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Introduction:

As more and more oil fields in the North Sea are developed as subsea fields, the monitoring and maintenance availability is becoming difficult to perform on the equipment used for subsea boosting. Often maintenance is looked upon as a necessary evil (Arthur, 2005, Bevilacqua et al., 2003) rather than a way to optimize the production of the field. This paper is looking at the problem of when to pull a damaged Subsea Water Injection Pump and replace it. Usually the practice is to keep the pump running until it breaks down and the production has to be shut down while the pump is being replaced with a new one. However, this practice can result in very high costs due to shut down of the oil wells and bad weather during the intervention. The operator of the pump is receiving data from the subsea control system which carries information such as temperature, flow, head pressure, lube oil level, and vibration that describes the state of the pump. The data received is not easily interpreted due to scarcity and uncertainty of the data and these data cannot be complemented by a physical inspection of the equipment because it is located subsea. So a model that analyses the uncertainties and the events related to the pump and the intervention is needed. In this work the problem is formulated in a Bayesian framework and a decision analytic approach to analyze and determine when the pump should be pulled is being used.

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Literature research:

The literature research contains a number of articles describing maintenance analysis of both electric submersible pumps, multiphase pumps, and also centrifugal pumps, which are relevant for the problem presented in this paper. However, the analysis methods described in these papers are mostly related to topside pumps describing inspection frequency, observable failures and vibration analysis, and do not take subjective probability or Bayesian methods into consideration, e.g. (Bevilacqua et al., 2003). There were also discovered papers that describes decision analysis regarding the design of water pumps (Russel and Rabideau, 2000, Goodacre, 1985), but it is assumed in this paper that the pumps used at the oil field is designed correctly for its purpose, so these articles are not applicable here. Some of the articles found are discussed in the following.

Delay-Time analysis:

A procedure that is often described in papers related to maintenance is the 'Delay-Time' analysis (Leung and Ma, 1997, Arthur, 2005, Dekker and Scarf, 1998, Scarf, 1997) which uses mathematical calculations to measure the time lapse between a fault is observed and the occurrence of an eventual failure. A fault is defined as "an unpermitted deviation of at least one characteristic property of a variable from an acceptable behaviour. Therefore, the fault is a state that may lead to a malfunction or failure of the system" p.642 (Isermann, 1997). Hence it is important to be able to detect a fault at an early stage so there is time to take action before a failure occurs. One problem with detecting faults is the reliability of the data available. The data used in delay-time analysis are based on the technician's observations during the inspection and his/her level of experience to recognize failures, and this will influence the accuracy of the analysis (Leung and Ma, 1997). This uncertainty is not accounted for in the delay-time analysis, but is accounted for in the model described later in this paper. There are certain criteria for the delay-time analysis to be valid. Two of these criteria are that there has to be a scheduled inspection frequency of the pump and that the defects detected by an inspection are assumed to be correctly detected (Leung and Ma, 1997, Arthur, 2005). This means that the delay-time analysis is not applicable for the problem given in this paper. The Water Injection pump is located at the seabed, so a physical inspection is impossible without pulling the pump. And there are so much uncertainty regarding the data received from the pump that a correct detection of a defect is not possible.

Other maintenance procedures from literature:

Some of the papers do discuss the subjective approach of the inspections, but argue that the subjective probability given by an expert regarding the state of the pump is not reliable since the ‘expert’ providing the opinion on the matter is the same person that is responsible for the maintenance. Thus the ‘expert may not see the true failure but give his/her opinion based on current practice and experience (Scarf, 1997, Arthur, 2005). The phenomenon of coming to hasty conclusions based on easily recognized events are called heuristics, and this is discussed further in the ‘Expert Opinion’ part of this paper. It is also mentioned in some of the papers (Dekker and Scarf, 1998, Isermann, 1997) that the Bayesian methods can be used for applying the subjective probabilities given by the experts in the maintenance models, but they do not describe the procedure of doing so. Neither do the papers use influence diagrams to visualize the situation at hand, which will be used in this paper. However they do describe the importance of the expert’s opinion and probabilistic reasoning, which is also used in the model in this paper.

A couple of the papers also consider the benefit of fixing the pump and compare the cost of maintenance with the gain received from the maintenance arguing that the most appropriate time to do maintenance is when a balance between the cost and benefit from maintenance is found (Arthur, 2005, Dekker and Scarf, 1998). This is relevant for the problem in this paper as a comparison of the cost of reduction of produced oil with the intervention cost is used to make the decision.

Bayesian and maintenance:

However, one article that was fairly relevant to the subject of this paper was found. The article that was most relevant to the maintenance problem describes the use of decision analysis and Bayesian methods to maintenance decision making (de Almeida and Bohoris, 1995). It is not specifically related to pumps per se, but maintenance practice in general. The article describes briefly the basic framework of the decision analysis model used in this paper starting with objectives, a set of actions, consequences of the decision, describing subjective probabilities, expert opinion, and the use of Bayesian methods to solve a problem. It also mentions the use of sensitivity analysis to see what parameters that influence the outcome of the decision. But it does not mention the use of influence diagram as a tool to visualize the problem. Thus it appears that it is scarce with articles published regarding pump maintenance and the use of influence diagrams.

Outcome of literature research:

The literature research was a helpful process as it gave the author some insight to what may cause failure to a pump, and also some general knowledge regarding how a pump is operating. The literature research also resulted in finding books and articles regarding decision analysis and Bayes' theorem, which also were helpful in giving further information and insight into the realm of decision analysis and Bayes' theorem.

