Prognosis - subsea oil and gas industry

P.Vaidya

Department of Production and Quality Engineering, NTNU, Trondheim, Norway
pratichi.vaidya@ntnu.no

Abstract: Life extension has been an important and highly discussed issue in nuclear and aviation industries for a long time and it has recently attracted a considerable attention in subsea oil and gas industry. Decision regarding life extension is primarily based on the remaining useful life. The paper explains the technical health and the other factors that influence the remaining useful life. Degradation mechanisms and the lifetime models are discussed, highlighting the limitations of classical approach and the need for Bayesian approach. A model to predict remaining useful life needs to have a capability of handling heterogeneous combination of requirements like degradation modelling, uncertain sensor data handling, and incorporating expert opinion. The paper explores the suitability of using Bayesian Belief Network as a modelling tool for such prediction in subsea oil and gas industry. [*]

1. INTRODUCTION

A subsea processing system is designed for a specific application and for particular service life. The service life is determined from the reservoir properties and the production plans and may for example be $t_0 = 10$ years. In practice, it is seen that the initial service life estimates have been too conservative. Improved methodology, new methods for enhanced oil recovery and tie-in of neighbouring wells frequently lead to an actual service life that is considerably longer than the initial planned service life. The following situation as shown in Figure 1 is typical: At some time $t_1 \leq t_0$, the operator has to decide whether to tie-in a neighbouring well to the existing sub-sea production system or to install a new system. The tied-in well and possibly enhanced oil production from the old wells will increase the planned service life up to t_2. The question is then: Can we at time t_1, trust that the existing subsea production system will survive and function satisfactorily till time t_2? Alternatively, should the current system be discarded and replaced by a new system either now (at time t_1) or in the near future (i.e. around t_0?).

This question can be answered if a suitable maintenance regime is implemented. Maintenance practices have evolved over the years. Initial practise of reacting to machinery breakdown (corrective maintenance) is outdated. Performing, time based preventive maintenance is also obsolete.

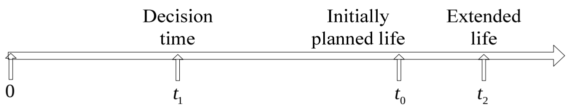

Figure 1: Timeline for remaining useful life

Today maintenance practise is in an advanced stage where the emphasis is on the ability to detect early forms of degradation. This is called condition-based maintenance. The thrust is on understanding the stressor levels. The aim is immediate detection and diagnosis of abnormal condition. This is achieved by finding the root causes responsible for this condition.

Thorough knowledge of the equipment and control over the operating conditions are the necessary factors in order to take any decision regarding life extension. The maintenance manager needs to be aware of various failure modes, failure (degradation) mechanisms or causes associated with the physical damage and their effects on the equipment performance. The paper gives an introduction to the problem. It explains the factors that influence remaining useful life i.e. technical health, future operating condition and future environmental condition. It explores the possibility of using Bayesian belief network as a modelling tool to identify root cause during diagnosis and to aid in decision making related to remaining useful life. The paper is organized as follows: In section 2, the definitions of prognosis are covered and various existing prognosis models are presented in brief. Section 3 explains the concept of remaining useful life and describes the influencing factors. Section 4 covers the degradation mechanisms and the lifetime models. Section 5 gives short description of the Bayesian belief networks. In Section 6, suitability of using this tool for the overall model is discussed. Conclusions are covered in Section 7.

2. PROGNOSIS- DEFINITIONS AND SUBSEA SPECIFICS

Assessment of the remaining useful life of technical systems has been discussed in several scientific papers. In the literature related to condition based monitoring, the word *Prognosis* is often used in relation with remaining useful life. ISO 13381-1(3) defines prognosis as a "Technical process resulting in the determination of remaining useful life" (ISO, 2004). Jardine et al. define two types of predictions for machine prognostics. The first that is commonly used is "To predict how much time is left before a failure occurs (or, one or more faults) given the current machine condition and the past operation profile". Remaining useful life is the time left before observing a failure. (Jardine et al., 2006). The acronym RUL is sometimes used. The second prediction type is for the situations, which are catastrophic in nature (e.g. nuclear power plant). "The need is to predict the probability that a machine operates without a failure up to some future time (e.g. next inspection interval) given the current machine condition and past operation profile" (Jardine et al., 2006).

"Damage Prognosis" is a frequently used term in structural safety studies. It is defined as "The estimate of an engineered systems remaining useful life" (Farrar et al., 2006). The same reference also introduces the concepts "usage monitoring" and "structural health monitoring".

The literature presents a wide range of methods and models for RUL prediction based on statistical methods, artificial intelligence techniques and physics based model interpretations. Some of them are listed below for reference. Goode et al. (Goode et al., 2000) separate the machine life into two stages viz. the stable zone (I_P interval) and the failure zone (P_F interval). Stable zone times and failure zone times are used to fit two Weibull distributions. Prognosis is based on these two distributions. Wang et al. (Wang et al., 2000) describe the prediction of residual life distribution using expert judgment as condition information. They proposed a gamma process model and used hazard rate as a residual life prediction criterion. Chinnam et al., (Chinnam & Baruah, 2003) suggest the use of hidden Markov models for life prediction. Yan et al. (Yan, Kok & Lee, 2004) calculate probability of failure of condition variables using logistic regression model and a trend of condition variables is prepared by ARMA time series model. The paper by Volk et al. (Volk et al., 2004) gives a proportional intensity model (PIM) using covariate extrapolation to estimate the remaining life of a repairable system. Banjevic and Jardine (Banjevic & Jardine, 2006) describe proportional hazard model (PHM) to estimate residual life for Markov failure time process. Haitao et al. (Haitao et al., 2006) propose proportional hazard model and logistic regression model to relate the multiple degradation features of sensor signals to the specific reliability indices and predict RUL. They further compare the two models to assess their effectiveness and computational effort. Feng Xue et al. (Xue et al., 2008) use an instance-based method for the estimation of remaining useful life of aircraft engines. They predict RUL of a given engine by a fuzzy aggregation of RUL with the peer unit. Wang and Zang suggest an expert judgment based model (Wang & Zang, 2008) for predicting an asset's residual life.

