Using Dynamic Bayesian Networks to Implement Feedback in a Management Risk Model for the Oil Industry

Daniela Hanea[a], Anca Hanea[b], Ben Ale[a], Simone Sillem[a], Pei Hui Lin[a], Coen van Gulijk[a], Patrick Hudson[a]
[a]Technical University of Delft, Safety Science
[b]Technical University of Delft, Mathematics Department

Abstract: The recent trend in modeling risks in hazardous industries is to include organizational and regulatory spheres of activities. Most disastrous accidents are caused not only by technical problems, but rather by combinations of technical, human and managerial factors. In modeling humans and human behavior towards risks, the perception of risk is an important factor. It is an operator's perception of the overall risks, together with other human-specific physical, cognitive or social properties which may determine if that operator complies with a certain safety rule or not. If the rule is not obeyed at first, and no incident occurs, the chance of breaking that rule a second time increases. Creating the expectation that rules will have to be bent to achieve production goals becomes one of the strongest determinants of whether rule-breaking occurs. Therefore, the risk perception of an activity often changes over time and as a consequence of earlier decisions. Oil and gas operations form high-risk ventures with significant consequences for companies, the environment and individuals. Therefore, the risk modeling program for the hydrocarbon industry being carried out at Delft University of Technology have to take into account these short and/or long term feedback loops, most especially in the human factors part of the model that attempts to capture the predominant source of failures in that industry. In this part of the model a Dynamic Bayesian Network (DBN) representation of the uncertain human factors and their interdependencies is proposed. This paper presents a first attempt to use a dynamic non-parametric BN (NPBN) in modeling human behavior towards risk. The challenges and limitations of using NPBN for dynamic modeling are discussed and possible solutions are proposed.

Keywords: Non-parametric Bayesian Belief Nets, Dynamic Bayesian Belief Nets, Human factors, Risk management

1. INTRODUCTION

The continuous development of technology and society leads to new risks for people and environment. The systems are more complex, meaning not necessarily with more components, but rather more interactions between system-components. Systems such as financial markets and process industry are rather intractable and therefore, unmanageable. Moreover, the analysis of recent accidents revealed yet again that the causes of those accidents are not only technical, but rather a combination of technical, human and cultural factors, in a domain that, although highly regulated, often faces managerial shortcomings and weak regulations. Therefore, the integration of human behaviour, especially at the global level, not at the individual level, is absolutely necessary for current risk management models. This leads to an increasing complexity of the model. As Hollnagel [1] pointed out, the simple linear deterministic models cannot cope with the actual tightly coupled and intractable systems. There is a need for inherently probabilistic models, which can capture not only average situations, but also those which occur with very low frequency, but lead to rather huge disasters [2].

Not only do systems increase in complexity, they often are also dynamic. There is time dependence in the technical part of a system, e.g. in the degradation or ageing processes, but also in the human and management sub-systems. For example, the perception of risk is stronger shortly after an accident has happened: people are more careful to follow the procedures and regulations, shortcomings are avoided, training is more intensive. On the other hand, the effect of new management actions cannot be seen immediately, but rather after several months. Therefore, time is an important factor in the risk management model.

In [3,4] the authors proposed non-parametric Bayesian Belief Networks (NPBBNs) as a serious candidate for the method which can deal with all the requirements for modelling complex system. Moreover, recent studies

[5] show that the NPBBNs can be used also for dynamic systems in which the time dependencies are expressed in terms of complex physical models.
The current paper shows the possibilities and the limitations of using dynamic NPBBNs in the oil and gas industry. The static version of the BBN model is presented in [4,6]. This model integrates the technical, human and managerial factors influencing the risk at a petrochemical plant in The Netherlands. The accent is on the incentive of people for taking risks and how this can be influenced. The resulting model contains hundreds of nodes and even more arcs. However, in the current paper, a reduced model will be used for exemplification.
The paper is organized as follows. In the next section, the definition of BBNs is given and different forms of BBNs are presented. Static and dynamic NPBBNs will be presented in more details. In Section 3, the steps of building and quantifying the dynamic BBN for the oil and gas industry are presented. Last section of the paper presents some conclusions and plans for further development.