Decision analysis:

Basics:

Every day humans face situations where they must decide on what action to take next. The situations can be what clothes to wear to office that day, what kind of transportation to facilitate to get to work, or whether it is a wise move to buy the new house that has been a temptation for so long. Some of these day-to-day decisions are not very difficult to make because the solution to the problem is obvious and clear to the person and the outcome does not make a big impact on him/her. However, for bigger and more complex problems the solution to a problem that is to be solved would not immediately be recognized. This is where the decision analysis comes in handy, because it formalizes the problem by using the decision makers intuition to visualize the problem more transparent and clearly.

It has been argued that for the decision to be made "there would always be at least two alternatives: if there were no alternatives, then it would not be a matter of making a decision!" p.25 (Clemen and Reilly, 2001). Say for instance that you are having breakfast and feel like having an egg, but you are all out of eggs. If you on this particular day have a day off from work you could either drive down to the shop and buy some eggs or have something else for breakfast and eat eggs another day. Here the alternatives are either to have something else for breakfast, or drive to the store and buy some eggs for the breakfast. But this decision is not very complicated. If you eat something else you save time for other activities, and if you drive to the store you use some gas and some time, but you get the eggs you wanted for breakfast. From this example it is seen that the consequences of the decision does not make any big impact on the person undertaking this decision, unless maybe he suffers from high cholesterol. But what if this person is to decide what clothes to wear for work one day? He knows that he is going to attend a board meeting that day so he would not use his Sunday leisure BBQ suit for work even if he really feels like it, because he knows that the consequences would be paramount for him.

Information:

The decisions in the previous examples describe fairly straightforward situations where the decision maker (the DM from now on) does not need very much information to make the decision. The DM chooses the alternative that he/she believes is the best one based on previous experiences, routines, knowledge base and intuition. This paper will discuss further on the subjects of experience, intuition and so on in the 'Expert Opinion' part. However, in other situations such as the problem in this paper, the decisions are much more complex and the need for information is crucial for the decision process. Lack of information regarding the problem at hand and an environment that seems unpredictable will make the DM uncertain about what will be a good decision (Hatch, 1997) (see a definition of good decisions in the next paragraph). Hatch (1997) continues arguing that in such an environment the DM will either experience too little information, or gain too much information and will be confused to what is relevant for the decision to be made. If the DM has got little information about the decisions to be made he/she will feel uncertain about what will be the best decision. Or the DM may not have information about some crucial aspects of the problem and may pick the wrong alternative. On the other hand, if the DM is faced with a huge amount of information about a complex and rapidly changing environment, the ambiguity of the decision process may be overwhelming and the DM will still have difficulty deciding on the best alternative. "The difference between ambiguity and uncertainty is that, whereas added information reduces uncertainty (since it is lack of information that produced the condition in the first place), ambiguity is often heightened by the addition of information because the new information contributes additional points over which decision makers can disagree" p.275 (Hatch, 1997). It is worth noting that decision-making under uncertainty is not difficult, as long as information is available and a decision model is used. It is working with uncertain information that may be difficult. Hence, it is important for the DM to process the information in such a way that he/she will recognize what is relevant for the problem he/she is faced with. So if the DM is going to make the best decision with the available information, there are certain steps that the DM should follow during the decision analysis process.

Good decision vs. good outcome:

But before these steps are discussed it would be in its place to comment on what makes up a good decision. A decision maker will not necessarily make a decision with a successful outcome every time he/she makes a decision. The outcome of a decision will depend on the decision made, how the decision model is implemented in the decision analysis, and chance. Chance is defined as "a possibility of something happening" (AskOxford, 2007) and will always play a role regarding the outcome because this is what actually happens regardless of the decision made.

One example that easily illustrates the coherence between a decision and its outcome is a person that is contemplating on driving home from somewhere. The state of the person could be 'drunk' or 'sober', the alternatives would be 'drive home' or 'not drive home', and the outcomes would be 'arrive home safely' or 'getting into an accident'. Then it can be seen from Figure 1 that even though the person drives home while drunk and arrives at home safely, it would still be a bad decision to make. It is a bad decision not because the outcome of the decision was bad, but because the decision to drive home drunk in itself was a morally wrong thing to do.

		Quality of outcome	
		Good	*Bad*
Quality of decision	*Good*	*Driving sober and arriving safely*	*Driving sober and getting into an accident*
	Bad	*Driving drunk and arriving safely*	*Driving drunk and getting Into an accident*

Figure 1. Good decision vs. good outcome. Bratvold (2006).

The fact that the person arrives home safely was mere a result of plain luck. On the other hand it can be seen from Figure 1 that even though the person drives home sober, an accident may still happen and the outcome will be a bad one.

This relationship between good and bad decisions and good and bad outcomes applies to decisions that a DM will make in his/her professional career as well. If a DM is using all the relevant information available together with decision analysis tools, the DM may still experience that the outcome of some of the decisions is bad even though he/she made the best decision with the information at hand. This is due to all the uncertainty and the ever changing environment related to the problem. However each time there is a bad outcome, the process will provide new information and learning for the DM (Daft, 1999). So if a DM consistently uses decision analysis tool to make the decisions, he/she will in the long run have a portfolio of decisions that all in all are the best in the long run. As the DM gain more experience with using the decision analysis tools, he/ she will have a better understanding of the problems to be solved, and the decisions are more thought through and meticulously carried through than just a haphazardly pick between the alternatives (Clemen and Reilly, 2001).

Steps for the decision analysis process:

Most of the problems that people encounter at work, and then especially in the petroleum business, are complex and with little available information (Smith, 1988). The DM should then use decision analysis as a tool to formulate the problem at hand and 'tap' information from his/her own previous experiences and experts on the field related to the problem. Decision analysis requires some preliminary work for the DM to make good decisions and there are certain steps that should be followed when embarking on the decision analysis process. Figure 2 illustrates how the DM should progress in the decision analysis process. The first three 'boxes in Figure 2 will be described in the theory part. Then subjective probability and influence diagram will be described, while the last four boxes are described in 'The Problem' part of this paper.