There are many models/methodologies, but it may not be proper to apply any of these models directly for life prediction of subsea equipment. Subsea production system historically was a relatively simple network of piping and related instrumentation designed to gather information from individual wells. Topside facilities were constructed for subsea processing and monitoring. Maintenance and control of topside system was managed by direct human access and simple observation data. These days, to get increased production from mature and marginal fields, to reduce the complexity of developing an offshore floating platform and to reduce the overall cost, subsea processing is shifted to subsea. Some of the subsea processes are - water removal and reinjection, multiphase/single phase boosting of well fluids, sand, solid separation, gas, liquid separation and compression. The equipment for such processes is designed to work flawlessly for approximately 10 or more years. Subunits are subject to varying operating conditions, constant degradation/wear and thus have to be monitored, repaired or replaced. These intervals depend on the use, actual operating and environmental conditions and on the location. Inaccurate predictions result in an occasional emergency stop in the production. "Additionally, with less than a decade of operating experience, subsea developments are still relatively a new area with exposure to high costs from unforeseen technical issues"(Horan et al., 2008). This necessitates thorough diagnosis and prognosis. Repairs to be performed on subsea equipment require preparations of remote operating vehicles (ROV) or divers, in addition to the parts that have to be repaired or replaced. This leads to long downtime periods related to unpredicted stops and thus large costs related to each breakdown in the subsea parts.

"Learning" from the experiences of other industries and study of the "best practices" would be a wise proposition. At the same time, being aware of the subsea industry specific particularities, for example, remote operations and limited availability of equipment condition data, design specifics of subsea equipment, part replacement constraints, field depth issues, physical - geological constraints of oil well, oil economics during the period, organizational dependencies and their interrelations is necessary. This would lead to a prudent and tailor made decision framework for prognosis and life extension of subsea infrastructure.

Literature on subsea diagnosis and prognosis is scarce. Paper by (Friedemann et al., 2008) examines the applicability of condition monitoring technologies to subsea infrastructure in oil and gas industry. The paper highlights the need of data and information handling that is required for prognostics and decision support. Paper by (Sandsmark & Mehta, 2004) describes the ongoing research project supported by Norwegian Research Council. The objective of the research is "to identify optimal set of real time data from reservoirs, wells and subsea production facilities, to improve and integrate it to provide an open standard information platform". Paper by (Altamiranda et al., 2009) presents a prototype diagnosis tool with a model based residue generation technique. They developed a hierarchical health index structure to diagnose the subsea electronic modules.
A measure named "Technical Condition Index" has been developed in EUREKA project "Ageing management" (Nystad, 2008) to find the technical condition of a topside system in an oil and gas industry. This is not applicable to subsea situation.

3. REMAINING USEFUL LIFE- SUBSEA SYSTEMS

The following section, gives a subsea industry specific perspective of RUL. As shown in Figure. 2, the factors influencing RUL of a system are (i) the technical health of the system at time t_1 denoted by TH_1, (ii) expected operational conditions and planned intervention as predicted at t_1,denoted by $O(t_1)$, and (iii) expected environmental conditions $E(t_1)$ as predicted at t_1.

In some cases, it may also be relevant to modify and/or refurbish the system at time t_1 and /or at time t_0. The decision about life extension must usually be taken before the end of the initial period at time $t_1(\le t_0)$. To take this decision, we need to determine how likely it is that; the system will be able to survive time t_2. This means one needs to find the $\Pr(T > t_2 \mid T > t_1 \cap TH_1 \cap O(t_1) \cap E(t_1))$ where T denotes the initial time to failure of the system. In some cases, it may also be of interest to find, the mean remaining useful life of a system that has been used, up to time t_1. The time concepts are illustrated in Figure 1. The factors influencing the decision about the remaining useful life are illustrated by influence diagram in Figure 2.

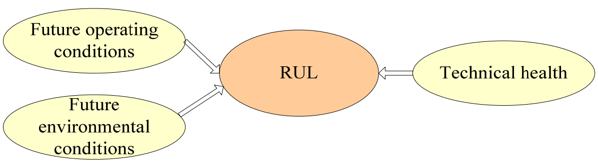

Figure 2: Factors influencing remaining useful life

3.1 Technical health of an equipment

The technical health (TH) is an assessment or judgment of the state of the equipment based on the measured factors related to: (1) The technical condition (2) the operational history that is determined by the stress history and the maintenance history, and (3) the design quality. The technical health is a semi-quantitative expression. Factors influencing technical health are shown in Figure 3.

Technical health at time t_1 is a representation of the knowledge (K) about the equipment up to time t_1. This knowledge is useful in taking decisions regarding the maintenance actions related to the equipment (Vaidya & Rausand, 2010). The relation between the technical health (TH) and the reliability of the equipment can be expressed by the survivor function $R(t \mid t_1, TH(t_1), K)$.