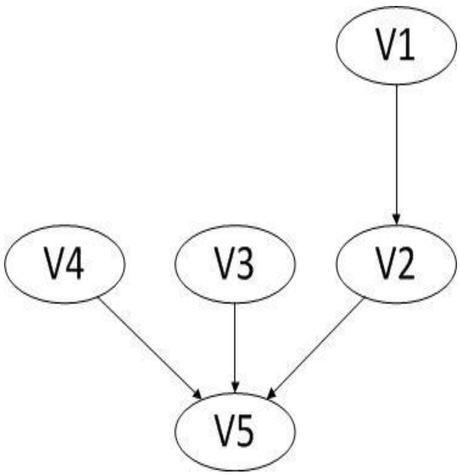
2. STATIC AND DYNAMIC NPBBNs – GENERAL DEFINITIONS

The research in the area or BBNs has been growing considerably in the last decade. A recent review [7] found more than 200 papers in international journals on applications of BBNs in different fields, i.e. dependability, risk analysis and maintenance between 1990 and 2008. Before 2000, the occurrence of BBN papers was rather seldom, with one to a maximum of four papers per year on this subject; after 2000, the number of papers on BBNs was considerably larger, reaching about 30 papers per year in the last three years of the analysed period, in de area of dependability studies. This demonstrates the recognition of BBNs as an analysis method for actual complex systems and the problems that these systems encounter.
Basically, a BBN is defined by a qualitative part and a quantitative part [8,9]. The qualitative part consists of a set of nodes which represent the system variables, and a set of directed arcs between variables, representing the dependencies or the cause-effect relations between variables. The quantitative part consists of conditional probability distributions for each node, given the states of the directly influencing nodes, also called *parent nodes*. Together, the quantitative and qualitative parts encode all the relevant information about the system variables and their interrelations, which, mathematically, means the joint distribution of these variables. The conditional independencies which are represented in the network by a missing arc between variables allow the decomposition of the joint distribution in a product of simplified conditional probability distributions. In this way, instead of working with a large joint probability distribution, one can work with smaller pieces of it, but preserving the overall component interaction within the system. A detailed description of BBNs will be provided in the next sub-section.
The big advantage of the BBN method over the former methods such as Fault Trees (FTs) is that once some of the variables are known or can be observed, this information can be introduced into the BBN and propagated through the network, such that all the other variables are updated according to the available information. In this way, it can be seen what is the most likely combinations of factors that cause that particular event (in a diagnostic or retrospective reasoning), or one can find the most likely result of a certain cause (in a predictive reasoning). BBNs provide a useful tool for dealing with uncertainty and with information from different sources, such as expert judgment, observable information or experience.
The current section gives basic description of BBNs in general and NPBBNs in particular. First, the static BBNs are presented, with their several forms; then, the concept of NPBBNs is introduced. The last sub-section presents the way in which the time dependent systems can be modeled with BBNs.

2.1. BBNs - general definition

The first form of belief networks is the discrete BBNs, in which the nodes are discrete variables, having a finite number of states. In this case, the relationships between variables are expressed in terms of conditional probability tables (CPTs). The nodes without influence from other nodes, or without parents, have to be associated with simple probability tables. A simple example of discrete BBN can be seen in figure 1**.** Each variable takes two values, OK/notOK. Variables V1, V3 and V4 have no parent nodes. Variable V2 has one parent node, V1; therefore, a CPT is associated with variable V2, showing the probability that this variable takes each of the two values, OK and notOK, given the values of its parent node. Node V5 has three parent nodes, V2, V3 and V4, and the CPT associated with V5 has, therefore, $16=2x2^3$ entries (see the last eight rows in table from figure 1. In general, if one node has k parent nodes and each of these has two possible states, the CPT associated with this node has 2^{k+1} entries that have to be assigned in a consistent way.

Although they are built on a solid theoretical base and show appealing features due to relatively simple visualisation of complicated systems, discrete BBNs suffer from severe limitations when they are applied to real problems. Firstly, in real systems, variables do not take only a finite number of states, but rather take values in a continuous interval, meaning that they are continuous variables. Therefore a mixture of discrete and continuous variables would be needed to model such real systems as realistic as possible. Secondly, for real problems, there are many influences between variables, leading to many incoming arcs into a node. Also, the discrete variables often take more than two values. These two problems lead to an explosion of inputs into a CPT.