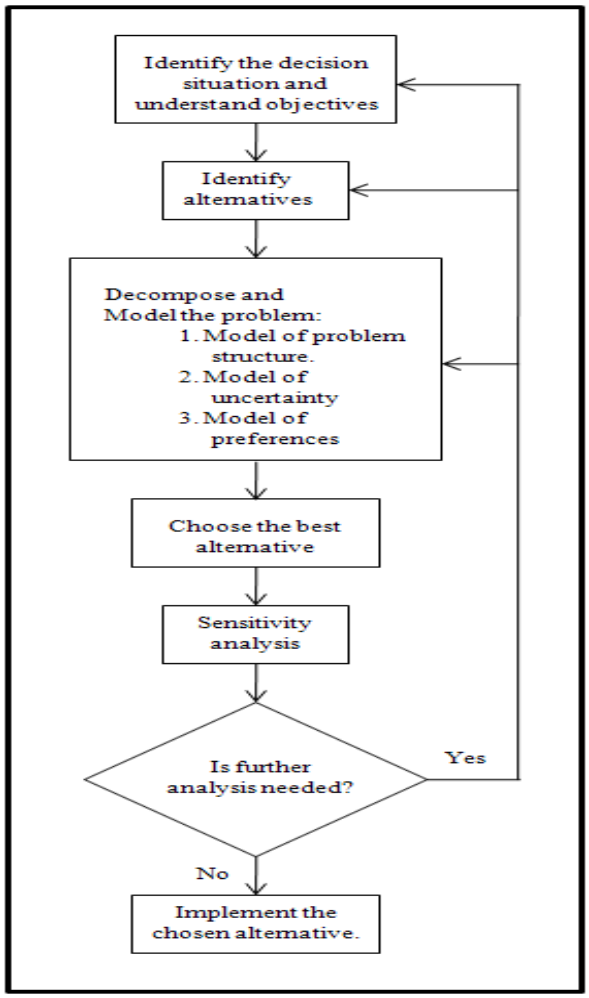

Figure 2. Decision Analysis Progress (p.6, Clemen & Reilly, 2001).

Identify values and objectives:

The first step in this process is to identify what the problem is and what decision is to be made to solve this problem. Then the DM has to identify what the values and the objectives related to this decision are. Values are defined as "an individual's basic standards about what is good and bad, worthwhile and worthless, desirable and undesirable, true and false, moral and immoral" p.67 (Carlopio et al., 1997). It is important for the DM to take his/her own and the company's values into consideration when making a decision because the consequences of the decision can end in a catastrophe and hurt the company's public relations if the decisions were immoral. One example of values regarding making a decision is the previous example with the person driving under influence of alcohol, which is an immoral thing to do. An objective is "a specific thing you want to achieve" p.22 (Clemen and Reilly, 2001), e.g. learn how to play guitar, wax the car before the next rain shower, or save money on a project you are working on. It is important that the objectives are clearly defined and that all the people involved in the decision analysis process, i.e. experts and such, understand and accept the objectives if the objectives are going to be meaningful for the process (Quible, 2001). Thus, the objectives tell the DM what outcomes he/she would like to see as a result from the decision and help him/her to make the best choice between the alternatives.

Identify alternatives:

As mentioned before, more than two alternatives are needed if there is going to be something to make a decision about at all. So after the values and objectives are identified, the DM should look for alternatives to base the decision on. One important benefit that the DM might experience from the decision analysis process is that not so obvious alternatives may surface from a thorough analysis of the objectives (Clemen and Reilly, 2001).

Decompose and model the problem:

The next step in Figure 2 is the 'Decompose and model' activity. In this step the DM decomposes the problem into smaller more manageable pieces, to get a better understanding of the structure of the problem. The decomposing of the problem helps the DM to see the uncertainties that are involved in different parts of the problem, and it opens for an understanding of what the consequences of the different alternatives might give. Sometimes a decision can contain alternatives that will be very specific so that it is more of an either/or decision, such as buy a certain car or not. And other times a decision may have alternatives

where the DM must choose from a range of values, such as how high does the DM want to go if there is a bidding round on the car he/she wants to purchase. If there are no alternative that seems more obvious than others at the moment the DM is working on the problem, another alternative may be to wait to get more information on the subject, or maybe even consider obtaining some sort of insurance or other ways of hedging against a bad outcome, provided there is time or means to do so (Clemen and Reilly, 2001).

When a decision is to be made in a complex and rapidly changing environment it can be difficult to see the obvious alternative to choose, because there are uncertainties of what will happen in the future. And the DM must take action to resolve these uncertainties (Kahneman et al., 1982). The uncertain events will then produce outcomes. Sometimes there are only a few outcomes from an uncertain event, an sometimes the outcome falls within a range of some sort, such as the bidding price for a car. However, not all the uncertain events that may surface when analyzing a decision situation are relevant for the decision. So to find the uncertain events that are relevant for the given problem the DM must pick the events that has got outcomes that impacts at least one of his objectives. In other words it should be significant to the DM what follows from the outcome. Otherwise the DM may focus on some uncertain event that it is easy to retrieve information from but not relevant to the problem, while more important uncertain events may be overlooked due to lack of information (Clemen and Reilly, 2001). It has been argued that a DM feels uncertain about an event because he/she lacks knowledge or information about the problem, and the complexity and rate of change also contributes to this uncertainty (Clemen and Reilly, 2001, Hatch, 1997, Kahneman et al., 1982). As it can be seen from Figure 3, the level of uncertainty about a problem increases as the complexity and rate of change increases. The DM will have trouble with keeping track of what information is relevant, and/or will not be able to keep up when the information is changing all the time (Hatch, 1997).