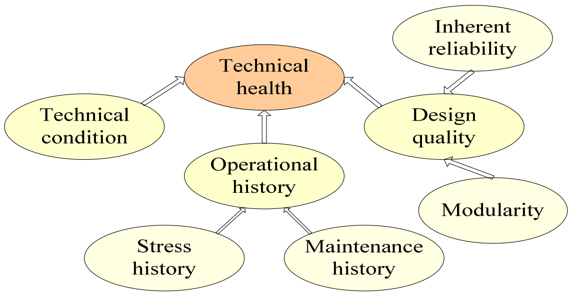

Figure 3: Factors influencing technical health

3.2 Future operational conditions

The future operational condition $O(t_1)$ is an estimate done at time t_1 of the operating condition that would prevail from time t_1 until the item's end of life. This estimate is based on the experience data and the expert judgement. Example of different operating conditions for pump is (Karassik et al., 2001): (i) Normal condition - The liquid is present, there is no leakage in the pumping chamber and pump production is 5000 barrels per day (bpd). (ii) Leak condition - The liquid is present, there is a leak in the pumping chamber and pump production is 2000 bpd. (iii) Air stroke condition- The chamber contains some air leading to pump production of 1500bpd.

3.3 Future environmental conditions

Future environmental condition $E(t_1)$ is an estimate done at time t_1 of the environmental condition that would prevail after time t_1. Such estimates can be done using data based modelling techniques (Kothamasu et al., 2006). In practice however, a system may have to be operated in an environment different from that originally considered during design. For subsea systems, typical scenarios could be:

- Pressure reduction with time

- Change in Gas oil ratio with time
- Increased water content in oil
- Change in chemical contents of oil
- More hostile environment depending on reservoir location

In such circumstances, there is a possibility of new failure modes and the overall frequency of failures may increase. Corrective actions can be impractical and/or expensive. If the system continues to operate in the new environment, there may be an impact on its remaining useful life.

4. TECHNICAL HEALTH ASSESSMENT - LIFETIME MODELS

4.1 Classical Approach

In maintenance models the important uncertainties are the uncertainty in time to failure (lifetime) and the rate of deterioration. Most mathematical models are based on describing the uncertainty in ageing using lifetime distribution. In the context of life extension of subsea equipment, we primarily pay attention to the ageing of the non-replaceable parts of the equipment. There are many parametric failure models such as exponential, Weibull, and log normal that have been used for such studies. According to Neiuwhoff, Rausand and Høyland (Neiuwhoff, 1984), (Rausand & Høyland, 2004), the most popular lifetime model is the Weibull distribution as it has the ability to accommodate various types of behaviours. The choice of life distribution however must be based on a thorough knowledge of the actual failure mechanisms and material properties (Reinertsen, 1996). It is difficult to choose the best-fit life distribution based on field data and data from laboratory testing (Rausand & Høyland, 2004). In practical subsea situations, there are multiple failure mechanisms acting simultaneously on a component. The combined effects of several failure mechanisms may be much higher than the sum of the effects of each of the individual failure mechanisms and the synergy effects are difficult, if not impossible, to explain (Reinertsen, 1996). The guidance for choice of distribution corresponding to failure mechanisms, like corrosion, wear, and erosion, can be found in the literature, but it is not consistent as it comes from different experts based on their personal knowledge and experience. Bolch and Geitner (Bolch & Geitner, 1994) compiled information about some selected failure mechanisms and their statistical distributions. Reinertsen (Reinertsen, 1996), as shown in Table 1 gives preliminary guidance proposing the distributions. The benefit of these models is that the results depend only on the data. When there is a large amount of data, these models produce good estimates. The models have a historical precedence and are easy to understand.

These models however have some limitations. They are based on two states, i.e., they only quantify whether the component is working or not (Singpurwalla, 1995). Some argue that the classical approach does not cover cases where little or no experience (evidence) is available and the cases where estimates concerning observations are intuitive. In such cases a broader definition is required (Lindley, 2007) and that is provided by subjective/Bayesian interpretation of probability.

Table 1: Degradation mechanisms and corresponding Distributions

Mechanism	Life Distribution				
	Gumbel	Weibull	Log normal	Inverse Gaussian	Birnbaum Saunders
Pitting Corrosion	*	*			
Fatigue Cyclic Or erosion			*	*	
Wear				*	
Fatigue Cumulative				*	*

4.2 Bayesian Approach

In this approach, the probability of an event is a measure of our belief about the occurrence of the event and is referred to as the degree of belief. Bayes formula gives the probability of the parameter, given the observation in the data. This data is not limited to sample data only. It contains empirical and external data (prior) in addition. Bayes formula given below implies that the posterior distribution of a parameter is proportional to the product of likelihood and the prior distribution of the parameter.

$$\text{Posterior} = \frac{\text{Prior} \times \text{Likelihood}}{\text{Normalizing Const.}}$$

Subjective prior belief is indicated by the prior distribution. The posterior distribution is the conditional probability of parameter given the observations. It is a powerful and coherent method to mathematically, combine the different types of information and to express the inherent uncertainties. It allows encapsulating our knowledge about the probability of the rare events for which there is very little information. The posterior distribution in the next iteration is used as a prior when the next set of data becomes available. A comprehensive presentation of Bayesian inference is covered in Gelman et al., (1995).