				OK	**notOK**
	V1			0.90	0.10
	V3			0.70	0.30
	V4			0.60	0.40
V2	**V1**				
	OK			0.75	0.25
	notOK			0.40	0.60
V5	**V2**	**V3**	**V4**		
	OK	OK	OK	0.90	0.10
	OK	OK	notOK	0.70	0.30
	OK	notOK	OK	0.75	0.25
	notOK	OK	OK	0.50	0.50
	OK	notOK	notOK	0.65	0.35
	notOK	OK	notOK	0.30	0.70
	notOK	OK	notOK	0.45	0.55
	notOK	notOK	notOK	0.85	0.15

Figure 1: Example of discrete BBN

Therefore, the next generation of BBNs tried first to solve the problem of continuous nodes. The first attempt was to use discretization, meaning dividing the continuous range of values into a set of classes, and further work with the discrete version of the continuous variable. However, in order to keep a good representation of a continuous variable, a large number of partitions have to be used, which leads to large CPTs that have to be assigned in a consistent way. Moreover, it has been proven that a BBN model with discretized variables is used is highly sensitive to the number of classes used for discretization [10,11].
For dealing with systems in which not all variables are discrete, a new form of BBNs was developed. This is the normal or Gaussian BBN [12,13], in which it is assumed that all the variables are normally distributed. In this case, a mean and a conditional variance have to be specified for each node and a regression coefficient has to be assigned for each arc. The good news is that the number of inputs is considerably lower than in the case of discrete BBNs. However, the assumption of normal distribution is quite strong. This means that not only all variables must have Gaussian marginal distributions, but also that the joint distribution has to be Gaussian as well. Therefore, before using this form of BBN, one should check first the normality of the distributions. In the case that at least one of the variables has a different distribution, this form of BBNs cannot be used for that particular problem.
An updated version of the Gaussian BBNs allows also discrete variables, but only as parent nodes of continuous variables [14]. However, the restriction on the continuous variables to be normally distributed is still strong and has to be checked before the application of the BBN method.
One of the most recent versions of BBNs, called non-parametric BBNs [15] has significantly fewer assumptions than the Gaussian BBNs and, moreover, are less expensive in terms of input. A detailed description of non-parametric BBNs is given in the next sub-section.

2.2. Non-parametric Bayesian Belief Networks
Non-parametric BBNs allow both continuous and discrete variables, called probabilistic nodes. Moreover, nodes which are defined as functions of probabilistic nodes are also allowed. The influences between variables are expressed in terms of (conditional) rank correlations, which show the strength of monotone association between ordered values of two variables. Rank correlations are numbers between -1 and 1, which can be assigned algebraically independently. High positive rank correlation (close to 1) between two variables means that high values of one variable are associated with high values of the other variable, while

low negative rank correlation (close to -1) means that high values of one variable are associated with low values of the other variable.
Quantification of a non-parametric BBN means assigning a marginal probability distribution for each node in the network and a (conditional) rank correlation for each arc. The marginal distribution, the rank correlations, and the shape of the dependence between variables can together specify all the relations between the random variables and determine in a unique way the joint probability distribution. In case a functional node is included, the formula of the functional relation has to be specified; neither the marginal distribution for functional node, nor the rank correlations for the incoming arcs to that node are needed anymore.
The use of functional nodes allows one to transform former FTs into BBNs, by representing the AND/OR gates as functional nodes [3,16]. The transformation is relatively straightforward and the logical deterministic relation of a FT is very well conserved into a BBN.
Non-parametric BBNs are a rather new method, but have already been applied in several real world problems, such as air transportation safety [3], benefit-risk analysis of food consumption [17], fire safety in buildings [18], air pollution [19], dams safety [20], permeability field estimation [5] and bridge loading [21].
Figure 2 shows an example of non-parametric BBN. The graphical structure of the network parallels the discrete example from figure 1. The figure shows the histogram of each variable, according to the marginal distribution associated, and the rank correlations for each arc. It can be seen that the amount of data needed to quantify such a non-parametric BBN is considerably reduced in comparison with the discrete BBN from figure 1. Both data and expert judgment can be used to quantify the network [22,23].