		Rate of change: *low*	Rate of change: *high*
Complexity	*low*	Needed information is known and available	Constant need for new information
	high	Information overload	Not known what information is needed

Figure 3. Links between conditions in the perceived environment, uncertainty, and information. (p.91, Hatch, M J, 1997).

Modeling preferences:

The modeling preferences part of the decision analysis model encompasses the area of the preferences and the risk attitude the decision makers have towards making a decision. The risk attitude is measured by a so called utility function (Clemen and Reilly, 2001). A utility curve is a plot of the wealth of the company or so, vs. the utility value found from the utility function. This means that the more wealth of the company that is to make a decision, the more risk it dares to take to 'close a deal'. The risk attitude of a person can be of three different kinds, risk-averse, risk-neutral, and risk-seeking. A risk-averse person will be reluctant to take a deal where he/she may lose money, and will often gladly pay an insurance premium that is higher than an expected amount he/she would claim in case of an accident. A risk-neutral person will most often follow the expected value of a deal because it ignores the risk of this deal. And a risk-seeking person will be more eager to enter into a gamble where there is a high chance that he/she will lose money, such as a poker game (Clemen and Reilly, 2001).

This paper will not discuss this topic any further as the risk attitude and utility function is not taken into consideration in the analysis of the problem. The reason that this is excluded is that the measurement of risk attitude and the use of a utility function require an in depth understanding of the company's risk attitude. To get such an understanding of the risk attitude it is necessary to create a questionnaire that is answered by the experts working on the problem, and the management that will have their saying in the decision. And unfortunately there were not enough time to perform such a questionnaire at this moment so this part is excluded from this paper. However it should be taken into consideration for further use of this model to make a decision on when to pull the WI pump, as the risk attitude and the utility function will optimize the decision further.

Influence Diagram:

Before the concept of an influence diagram is discussed, it is important for the understanding of the influence diagram to describe what relevance is.

Relevance:

The subsea WI pump system consists of many components that work in collaboration to perform what it is designed to do. These are components such as an electric motor, the pump housing, lubrication system, cooling system, bearings, impellers, control system, and more. Since these components work together in a system they can be said to have relevance to each other. Relevance is the noun of the adjective 'relevant' which is defined as "closely connected or appropriate to the matter in hand" (AskOxford, 2007). This means that if a failure is experienced in one component in the system, this failure may be relevant to another component in this system. Take for instance a failure in the motor driving the pump. This may lead to a decrease in the flow through the pump, because the motor is running slower due to the failure. Hence the efficiency of the motor is relevant for the flow of water through the pump and into the reservoir. But a failure in the motor may result in an increase of the temperature in the cooling unit because the motor will use more energy due to the failure. This shows the relevance between the motor and the cooling unit as well. Thus one failure may have an effect on several of the components in the subsea system that means that these components are relevant to each other. Another example of relevance considering subsea production system can be illustrated by comparing injection rate and production rate in a reservoir. If the water injection rate decreases, the reservoir will experience a decrease in the pressure inside, and thus the oil production will decrease as well. However it is important to be aware of the fact that not every component-failure situation is relevant to every other component in the system.

Two events C and D are said to be relevant if the probability of D given that C has occurred is different from the probability of D given that C has not occurred. This is written as $P(D|C) \neq P(D|(\overline{C})$ (also see the paragraph 'Some probability theory' for further explanation). From that it can be said that two events are relevant if the DM changes the given probability of one event after he/she has learned what the outcome of the uncertainty in the other event will be. This also implies that relevance can be something cognitive based on

personal experience and knowledge about the problem. Two persons may well have different views as to whether two events are relevant or not, based on their information and interpretation of the situation (Clemen and Reilly, 2001). It is worth noting that relationship between events should be carefully checked as they may not be relevant even though they occur together frequently. If there seems to be a frequently co-occurrence of two events they may be perceived as relevant to each other even though they are not. The DM creates an illusion of relevance due to the frequency the events occur together (Kahneman et al., 1982, Clemen and Reilly, 2001).

If we want to illustrate the relevance between different components and their failure modes, we can make a relevance diagram to more easily see which uncertainty is relevant to which components. Relevance diagram is also called influence diagram.

Influence diagram:

So, when the DM has identified the objectives and the uncertainties related to the problem at hand, he/she should draw an influence diagram and include the events and their respective subjective probabilities into the diagram. An influence diagram is made up by elements that are represented by different shapes (Clemen and Reilly, 2001). The good thing about influence diagrams are that they can present large highly complex problems in a way that is easily understood even for people with limited training and experience in reading mathematical models. Influence diagram is a great tool both for decision analysis, and also for more general purpose such as a description of relationship within a project. It can be used to visualize probabilistic dependencies between aleatory decisions and uncertainties (Howard and Matheson, 2005). However, an influence diagram must not be confused by a flow chart even though it may look like one. The influence diagram is a visualization or a snapshot of the situation the DM is facing at a particular time, with the available information about the problem and his/her beliefs of probabilities about the future (Clemen and Reilly, 2001). Different types of shapes called ‘nodes’ will represent different types of decision elements in the decision diagram. As can be seen in Figure 4 below, oval shapes represent uncertainty, rectangles represent decisions, and a diamond shape represents the outcome or the pay off of the decisions to be made (Clemen and Reilly, 2001).

