.<br>-GeNIe is readily available, open source tool.<br>-In areas of high uncertainty, such as the arctic, where historical industry data may not apply, a Bayesian approach might be an option. | -Replacing large parts of the QRA engine with BN in order to aggregate the risk level of an entire installation could be prohibitive. |

| | Strengths | Weaknesses | Opportunities | Threats |
|---|---|---|---|---|
| **SBM** | - In operation, BNs can be used to update the risk picture given the condition of barriers. Backwards inference allows for flexible use in decision-making processes.<br>-Bow Ties provide a good, but simplified visualization of barriers in place to prevent accidents. The bow ties contain little information on how the failed barriers actually affect the system and other barriers. BNs will focus on identifying and displaying the causal relationship between barriers, and their relative criticality.<br>- It can take into account the commune causes for barrier failure. In the bow-tie analysis it is assumed that the barriers are independent.<br>- It can facilitate the integration of human and organizational factors into SBM<br>- It can integrate the SBM into QRA into a more structured way | - If bow ties are redrawn as BNs, some of the visibility of the direct paths from Threat to Top Event to Consequence will be lost because of the cross-linking of causal factors which may appear in several branches of the bow tie.<br>- BNs can appear more complex. For simple assessments and for visualisation purposes, bow ties may be useful. The same may be true for coarse semi-quantitative analysis tools such as EasyRisk. | -BNs could have value in tools such as TIMP, in order to establish a connection between barrier condition and risk level.<br>-A barrier status model has been developed by Peter Boyle, assigning relative importance of safety critical elements with respect to major accident risk. This could be a potential area where a BN could be applied.<br>-IO JIP has looked at fast visualisation tools of barrier conditions. | |
| **HF** | -BN modelling allows inclusion of risk influencing factors of any kind, including human factors. Not limited to events or technical components.<br>- Combined with methods such as SPAR-H, BN could be used to increase robustness of HRA (by inclusion of uncertainty and larger outcome spaces). Currently nominal values are applied where there is insufficient knowledge. BNs could be used to create a distribution, quantifying the uncertainty, rather than ignoring it. BNs could therefore supplement e.g. SPAR-H assessments. | | -Many issues related to ship collisions and DP operations in QRA. A JIP is being initiated by maritime advisory on HF. BNs could be a possible way of integrating HF in the ship collision assessment.<br>- Many organisations are trying to find a way of addressing MTO. BNs seem to be a useful tool for addressing this issue from a risk perspective. | |
| **SMS** | | | | |

| | **Strengths** | **Weaknesses** | **Opportunities** | **Threats** |
|---|---|---|---|---|
| **Technical** | -Software readily available (GeNIe etc) | -BN software not made available through RiskNet, or recommended to DNV employees in any way | -DNV has its own in-house software development. This could be a great strength in including BNs in future risk assessment tools, but could also be a hindrance if BNs are viewed as a competitor to existing software. | -HUGIN does not allow for flexible post-processing of data.<br>-Reliance on traditional software models, may not encourage application of BNs. (Input parameters perhaps an exception)<br>-The long history and previous experience with traditional tools has resulted in a large amount of models which can be reused, resulting in an ability to relatively quickly build new QRAs. A switch to BNs will in some respects mean starting from scratch, and will require a certain investment in time. |
| **Organization** | -Some key resources in different areas with practical knowledge of BN | - Resources are scattered (little or no formalised contact).<br>-Very few people have been trained in using BNs or Bayesian statistics | | - Experience indicates that consultants with technical background may find BNs more difficult to grasp than traditional QRA. It may require more "analytical" strength, and a shift in mindset.<br>- A shift from current tools to BNs will require a certain investment in service/tool development and competence building, and would therefore require active encouragement and support from DNV leadership. |

| | **Strengths** | **Weaknesses** | **Opportunities** | **Threats** |
|---|---|---|---|---|
| **Market** | | | - Client organisations are looking for methods to address the complexity of risk. BNs address aspects of this challenge. | -We do not have a clear understanding of where BNs will give sufficient advantage compared to traditional QRA (in a commercial aspect). Customers may not be willing to pay for a full BN approach in place of traditional QRA, if the perceived value is not proportional with the amount of work required. Further exploration, perhaps through JIPs or in service development, of BNs may be required to obtain the practical experience necessary to be able to make informed comparisons between approaches.<br>-If a customer sees the QRA as useful only for compliance and/or benchmarking, they may not want to invest in the additional focus on more complete risk models.-Risk OMT uses BNs. This may affect DNVs use of offshore QRA.<br>-Customers may not fully understand the need, or appreciate the benefits of BNs (market maturity). -Clients are accustomed to fault trees, event trees and getting a point estimate. Some may feel more comfortable with a fixed point estimate to compare to acceptance criteria. In order to see the value that a BN assessment can give to decision-making processes, some learning might be required by clients.<br>-Quick identification of market opportunities may not be easy because of the "mental shift" that is necessary for use of BNs. |

# *Appendix 2*
# *BN Questionnaire*

As part of the Technology Leadership project "Bayesian Networks in DNV", this questionnaire is distributed to employees with previous experience related to Bayesian Networks (BNs) either internally in DNV or otherwise. The objective is to map resources with competence regarding BNs in DNV, and examine the potential for further use of BNs. Please take a moment to answer the questions below. Your input is greatly appreciated.

Name:
DNV Unit:

1. Please describe your previous experience with Bayesian Networks (BNs). Include any experience with the use of BNs. Projects within DNV are of particular interest.

2. Describe the role of BNs in the project(s) listed above. (if any)

3. What are the advantages of BNs compared to conventional tools?

4. What are the disadvantages?

5. Are there any specific areas where you see potential for more widespread use of BNs in DNV's services?

6. Are there any specific reasons why BNs have not been more widely embraced in DNV's services? Please distinguish between disadvantages with the tool itself (Ref. Q4), and possible roadblocks preventing the use of BNs where they may be useful.

7. Should BNs be considered a tool for the future within DNV?
   - If yes, what can be done to encourage/enable the use of BNs in our services?
   - If no, why not?
   - What should be DNV's approach?

8. Are you aware of any other applications of BNs in DNV outside your own work? If yes, please list these. Include names of personnel involved if possible.

9. Are you aware of BNs being used by any of our competitors? Please describe these applications.

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