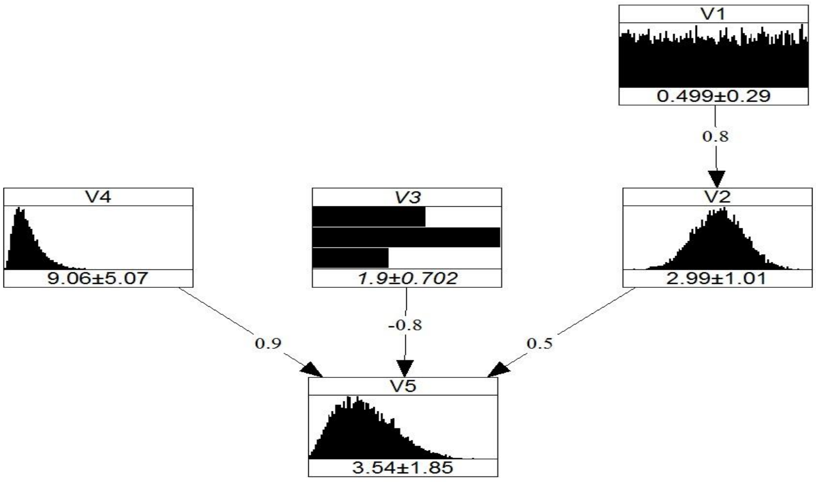


Figure 2: Example of non-parametric BBN

2.3. Dynamic BBNs
A DBBN consists of a sequence of sub-models (static BBNs), each representing the system at a particular point in time (time slice). The relations between variables in a time slice are represented by inter-slice arcs (black arcs in figure 3). In general, the structure of a time slice (or a static BBN) does not change over time, as in figure 3. However, this is not a theoretical restriction, but rather one which simplifies the computations [24]. Therefore, DBBN can theoretically work with the same or with different structures over time. The connections between different time slices are realized by inter-slice arcs (red arcs in figure 3). The arcs between slices are drawn from the left to the right reflecting the flow of time, from the past to the future.

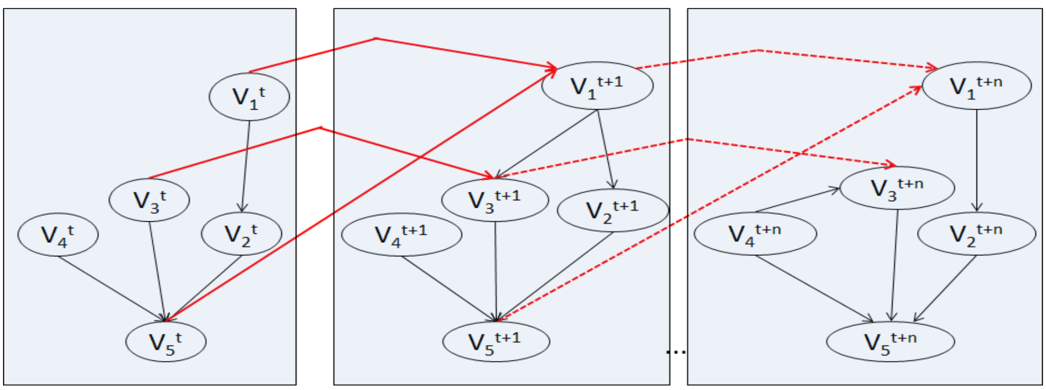


Figure 3: Dynamic BBN with different structures for each time-slice

As can be seen from the example given in figure 3, the size of a DBBN quickly becomes very large. Therefore, for practical considerations, it is assumed that each time the BBN has the same structure. Moreover, it is assumed that the state of any system described by a DBBN satisfies the first order Markov property, which says that the state of a system at time t depends only on its immediate past, i.e. the state of the system at time t-1. If these two conditions are satisfied, then the dynamic system can be represented by two successive time-slices, as in figure 4.

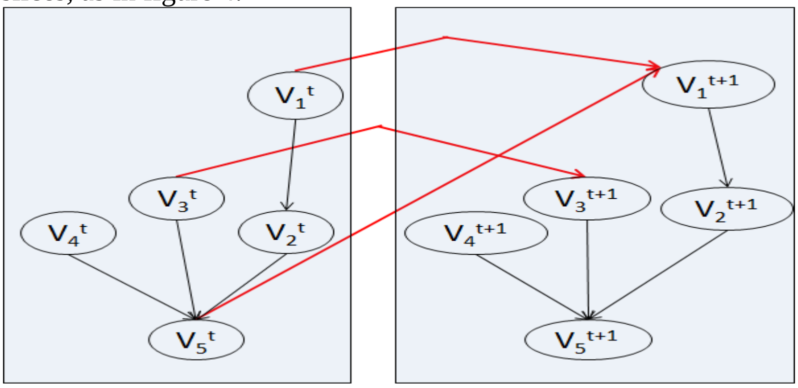


Figure 4: Two time-slices of a DBBN satisfying the Markov property

Each time-slice of a DBBN is in fact a static BBN, which can be either discrete or continuous, as presented in the precious sub-sections. For the non-parametric version, the dependencies over time can also be expressed in terms of rank correlations, functional relations or, for more complex systems, can even be determined by complex physical models expressed in terms of differential equations [5].