5. BAYESIAN NETWORK - MODELLING TOOL

Bayesian Belief Network (BBN) is referred by Charniak as "a method of reasoning using probabilities" (Charniak, 1991). "BBNs have their background in statistics and artificial intelligence and they emerged in 1980s at the time when there was a need for formalism, which could adequately deal with uncertainty in knowledge-based systems" (Sigurdsson et al., 2001). It is a popular method of modelling uncertain and complex systems in power/nuclear and aviation industries (Kang et al., 1999), (Helminen et al., 2003), (Yongli et al., 2006), (Mengshoel, 2007), (Mengshoel et al., 2008) and the modelling has been done for diagnosis purpose. This kind of modelling is not yet done in Norwegian subsea oil and gas industry. Paper by Willy et al. (Willy et al., 2009) discusses the applicability of aviation industry based hybrid causal logic (HCL) framework to offshore industry. However, HCL combines traditional risk analysis tools with BBN not prognosis. Papers by Mahadevan (Mahadevan, 2001), Boudali and Dugan (Boudali & Dugan, 2005), Langseth and Portinale (Langseth & Portinale, 2007), (Langseth, 2008) explain the importance of Bayesian Networks in the field of reliability engineering. Therefore, it is worthwhile to evaluate the BBN as a choice of modelling tool in the context of "prognosis" for Norwegian subsea oil and gas industry.

BBN is described (Pearl 1988; Jensen, 1996) as a directed acyclic graph (DAG) that defines the factorization of a joint probability distribution over the variables. The nodes of the DAG represent the variables. The directed links of the DAG give factorization. BBN provides an intuitive graphical model for reasoning under uncertainty. It provides a mechanism for representing the causal relationships between the entities of problem domain. The entities are represented as discrete variables over finite sets of mutually exclusive and exhaustive sets of possible values (Jensen, 1996). The entities can also be represented as the continuous variables that range from minus infinity to plus infinity. The dependency between the variables is captured by the conditional probabilities (Van der Gaag, 1996). For the relations in the graph, the wordings used are same as family relationships. If there is a link from node X to node Y, then node Y is the child of node X and node X is the parent. The node having no parent is called a root node. The information about a variable is presented in the form of probability distribution/s. If a variable has no parents, (no incoming arcs) then it has one probability distribution. The variable with parents has many probability distributions corresponding to combinations of possible values of parents (Jensen, 1996). Probability distributions represent the beliefs about the values of variables. Wide/broad probability distribution implies high uncertainty about the value. As the knowledge about the variable increases, the distribution becomes narrow (Pearl, 1988).

6. PROGNOSIS MODEL

Prognosis/RUL model can be divided into following modules:

- Technical health – Capability of identifying the root cause of failure and carrying out degradation modelling for various failure mechanisms
- Future loading – Capability of processing intermittent sensor data, experience data and expert opinion

The overall RUL model needs to have a capability of combining and analyzing inputs from the two modules mentioned above. Technical health of an equipment changes with time. Additional information becomes available about future loading. Updates on information are received from different experts. Thus, the model needs to respond to the changing information and needs to have a capability of "learning". Subsequent sections explain the theory, provide simple examples and evaluate suitability of BBN as a modelling tool for prognosis in subsea oil and gas industry.

6.1 Suitability of BBN for Technical health model

Bayesian networks represent causal statements of the kind $X \to Y$, where X is a cause of Y and Y is an observable effect of X. The posterior probability distribution $P(X \mid Y = y)$ can be derived, knowing the observation $Y = y$ and using the prior distribution $P(X)$ and the conditional probability distribution $P(Y \mid X)$, which is specified in the model. According to Baye's rule, it is calculated as: $P(X \mid Y = y) = \dfrac{P(Y = y \mid X)P(X)}{P(Y = y)}$. It is known that $P(Y = y) = \sum_x P(Y = y \mid X = x)P(X = x)$.

Probabilistic inference amounts to updating our belief about event given observations (Jensen, 1996). Such observations are referred to as evidence. In BBN, transmission of evidence is through serial, diverging or converging connections (Jensen, 2001) as shown in Figure 4. The transmission of evidence rules for these connections are combined into a general rule called d-separation. BBN have a capability of performing "deductive" and "abductive" reasoning (Kjaerulff & Madsen, 2008). Abductive reasoning which is also called as diagnostic reasoning has a direction opposite to the causal links. For example, observing a leakage provides a supporting evidence for the development of crack in a pipe. Deductive reasoning follows the direction of causal link and is known as the causal reasoning. Inter causal reasoning is also possible in BBN. This property is an important feature of BBN. "Getting evidence, which totally supports a single hypothesis, naturally leads to a decreasing belief in the unsupported competing hypotheses". This property of BBN is referred to as the "explaining away effect" (Jensen, 1996).

Let us take an example of a pump. There could be many possible causes because of which a pump may need replacement; one being leak of oil through seals. Observing that the leak detector provides a strong evidence for seal leakage, the belief in the other possible causes reduces significantly. This means that they are "explained away" by this observation. The capability of BBN to perform inter causal inference gives it the reasoning power and this capability makes BBN a preferred choice for the technical health model.

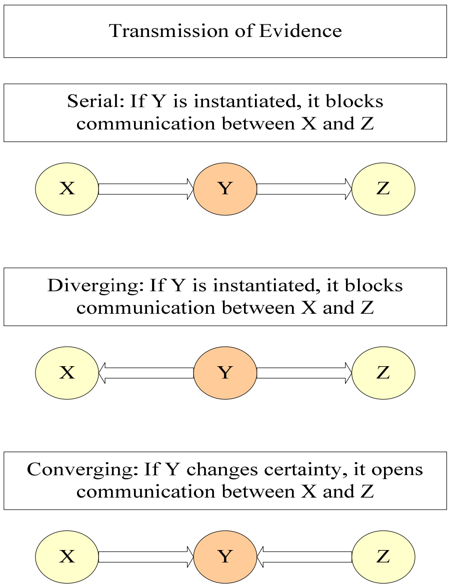

Figure 4: Serial, diverging and converging connections

BBN modelling is carried out in two-steps. The structure of the model, which is a qualitative part, is modelled first. The variables, the relations among variables viz. the causal, functional, and informational relations are identified first as a part of qualitative modelling. The parameters i.e. conditional probabilities and utilities, which are quantitative in nature, are modelled in step two. Determining the structure of a model is an iterative process and needs interaction with domain experts. Domain knowledge is thus captured in the structure while defining variables, conditional independence and identification of links and their directionality. This modelling approach is in line with the requirement of technical health modelling approach where correlation and causal relations of degradation mechanisms need to be identified in close communication with the domain experts. In case of subsea equipment, not all the causes and effects of failure are deterministic. Various kinds of uncertainties are related with cause effect mechanisms, for example imperfect knowledge about the factors affecting degradation mechanism, measurement errors, noisy sensor readings or discretization of the real valued observation. BBN can handle such uncertainties and hence it seems to be a proper tool for modelling technical health i.e. diagnosing a system.