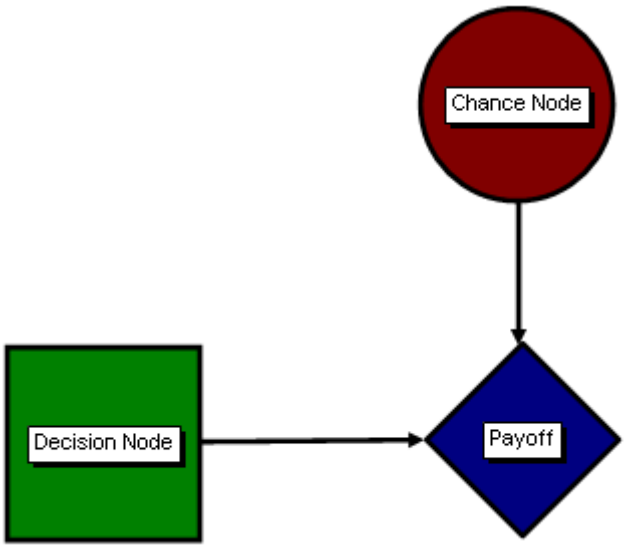

Figure 4. Decision node, uncertainty node, and pay-off node with appurtenant relevance arcs.

Nodes in an influence diagram:

One rule that is important regarding the chance nodes are that their outcome must be 'mutually exclusive' and 'collectively exhaustive'. Mutually exclusive signifies that only one of the possible outcomes can happen e.g. Viking Fotballklubb will play in the elite series in 2008, or they will not play in the elite series in 2008.

And collectively exhaustive signifies that one of the possible outcomes must occur, so there are no other possibilities that are not included in the chance node. These two properties combined means that "when the uncertainty is resolved, one and only one of the outcomes occurs" p.70, (Clemen and Reilly, 2001).

From Figure 4 there are also some arrows or 'arcs' presented. These arcs represent the relationship that occurs between the different nodes. A node that is presented at the beginning of an arc is called the 'predecessor', and a node that is at the end of an arc is called the 'successor'. There are some rules regarding the arcs in an influence diagram to be followed when they represent the relationship between the nodes. An arc can represent relevance between two nodes, or it can represent a sequence of two nodes. These rules are shown in Figure 5. When a chance node is the successor of either a chance node or a decision node, as it is with the nodes A, B, and C, the arcs represent relevance between the two nodes respectively. The probabilities associated with chance node C may be influenced by the outcomes of chance node A. The reason for the expression 'may be influenced by' is that

influence diagrams are based on subjective probabilities and hence the successors may have different probabilities due to different outcomes from the predecessors. The same goes for nodes B and C. The outcome of decision B may be relevant for the probabilities of node C, e.g. the probability that a person will be rich may depend on the persons choice of career or some other event happening (Clemen and Reilly, 2001).

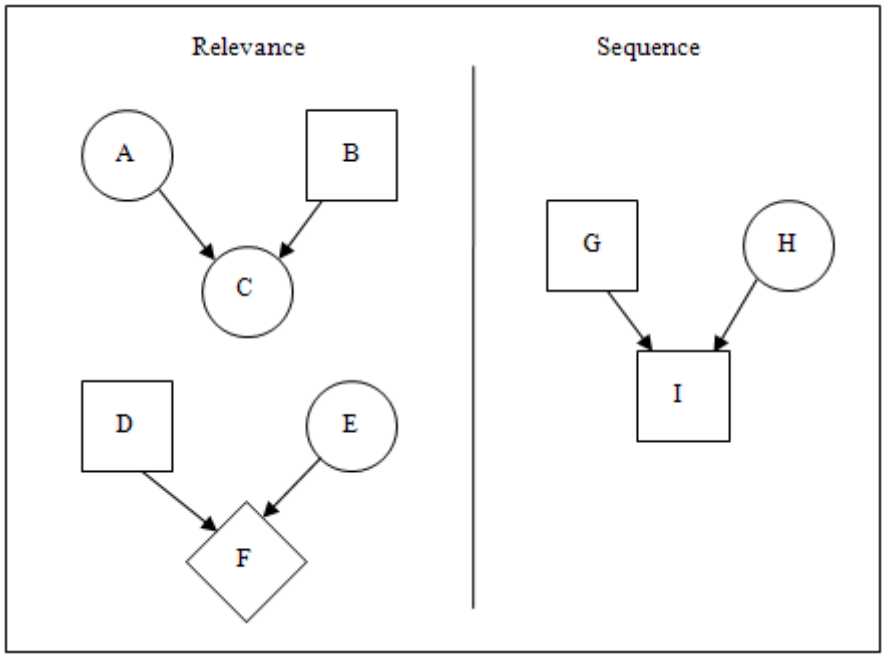

Figure 5. Rules for using arcs to represent relationships among nodes. (p.56, Clemen and Reilly, 2001)

Arcs representing relevance can also be drawn from a decision node or a chance node into a pay-off node, as shown in the relationship between D, E, and F. Here the decision to be made and the uncertainty related to the problem may influence the consequence of the decision. However, if the successor in a set of nodes and arcs is a decision node the relationship between predecessor and successor represent a sequence. In a sequence situation, the DM knows the outcomes of the predecessor nodes before he/she has to make the decision. The DM has resolved the uncertainty in chance node H, and also knows the outcome of decision node G before making decision in node I. Figure 6 explains the relevance and sequence in an easy way.