3. DYNAMIC MODEL FOR OIL INDUSTRY

The current section presents the steps of building the dynamic BBN for the oil industry. First, the static model has to be built up. Its technical part is obtained from the existing information gathered from the petrochemical plant, after being transformed into FTs, using methods developed in previous projects. The human and management parts of the static BBN are added where appropriate. More details of these steps are given in the next sub-sections. The second sub-section presents a reduced model of the static BBN which can be used for exemplification of the possibilities to model the dynamic aspect. The last sub-section discusses these possibilities and shows limitations and solutions.

3.1. Static BBN model

The current static BBN model builds on the earlier developments in the IRISK [25], WORM [26] and CATS [3] projects, in which the management actions, human behavior and technology were integrated into a single framework that allows a more in-depth analysis of the interdependencies between these factors. This allows the use of probabilistic distributions instead of point estimates, taking into account a wide range of possible states of the context dependent factors that can ultimately result in a disaster or, alternatively, providing knowledge essential to take risks and run them successfully and profitably. The BBN method can integrate all these factors, and it has been successfully applied in aviation safety.

The methodology of building the static BBN is described in [4,6]. Basically, the available information from the petrochemical plant about the main industrial processes is translated into an FT. These are further easily transformed into BBNs. One more module is built, which is based on the information about the Dutch occupational accidents available in [26]. The four BBN modules, corresponding to the failures of the three processes and the occupational accident model, are combined into a single, still predominantly technical, model that estimates the probability of a process failure or an occupational accident. The general scheme of this combination can be seen in figure 5. The use of the NPBBNs makes the combination straightforward. The quantification made for each module is still used in the combined model. Only the arcs added between factors belonging to different modules have to be quantified at this stage.

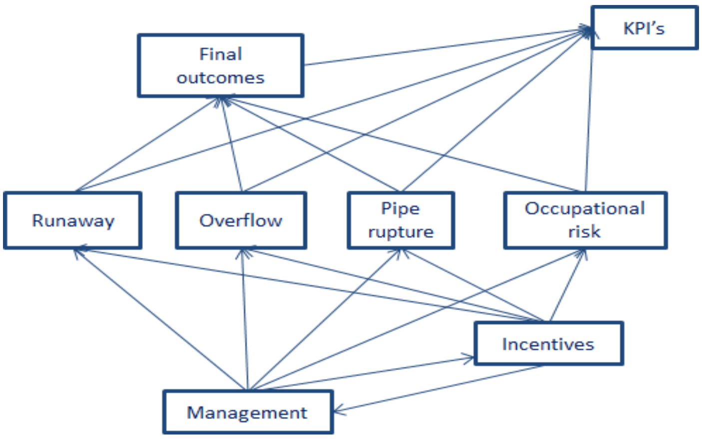


Figure 5: Schematic model

Once the technical part has been built, the human and management factors can be added. First the human model has to be built up separately. More detailed information about this can be found in [4,27,28]. Then, the human model has to be linked to the technical part of the model through the nodes that relate to human intervention in the operation process.
The end points of the model, the variables that we want to estimate and on the bases of their values take decisions are either Key Performance Indicators (KPIs) [4], the position of events in a the familiar risk matrix, or both. The resulting model, not including the human and management factors is presented in Figure 6. In total, the BBN model has 375 nodes and 430 arcs, not including the human and managerial factors and their influences.

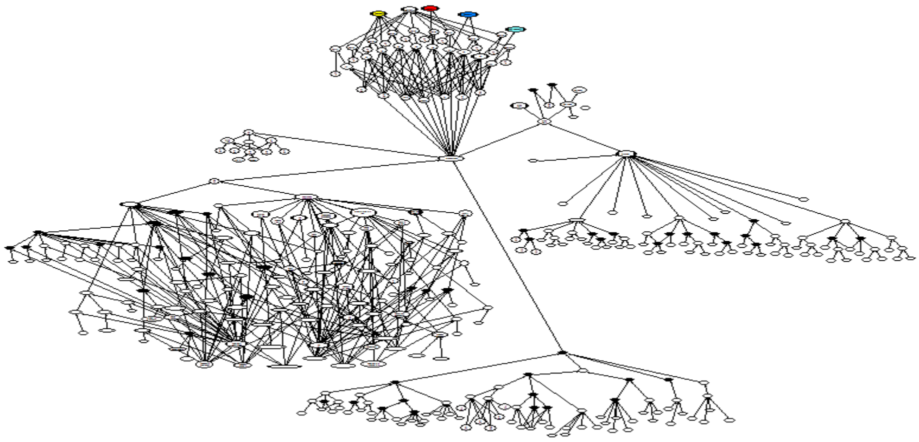


Figure 6: Static BBN model

However, for the purpose of exemplification of the dynamic aspect, a reduced static model will be used. Next sub-section presents this reduced or toy model.