Let us take an example of a master valve in a subsea X-mas tree. An overall causal model is shown in the Figure 5. Further diagnosis (HUGINEXPERT http://www.hugin.com) of LTE failure is shown in Figure 6.

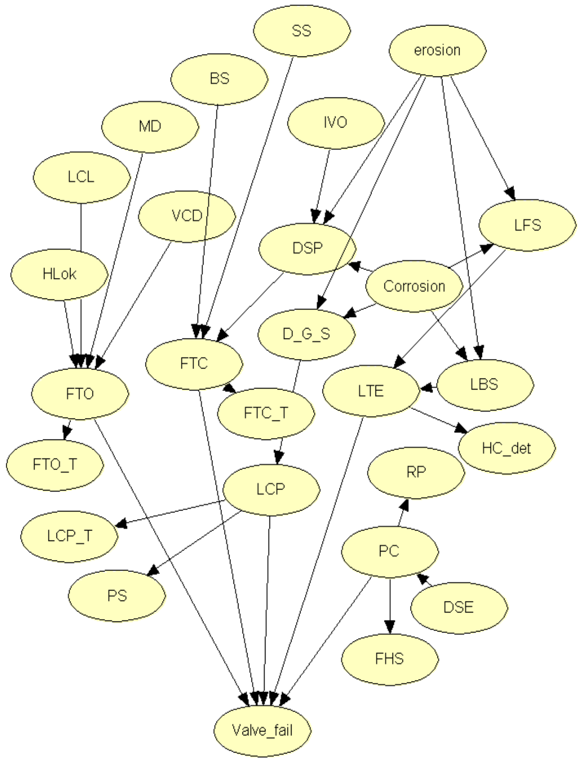

Figure 5: BBN model - valve failure

Failure modes and mechanisms/causes that are identified based on expert opinion are as follows:

Fail to close on command (FTC) failure – Caused by damage to steel parts such as gate, piston, stem or seat (DSP) caused by corrosion, erosion or improper valve operation (IVO), broken springs (BS), or sticking seals (SS). Failure detected during test (FTC_T).

Leakage through the valve in a closed position (LCP) failure – Caused by damage to gate or seat (D_G_S) which are caused by erosion and corrosion. Failure detected during test (LCP_T) or pressure sensor (PS).

Fail to open on command (FTO) failure – Caused by leakage in the control line (LCL), mechanical damage to the valve (MD), deposit in the valve cavity (VCD), and hydraulic locking of two valves (Hlok). Failure detected during test (FTO_T).

Leakage to the environment (LTE) failure – Caused by leakage through flange seals (LFS) and through bonnet seals (LBS) because of corrosion, erosion or as a result of external impact. Failure observed by camera or detected by hydrocarbon detection sensor (S_HC). Evidence on S_HC (Figure 6) implies that the cause could be erosion or external impact. Further analysis can be done by extending the BBN with additional nodes to represent causes of erosion and external impact.

Premature closure (PC) failure – Caused by damage in the seal element (DSE). Failure detected by reduced production rate (RP) or by feedback from the hydraulic system (FHS).

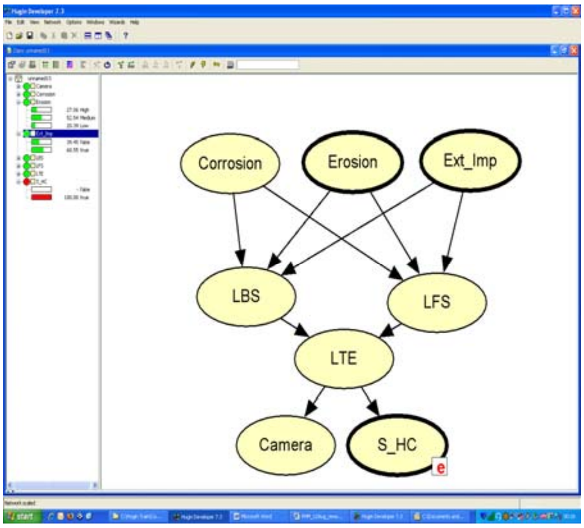

Figure 6 : BBN model - LTE failure

There could be some issues in technical health modelling using BBN approach. BBN consists of a structure and parameters. Creating a structure is a not a simple task and the most difficult part is expert judgment (Gran, 2002). Details of elicitation process to construct BBN are covered in (Norrington et al., 2007). It is a good idea that analyst creates a draft model structure based on the preliminary interviews with the individual experts, and then modifies/refines it iteratively based on the common discussions until the consensus is reached. It is necessary to use several sources of information for developing a structure (Celeux, 2006). Combining expert judgment and feedback data while creating a structure, is discussed in (Bouissou et al., 1999) and (Helminen & Pulkkinen, 2003). Causal relations are difficult to capture and there are always chances of reversing or misplacing links.