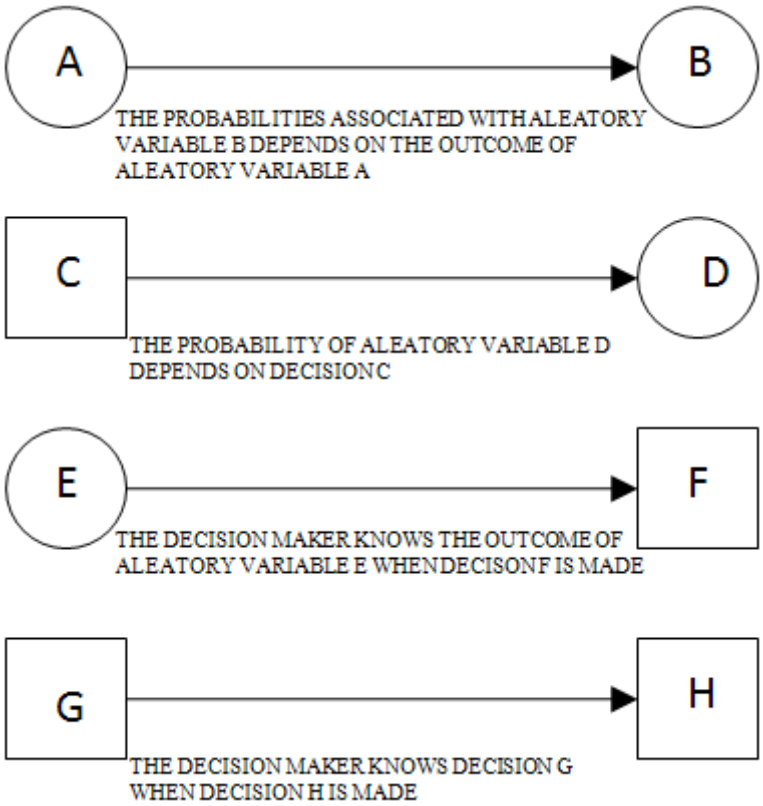

Figure 6. Definitions used in Influence Diagrams. p. 130 (Howard and Matheson, 2005)

As the arrows between two nodes may represent either relevance or sequence between them, a stronger statement is made with an exclusion of an arrow. That is, from Figure 5 it can be seen that there is no arrow presented between chance node A and decision node B. This states that there is no relevance at all between those two nodes. It says that the uncertainty in A has absolutely no influence over the decision in B and vice versa, the decision in B has no influence over the uncertainty in A. Hence the DM must be certain that there is no relevance between the two nodes when he/she excludes an arrow between the two. To be sure not to miss out on relevance between the two nodes the DM could add an arrow between them just in case, because an arrow implies that there may be a relationship between the two nodes but it doesn't have to be one. However, the more arrows drawn in an influence diagram, the more complicated it looks, and might be difficult to solve.

Also, when drawing arrows the DM must be careful not to create 'loops' in a set of nodes. A loop is created when a given node have an arrow coming in from a successor node. This is prohibited because "it could not represent any possible expansion order" p.134, (Howard and Matheson, 2005). Often, 'loops' or cycles are draw to represent feedback between the nodes as it is done in flowcharts. But as mentioned earlier, influence diagrams are

snapshots of the situation at a certain point in time where there are no possibilities for giving feedback (Clemen and Reilly, 2001). Thus, loops are not allowed in an influence diagram.

One way to solve an influence diagram is by using decision analysis tools such as @Risk and create a decision tree, where the outcome of each node will create new branches to the tree, and the probabilities for each node creates an expected best path to follow which gives the best expected decision for a given problem. This paper will use a decision tree for illustrating how to calculate the probabilities using Bayes' Theorem, but the tree will not be used as a mean in itself for the calculations, so any further explanation regarding decision trees will not be emphasized here. Another way of solving an influence diagram is by using Bayes Theorem to calculate the probabilities of the different events in the diagram. But first it is in its place to describe some basic probability theory.

Some probability theory: (Walpole et al., 2002, Clemen and Reilly, 2001):

- Probabilities must have a positive value between 0 and 1
- The notation of probability is written as a P-of-value such as P(of something) = 1
- The notation of an event not occurring is written as $P(\overline{of\ something})$ = 1 - P(of something)
- The probability that on or the other of two mutually exclusive events (meaning that only one can occur) is the sum of the two probabilities.
- The set of outcomes from each chance node must add up to 1 because they are mutually exclusive and collectively exhaustive, meaning that one and only one outcome can occur.

Conditional probability is when one event B occurs when it is known what will happen to an event A that is relevant to event B. The notation of conditional probability is written P(B|A) and is read as 'the probability of event B occurs given that event A occurs, or in short 'the probability of B given A' (Walpole et al., 2002, Clemen and Reilly, 2001).

Bayes Theorem:

The problem given in this paper will be solved using the 'Bayes' Theorem' and 'Bayesian data analyses'. Bayesian data analyses involves "practical methods for making inferences from data using probability models for quantities we observe and for quantities we wish to learn" p.3, (Gelman et al., 2004). Inference is defined as a "conclusion reached on the basis of evidence and reasoning" online (AskOxford, 2007). So Bayesian data analyses use reasoning and evidence given by the experts and the DM to gain better insight to a given problem. The probabilities used in the analyses are the subjective probabilities described in the 'Expert Opinion' part of this paper. These probabilities are saying something about how likely an expert may think an event is to happen. An example related to the WI pump could be regarding the problem with algae growing on the cooling system of the pump. An expert may say 'I think there is a probability of 60% that there will grow algae on the cooling element, (i.e. P(algae growing) = 0,6), and this may make an increase in the temperature readings'. So we put this into a simple influence diagram and it might look like the upper part of Figure 7. But what the DM really wants to know is 'If there is an increase in the temperature readings, what is the probability that this is caused by algae growing on the cooling element? (i.e. P(Algae growing|Increased Temp)'. To get an answer to this, the DM must flip the influence diagram around by using the Bayes' Rule (Howard and Matheson, 2005) so the influence diagram looks like the lower part of Figure 7.