3.2. Reduced static BBN model

The model used for exemplification in this section has a general character, but reflects the basic principles used in the large BBN model. The quantification is also fictitious and serves only the purpose of exemplification, so it cannot be taken as fact. A schematic static model is presented in figure 7. Basically, in this simple model, an accident happens because there is a technical failure and the operator fails to take the proper actions to stop the propagation of the accident. The causes of a technical failure are due to ageing of a piece of equipment and its improper maintenance, which further means either low frequency of the maintenance or failure of the technician to execute the right task. Both events of failure of the operator to intervene when there is a technical failure and the technician error are human models and are considered to be (differently or not) influenced, in this simple example, by the training of the personell, his/her experience/knowledge and their commitment to safety. A more detailed description of the human model can be found in [28].

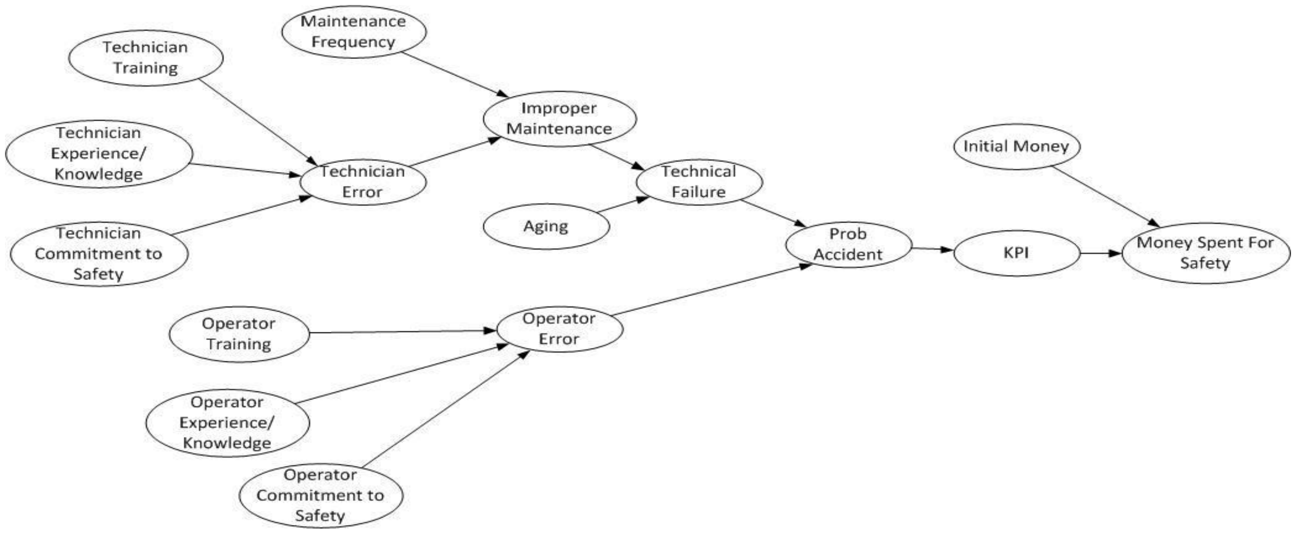


Figure 7: Schematic static model

At the upper part of the network, the values of the KPI's [4] are influenced by the probability of an accident. Based on a comparison of the values of these KPIs with set target values, the decision to spend or not more money on safety is taken. Other management factors might influence this decision, but to keep the model simple at this point, these factors are not included. The logical relation is that when the target KPI's values are not reached (or there is a small probability of reaching these target values), then more money is spent on safety measures; otherwise, the money spent on safety is left approximately constant. An example representation of the relation between money spent for safety and the level of safety can be seen in figure 8. The decision to spend more money on safety could be due to the occurrence of an accident, or because the safety level approaches the acceptable level. No matter what the reason is, the influences of the decision on the safety level will not be seen immediately, but after a while, which is exactly the dynamic aspect that has to be included into the model.