Once the structure is finalized, the experts can be asked to give the estimates of probabilities. In this type of problem solving method, it is necessary that the experts agree on definitions and have good clarity about what is expected from them (Peres et al., 2007). It is sometimes difficult to get an expert knowledge in the form required by a BBN model, i.e. input that can be converted into a probability distribution. The main reason for this is that the maintenance engineers work with the actual sensor reading or machine condition observations. Therefore, they end up describing or explaining the machine condition. They are not aware of the probability distributions and they have extremely limited knowledge of actual modelling using BBN software. This may lead to distrust in the entire process. Therefore, it is a practise to rely on heuristic methods even if they are biased (Clemen & Winkler, 1999). Studies have shown that the human estimations are subject to either overconfidence or under confidence irrespective of the elicitation technique used (Noortwijk, 1992). It is not easy to think in terms of conditional probabilities specially when there are many conditioning factors. Breaking down the problem to a lower dimension is possible in BBN and this feature can be used to overcome the issue with conditional probabilities. Identifying and applying appropriate modelling techniques to reduce the computational complexity however is always an issue.

6.2 Suitability of BBN for future loading model

A very useful property of BBN is that it can be used even if the data is limited or if there are some missing observations in the data. EM algorithm is one of the promising algorithms for finding maximum likelihood estimates for a set of parameters when there is an incomplete data set. In BBN, it is used to estimate conditional probabilities of the model from the data (Laurizen, 1995 & Spiegelhalter et al., 1993). In condition monitoring maintenance scenario, the sensor data always have some measurement error (uncertainty) and missing observations. This situation can be handled by BBN. In addition, extrapolation and expert judgment can be used to get future loading.

6.3 Suitability of BBN for RUL model

BBN support models of dynamic systems changing over time. Such models are called dynamic Bayesian networks (DBN) or time sliced Bayesian network (Jensen & Nielsen, 2007). A generic framework for stochastic modelling of deterioration processes is proposed by (Straub, 2009) based on DBN. The author has demonstrated two applications to probabilistic modelling of fatigue crack growth. Papers by (Weber & Jouffe, 2006) and (Boudali & Dugan, 2004) investigate timed Bayesian networks to find a suitable reliability framework for dynamic systems. For subsea situations, erosion, corrosion, wear and fatigue modelling is a primary requirement. Very few researchers have applied BN for deterioration modelling and it is an area of advanced research. The capability of BBN to handle physics based deterioration modelling qualifies it as a modelling tool for technical health and prognosis.

One of the promising features of the BBN is that it can be extended to influence diagram for solving a decision problem. Vatn has done extensive work in maintenance optimization (Vatn, 1996) with influence diagrams from a decision theoretical point of view. An influence diagram consists of a DAG with chance nodes corresponding to random variables, decision nodes representing decisions to be taken, and utility nodes, which associate utility value. The expected utility for each decision option in the domain is calculated by using the probability-updating feature of the BBN framework (Langseth, 2007). In addition, it is possible to supplement BBN with other decision support tools (Spiegelhalter et al., 1993). Strategic decision for improving offshore pipeline lifetime through a cost benefit analysis is presented in (Friis-Hansean & Hansean, 2008).

Simple example of influence diagram is given in Figure (7). Assume that a decision has to be taken about subsea ROV intervention. There is always an uncertainty whether the machine component/s are about to fail resulting in downtime (cost) or can continue operating for some time. Technical health is an input for such decision. Assessment of technical health is a decision associated with a price.

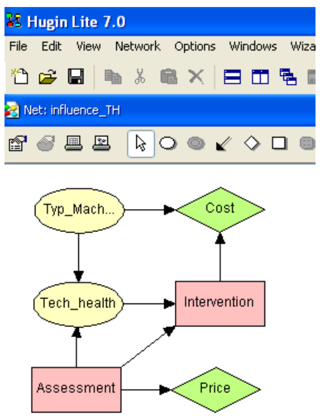

Figure 7: Influence diagram - technical health and intervention

7. CONCLUSION

- Paper explains the problem of life extension and need of prognosis (RUL prediction) in the context of subsea oil and gas industry
- Technical health, future operating and future environmental conditions are the factors that influence prognostics
- BBN has been successfully used in nuclear and avionics industries for complex system diagnosis. Attempts are being made to integrate Bayesian updating and structural reliability modelling. Resulting DBN can be used for modelling deterioration process.
- Possibility of incorporating expert knowledge and explicit accounting for uncertainty are the main advantages of BBN model and hence it seems to be a suitable modelling approach irrespective of some limitations
- Graphical representation of the model and visual cause-effect relationships is very useful in communication across operators, vendors, maintenance personnel and decision makers in oil and gas subsea industry.

ACKNOWLEDGMENT

I wish to express my heartfelt gratitude to my supervisors at the Department of Quality and Reliability Engineering at NTNU and to the centre for integrated operations in Petroleum Engineering at NTNU Trondheim for their direct and indirect support.