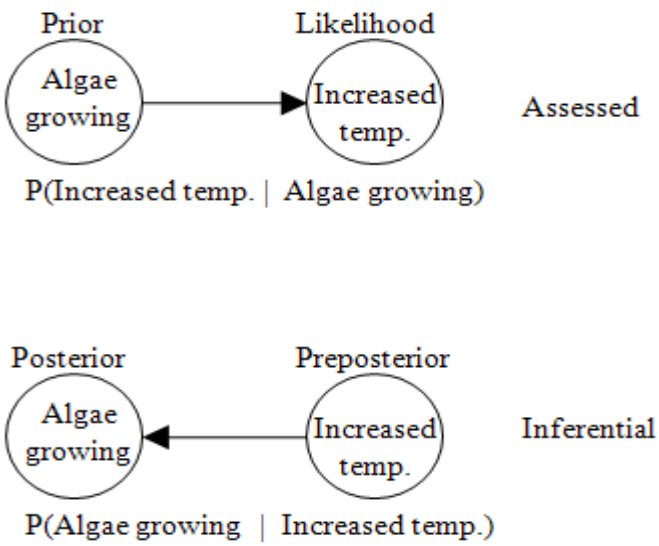

Figure 7. Simple influence diagram which shows the assessed and the inferential probabilities using Bayes' Rule.

So the prior information from the expert is that there is a 60% chance that there will grow enough algae causing the temperature to increase. And if it is thought that from previous experiences the experts are correct in identifying the right cause of an increase in temperature 70% of the times. From this we have the assessed information saying: P(Algae growing) = 0.6 and P(Increase temp. | Algae growing) = 0.7. Since the probabilities in the chance nodes have to be mutually exclusive and collectively exhaustive, the sum of the probabilities in each chance node must add up to 1. Thus we get P(Algae not growing) = 1 – P(Algae growing) = 1 - 0.6 = 0.4, and P(No increased temp | Algae growing) = 1 - P(Increase temp. | Algae growing) = 1 - 0.7 = 0.3. These probabilities can be put into a table that will look like Figure 8

Prior probabilities		
P(Algae growing)		0.6
P(Algae not growing)		0.4
	Sum	1.0

Assessed probabilities			
		True algae status cooling elements	
Expert reliability		Algae growing	Algae not growing
Expert says	Temp. increase	0.7	0.3
	No temp. Increase	0.3	0.7
	Sum	1.0	1.0

Figure 8. Assessed probabilities table

And by applying the Bayes' Rule, the DM will get the conditional probability of what the probability for algae growing on the cooling device given that the temperature is increased may be.

Bayes' Theorem in its usual form is given as:

$$P(B|A) = \frac{P(A|B)\cdot P(B)}{P(A)}.$$

From conditional probability concepts, and Figure 9 on the next page shows a Venn diagram of the relationship between two events A and B, it is given that event A can occur in two ways, with event B occurring as well, or without event B occurring.

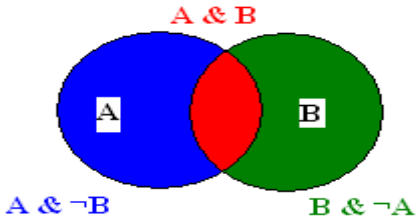

Figure 9. Venn diagram showing relation between event A and B (Bratvold, 2006).

This example also illustrates the concept of 'imperfect information' that will be further emphasized in the 'Expert Opinion' chapter.

Hence, the expression for event A occurring is then:

$$P(A) = P(A|B) \cdot P(B) + P(A|\overline{B}) \cdot P(\overline{B}).$$

If the expression for P(A) is then inserted into the usual form of Bayes Theorem, the expression that will be used in this paper becomes as follows:

$$P(B|A) = \frac{P(A|B) \cdot P(B)}{P(A|B) \cdot P(B) + P(A|\overline{B}) \cdot P(\overline{B})}.$$

So by applying this rule to change the assessed probability to the more useful inferential probability in the algae example, the DM will be able to calculate that:

$$P(Algae\ Grow\,|Incr.Temperature) = \frac{P(Temp\,|Algae) \cdot P(Algae)}{P(Temp|Algae) \cdot P(Algae) + P(Temp\,|\overline{Algae}) \cdot P(\overline{Algae})} = 0{,}78,$$

or 78%. Calculations for the other situations are shown in Figure 10:

Inferential probabilities			
Revised cond. prob.		Expert says	
		Temp. increase	No temp. Increase
True algae status cooling elements	Algae growing	0,78	0,39
	Algae not growing	0,22	0,61
	Sum	1,00	1,00

Figure 10. Inferential probabilities table

Expert Opinion:

When the DM is not familiar with the technical environment that encompasses the problem he/she is facing or the problem is very complex, the DM must turn to experts in the field to get relevant information and their subjective probabilities regarding the uncertainties (Clemen and Reilly, 2001). Even though the decision maker is an expert in the process of decision analysis, he/she may have no previous experience of the specific area that the decision is to be made (Howard, 1988). Thus the DM in this context is a person that is skilled with the decision analysis process and has the authority to make the decision that is called upon, but is not skilled in the technical environment of the problem. This is in the realm of the experts. Then it is crucial that there is an open communication between the DM and the experts in the different areas, so that all parties involved have the same understanding of the problem, and that objectives and relevant uncertainties are agreed upon. A good way of improving the communication between the parties involved is by use of influence diagrams because they easily visualize the problem and the alternatives (Howard, 1988).