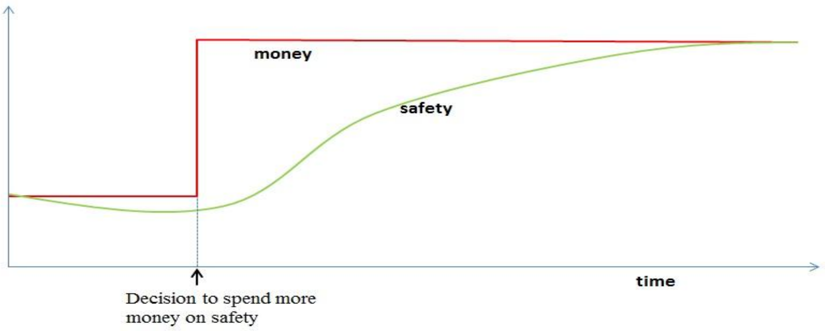


Figure 8: Safety level versus money spent for safety

In the next sub-section, the schematic static model from figure 7 will be translated into a BBN model and then the dynamic aspect will be modeled.

3.3. Reduced DBBN model

Once the static model is constructed, the dynamic aspect can be introduced by considering the mutual influences between factors over time. These can again be expressed in terms of rank correlations, simple functions or complex systems of differential equations [5].

However, one of the main restrictions of the sampling algorithms for NPBBNs (see [29]) is that the probabilistic nodes (those that are assigned with marginal probability distributions) should not be the children of functional nodes. This is mainly because, in such a situation, the algorithm would have to compute the marginal distribution of the functional node and replace the functional relation with a rank correlation. This is not wrong from a theoretical point of view, but in practice, a functional relation contains much more information about the joint behavior of two variables than a rank correlation does. Moreover, for very complex functional relations, the rank correlation would not describe correctly the relation1 between

these variables. To avoid the introduction of such possibly incorrect interpretations, the software[1] does not allow any arc directed from a functional to a probabilistic node.
This is a restriction that has to be considered when the dynamic aspect of a system is modeled with a NPBBN. The restriction holds not only within a time slice of the DBBN, but also between time slices. Therefore, one node that is situated at the top of the BBN in one time slice, most often expressed as a functional node, cannot influence (directly or indirectly) the bottom nodes of the BBN in the next time step.
This is a major problem, since in practice it is the values of the safety indicators, including money spent for safety, which form – among other things - the basis for decisions on the management actions, which influence the human factors situated at the bottom of the BBN network.

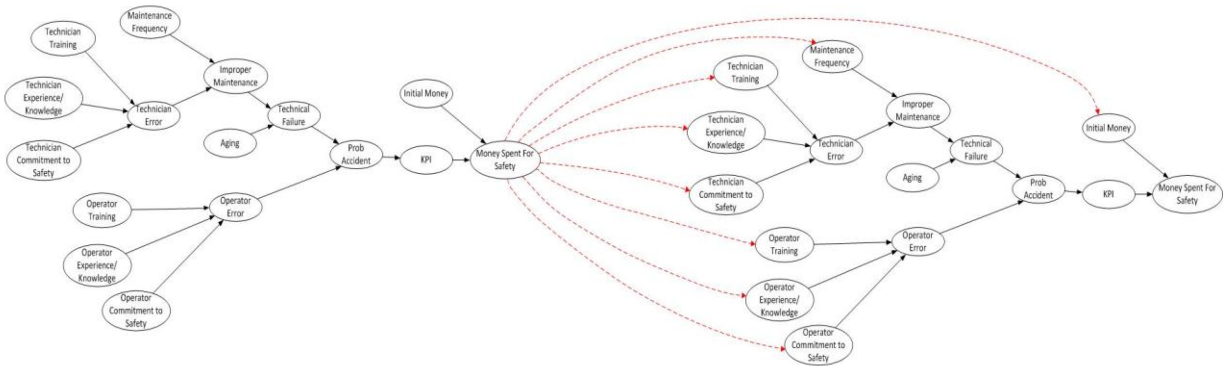


Figure 9: Two time-slices of the DBBN model

Therefore, the influences over time come mainly from the amount of money spent for safety on the human factors. If there is a reduction of the money spent for safety, then the company will try to hire operators with less experience, will reduce the training frequency and will also reduce the bonus for working safety, which influences the commitment to safety. Also, when less money are budgeted for safety, the company will hire contractors not from the best contractor company (which is expensive), but from the second best, or even from a new company on the market. This has an (indirect) influence on the technician training, experience and commitment to safety. There is also an obvious influence of the amount of money spent for safety on the maintenance frequency. All these influences are valid even for this reduced scale model. In the large model, there might be more intermediary factors between the money spent for safety and these human factors.
Given these characteristics of the influences over time needed in the model and the restrictions related to the use of NPBBN, the solution is to introduce an intermediary step between two time slices, either expressed in terms of a BBN or as a more complex system of equations, or both. The transition model includes all the influences over time (red-dashed lines) together with the nodes that are connected by these influences. For this reduced model, the nodes included into the transition BBN are the money spent for safety and the nodes related to the human factors.
In the next section, some simulations results based on the reduced dynamic model will be showed and discusses.