References

Altamiranda, E., Kiaer, L. & Hu, X. (2009) Condition Monitoring and Diagnosis for Subsea Control Systems: A subsystem prototype, *OCEANS-EUROPE' 09*

Banjevic, D. & Jardine, A. K. S. (2006) Calculation of reliability function and remaining useful life for a Markov failure time process , *IMA journal of management mathematics*, 17(2), 800-8005

Bolch, H. P. & Geiter, F. K. (1994) *An Introduction to Machinery Reliability Assessment*, Gulf Publishing Company: Houston, TX

Boudali, H. & Dugan J. B. (2005) A discrete time Bayesian Network reliability modelling and analysis framework, *Reliability engineering and system Safety*, 87(3), 337-349

Bouissou, M., Martin, F. & Ourghanlian, A. (1999) Assessment of safety critical system including software: A Bayesian belief network for evidence sources, *Reliability and Maintainability Symposium (RAMS 99)* Washington

Bouissou, M. & Nguyen, T. (2002) Decision making based on expert assessments: Use of Belief Networks to take into account uncertainty, bias, and weak signals, *13th European Safety and Reliability International Conference (ESREL)*

Bugaenko, S. E., Arzhaev, A. I., Evropin, S. V. & Savchenko, V. A. (2002) *Management of the service life of a nuclear Power Plant*, Atomic Energy, 92 (4), 279-286

Celeuex, G., Corset, F., Lannoy, A. & Ricard, B. (2006) Designing a Bayesian network for preventive maintenance from expert opinions in a rapid and reliable way, *Reliability Engineering and System Safety*, 91(7), 849-856

Charniak, E. (1991) Bayesian networks without tears, *AI Mag.* 12 (4), 50–63

Van der Gaag, L.C. (1996) Bayesian belief networks: odds and ends, *Computer J.* 39, 97–113

Chinnam, R.B. & Baruah, P. (2003) Autonomous diagnostics and prognostics through competitive learning driven HMM-based clustering, *Proceedings of the international joint conference on neural networks*, New York 1(4), 2466-2471

Clemen, R.T. & Winkler, R.L. (1999) Combining probability distributions from experts in risk analysis, *Risk Anal.* 19 (2), 187–203

Daley, C. P. (1999) *Aircraft Update Programmes. The economical alternative?*, RTO SCI symposium, Ankara, Turkey, 26-28, published in RTO MP -44, April1999

Farrar, C. R., & Lieven, N. A. J. (2006) Damage prognosis: The future of structural health monitoring, *Philosophical Transactions of the Royal Society*, 365, 623-632

Peres, F., Bauzaiene, L., Bocuet, J. C., Billy, F., Lannoy, A. & Haik, P. (2007) Anticipating aging failure using feedback data and expert judgment, *Reliability Engineering and system safety*, 92, 200-210

Friedemann, J. D., Verma, A., Bonissone, P.,Iyer, N. (2008) Subsea Condition Monitoring – A path to increased availability and increased recovery, *SPE* 112051

Friis-Hansen, A., Hansen P., Christensen C.F. (2008) Reliability analysis of upheaval buckling updating and cost optimization, *8th ASCE Specialty Conference on Probabilistic mechanics and Structural Reliability,* PMC

Goode, K. B, Moore, J. & Roylance, J. (2000) Plant machinery working life prediction method utilizing reliability and condition monitoring data., *Proceedings of the Institution of Mechanical Engineers, London* 214,109-122

Gelman, A., Carlin, J. B., Stern, H.S. & Rubin, D.B. (1995) *Bayesian data Analysis, Texts in Statistical Science*, Chapman & Hall, ISBN 0-412-03991-5

Gran, B.A. (2002). Assessment of programmable systems using Bayesian Belief Network, *Safety Science,* 40,797-812

Haitao, L., Wenbiao, Z. & Huairui, G. (2006) Predicting remaining useful life of an individual unit using proportional hazard model and logistic regression model, *IEEE*, 1,127-132, 2006

Heckerman, D., Geiger, D. & Chickering, D.M. (1995) Learning Bayesian networks: the combination of knowledge and statistical data, *Machine Learning*, 20, 197–243

Helminen, A. & Pulkkenien, U. (2003) *Reliability Assessment using Bayesian network - Case study on quantitative reliability estimation of a software based motor protection relay*, VTT industrial system, STUK-YTO-TR, 198, Helsinki

Horan, C. S., Starky, S. G., Lucas, M. G. (2008) New deepwater subsea equipment qualification system eases execution, improves reliability (SUBSEA), *Offshore*

ISO 13381-1. (2004) *Condition monitoring and diagnostics of machines – Prognostics - Part1: General guidelines*, International Organization for Standardization, Geneva

Jardine, A. K. S., Daming, L. & Banjevik, D. (2006) A review on machinery diagnostics and prognostics implementing condition-based maintenance, *Mechanical systems and signal processing*, 20, 1483-2510

Jensen, F. V. (1996). *An introduction to Bayesian Networks,* UCL Press, London, UK

Jensen, F. V. (2001) *Bayesian Networks and Decision Graphs,* Springer-Verlag, ISBN 0-387-95259-4, NY

Jensen, F. V. & Nielsen, T. D. (2007) *Bayesian Networks and Decision Graphs,* Second Edition, Springer Science, ISBN 0-387-68281-3 NY

Kang, C. W., Golay, M.W. (1999) Bayesian belief network based advisory system for operational availability focused diagnosis of complex nuclear power systems, *Expert Systems with Applications*, 17, 21-32

Karassik, I. J., Joseph, P., Messina, Cooper P., Charls, C., Heald. (2001) *Pump Handbook,* McGraw Hill, 3rd Edition

Kjaerulff, U. B. & Madsen, A.L. (2008) *Bayesian Networks and Influence Diagrams*, Springer Science (ISBN 978-0-387-74100-0), NY

Kothamasu, R., Huang, S. H. & William, S. V. (2006) System health monitoring and prognostics – a review of current paradigms and pratices, *International Journal of Advanced Manufacturing Technology*, 28, 1012-1024

Langseth, H. & Portinale, L. (2007) Bayesian Networks in reliability, *Reliability Engineering and System Safety,* 92(1), 92-108

Langseth, H. (2008) *Bayesian networks in Reliability: The good, the Bad and the Ugly*, Advances in mathematical modelling for Reliability, IOS Press, Amsterdam, Netherland

Laurizen, S. L. (1995) The EM algorithm for graphical association models with missing data, *Computat. Stat. Data Anal*. 19, 191–201

Lindley, D.V. (2007) *Understanding Uncertainty*, Wiley: Hoboken, NJ.