4. RESULTS AND DISCUSSIONS

The results presented in this section of the paper are obtained using the dynamic model from Figure 9. The reader should keep in mind that the quantification of the model is not made using real data, therefore the results are not important in their absolute value. Rather, the trends in the results and the general behavior of the model are what are important to demonstrate.
The simulations are made for the case where it is assumed that a low commitment of safety for both operators and technicians is observed. Conditions are put on these factors in the BBN at the first time step and the distributions of the other variables are computed. It is assumed that the amount of money spent in the next time period equals the average conditional value of the variables money spent for safety. This value is used in the transition BBN to conditionalize on. The resulting conditional distributions for human factors influenced by the variable money spent for safety are then used in the second time step as marginal

[1] The software application used for designing and working with (the) NPBN(s) is called Uninet. It has originally been developed specifically for the CATS project and is now in development by Lighttwist Software under licence from the TU Delft.

distributions for these nodes. The distribution of initial money in the second time step equals the distribution of the money spent for safety at the time before. Computations are made in the second time step and a new distribution for money spent for safety is obtained. The transition BBN is again used, and the procedure is repeated as many times as desired. Simulation of 10 time steps are made, and the average probability of an accident, and the money spent for safety at each time step are represented in Figure 10. As it can be seen, the money spent for safety is continuously increasing, while the probability of accident is rapidly increasing in the first few steps, after which it reaches an almost constant value. This coincides to the general belief that, nothing else being changed, there is a need of constantly increasing costs to keep the probability of accident below a certain level. However, this model is based on the assumption that money for safety is spent mainly on changing the human behavior, and less on technical components. In reality, the money spent on safety are split with a certain percentage on several safety measures, including human behavior.

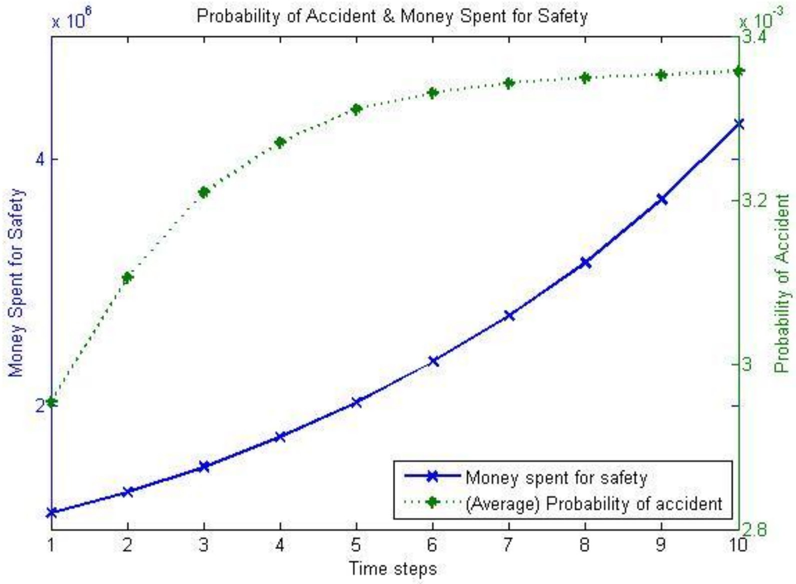


Figure 10: Money spent for safety and Probability of accident - Simulation results for 10 time steps

However, the main goal of the simulations results is to prove that the mechanism works and can be used to show the dynamic behavior of some of the variables.

5. CONCLUSIONS AND FURTHER WORK

The main goal of the current paper is to present the basic mechanism of simulating dynamics in a model using NPBBNs. The proposed algorithm overcomes the restrictions associated with the NPBBNs and shows potential for application to the large scale model.

Further work is needed to implement such dynamics in a risk management model for the oil and gas industry. First of all, it has to be recognized that the feedback cycles which give the dynamic aspect of the system have different lengths. There are short time feedbacks, mainly those related to individual human behavior, which have a time step of about three months. Another feedback cycle is related to budget, which is yearly based. Then there is a change in company policy, which might take years to percolate through an organization. There also are feedback cycles related to projects or even facilities. This means, in fact, that the first order Markov property is not maintained, but, rather, a higher order Markov property is appropriate. From the theoretical point of view, there is no problem in principle to use DBBNs in this case. However, this is the subject for further work.

Acknowledgements
The work reported above was fully funded by Royal Dutch Shell plc.

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