Pearl, J. (1988) *Probabilistic reasoning in intelligent systems: network of plausible inference*. Morgan Kaufmann Publishers Inc. San Fransisco, USA

Mahadevan, S., Zhang, R. X. & Smith, N. (2001) *Bayesian Networks for system reliability reassessment*, Structural Safety, 23(3),231-251

Mengshoel, O. J. (2007) *Designing resource-bounded reasoners using Bayesian networks: System health monitoring and diagnosis*, Proceedings of the 18th International Workshop on Principles of Diagnosis (DX-07), 330-337, Nashville, TN

Mengshoel, O. J., Darwiche, A. & Uckun, S. (2008) Sensor validation using Bayesian networks, *Proceedings of the ninth international Symposium on Artificial Intelligence, Robotics and Automation in Space* (iSAIRAS-08) Los Angelis, CA

Nieuwhof, G. W. E. (1984) The concept of failure in reliability engineering , *Reliability Engineering*, 7, 53-59

Noortwijk, van, J. M., Dekker, A., Cook, R.M. & Mazzuchi, T. A. (1992) Expert judgment in maintenance optimization, *IEEE Transactions on Reliability,* 3, 427-432

Norrington, L., Quigley, J., Russel, A., Van der Meer, R. (2007) Modeling the reliability of search and rescue operations with Bayesian Belief Networks, *Reliability Engineering and System Safety*, 93 (7), 940-949

Nystad, B. H. (2008) *Technical Condition Indexes and Remaining Useful Life of Aggregated Systems*, PhD Theses, Norwegian University of science and Technology

Rausand, M. & Høyland, A. (2004) *System Reliability Theory; Models, Statistical Methods, and Applications,* Wiley, Hoboken, NJ, 2nd edition

Reinertsen, R. (1996) Residual life of technical systems; diagnosis, prediction and life estimation, *Reliability Engineering and System Safety*, 54, 23-34

Sandsmark, N. & Meheta, S. (2004) Integrated Information Platform for Reservoir and Subsea Production systems, *Proceedings of the 13th Product Data Technology – Europe Symposium* 2004, Stockholm

Sigurdsson, J. H., Walls, L. A. & Quigley, J. L. (2001) Bayesian belief nets for managing expert judgment and modelling reliability, *Quality and Reliability Engineering International, Special issue:14th advances in reliability technology symposium* (ARTS), 17(3), 181-190

Singpurwalla, N. D. (1995) *Survival in dynamic environments*, Statistical Science, 10(1), 86-103

Spiegelhalter, D. J., Dawid, A. P., Laurizen, S. L. & Cowell, R.G. (1993*)* Bayesian analysis in expert systems, *Stat. Sci*. 8 (3), 219–247

Status Report on Nuclear Power Plant Life Management-*Nuclear Energy Agency Committee for technical and economic studies on Nuclear energy development and fuel Cycle* NEA/SEN/NDC/2000

Straub, D. (2009) Stochastic Modelling of Deterioration Processes through Dynamic Bayesian Networks, *Journal of Engineering Mechanics*, 135 (10), 1089- 1099

Vaidya, P. & Rausand, M. (2009) Life extension of machinery in the oil and gas industry, *Proceedings of European Safety and Reliability Conference ESREL*, Praha

Vaidya, P. & Rausand, M. (2010) Technical health – in the context of condition based maintenance, *Proceedings of European Safety and Reliability Conference ESREL*, Crete

Volk, P. J., Wnek, M. & Zygmunt, M. (2004) Utilizing statistical residual life estimates of bearings to quantify the influence of preventive maintenance actions, *Mechanical Systems and signal Processing*, 18(4), 833-847

Van der Gaag, L. C. (1996) Bayesian belief networks: odds and ends, *Computer J*. 39, 97–113

Vatn, J. (1996) *Maintenance Optimization*, *Models and Methods*, PhD Theses, Norwegian University of science and Technology

Wang, W. & Zang, W. (2008) An asset residual life prediction model based on expert judgments. *European Journal of Operational Research*, 188(2), 496-505

Wang, W., Scarf, P.A. & Smith, A. J. (2000) On the application of model of condition-based maintenance, *Journal of the Operations Research Society*, 51,1218-1227

Weber, P. & Jouffe, L. (2006) Complex System Relaibility Modelling with Dynamic Object Oriented Bayesian Networks (DOOBN), *Reliability Engineering and System Safety*, 91(2), 149-162

Willy, R., Mosleh, A., Vinnem, J. E., & Aven, T. (2009) On the use of hybrid causal logic method in offshore risk analysis, *Reliability Engineering and System safety*, 94, 445-455

Xue, F., Bonissone, P., Varma, A., Yan, W., Eklund N. & Goebel, K. (2008) An instance –based method for remaining useful life estimation for aircraft engine, *Journal of Failure Analysis and Prevention*, 8(2), 199-206

Yan, J., Koc, M. & Lee, J. (2004) A prognostic algorithm for machine performance assessment and its application. *Production planning and control*, 15,796-801

Yongli, Z., Limin, H. & Jinling, L. (2006) Bayesian network based approach for power system fault diagnosis, *IEEE Transactions on Power Delivery*, 21: 634-639

Note: This paper has extracts from the earlier paper written by the author referred above (Vaidya and Rausand, 2009) and (Vaidya and Rausand, 2010)