An expert is someone who is "very knowledgeable about or skilful in a particular area" (AskOxford, 2007), that is, someone that master an area relevant to their background knowledge (Matlin, 2003). However it has been argued that it requires up to ten years of intense practice in relevant activities to gain enough knowledge to be an expert in a specific domain (Matlin, 2003, Davidson and Sternberg, 2003). This implies that the DM should be certain that he/she is consulting with persons that truly know their field of expertise. Although an expert is working continually with his/her field of expertise, the DM should be aware that the expert still may assign erroneous probability and overlook important information regarding a problem (Hume, 2000) because after all, "human beings are imperfect information processors" p.5, (Clemen and Reilly, 2001). The expert may compare the situation at hand with experience from previous problems and look at surface issues rather than important information in the new situation. A situation that might occur regarding experts when they are assessing uncertainty is that they can be overconfident toward their base of knowledge of their field (Matlin, 2003). "People seem insufficiently sensitive to how much they know, so that changes in knowledge are accompanied by inappropriate changes in confidence" p.667, (Gilovich et al., 2002). This overconfidence may trick the DM to think that the person(s) have

more expertise on the subject than what is the real case. This introduce another uncertainty to the decision process called imperfect information.

Imperfect information:

Imperfect information can be explained by an example given by Clemen (2001). A plant manager is facing some defect products and must decide upon what to do with the situation. His maintenance engineer indicates that machine nr. 3 is the culprit and carry out an inspection on this machine. The manager could change the machine immediately but is then facing a risk that machine nr. 3 is not really the problem, and must stop production while tracking down the problem. Or alternatively he could wait for the maintenance engineer's report and make a decision based on this 'expert's' opinion. However, assuming there is no obvious error with machine nr. 3, there will be some uncertainty regarding the reliability of the maintenance engineer's report. Both in the information and level of expertise the engineer possesses, and also to how much the manager trusts the level of expertise of the maintenance engineer. This situation can be illustrated in an influence diagram shown in Figure 11 below. There it is shown the uncertainty regarding whether the machine is ok or not and also the uncertainty regarding the expert's opinion on the matter (Clemen and Reilly, 2001).

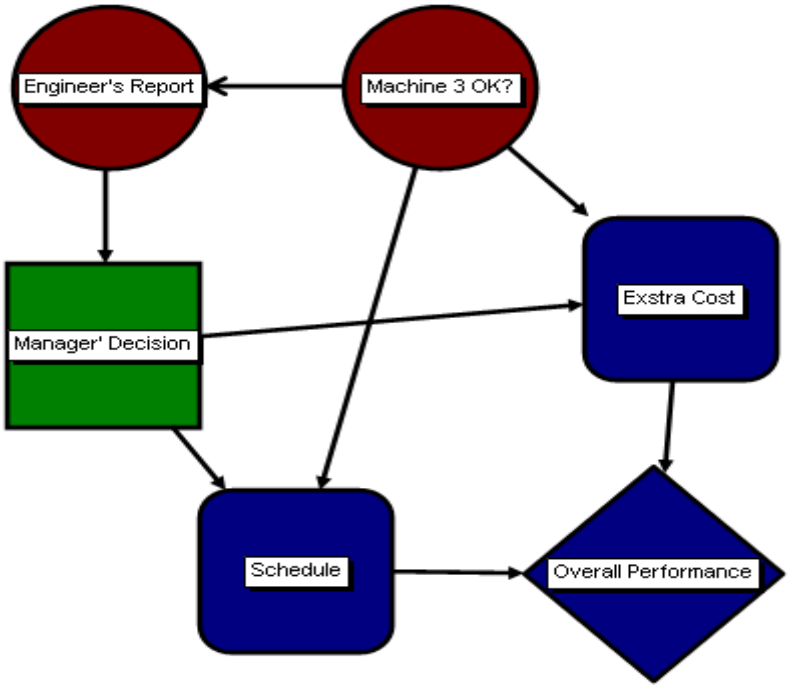

Figure 11. Expert's Impertfect Information Influence Diagram. p.59 (Clemen, R. T. & Reilly, T. 2001)

Subjective Probability:

It has been argued that "decision analysis *requires* personal judgments; they are important ingredients for making good decisions" p.5, (Clemen and Reilly, 2001). So to be able to make a decision in these complex environments where there is scarce information, the DM has to use his/her personal judgments to help solve the problems. The decisions related to the problem addressed in this paper are all based on the DM and the expert's beliefs regarding the likelihood of the uncertain events that may happen with the Subsea WI system. The probability of the event is in the mind of the DM because there is no relevant objective model to use. So the DM uses elements of probability to "quantify the strength or 'confidence'" p.4, (Walpole et al., 2002) in his/her conclusions. When uncertainty and probability are produced from a person's mind, a subjective interpretation is adopted with the "probability representing an individual's *degree of belief* that a particular outcome will occur" p.297, (Clemen and Reilly, 2001).

Subjectivity:

Subjective is defined as an adjective that describes something that is "based on or influenced by personal feelings, tastes, or opinions" online (AskOxford, 2007). This means that the probabilities used in the decision analysis models are assigned to the uncertain events based on their beliefs and experiences regarding previous and similar events to how likely they feel the uncertain event may take place, and also how the DM and the experts understand the uncertain events. Further, when the DM and the experts are assessing the probabilities of events that are complex, they will not be able to assign the probabilities right away by intuition only, so they are using mental heuristic principles in the process (Kahneman et al., 1982).

Heuristic:

Heuristic is defined as something that is "enabling a person to discover or learn something for themselves" online (AskOxford, 2007), or as "deterministic rules of thumb" p.667, (Gilovich et al., 2002) . In other words, heuristics are principles that try to explain how people make their judgments and assign the probabilities for the uncertain tasks. The heuristics do not guarantee that the DM will make the correct decision, and they may lead to predictable biases (Gilovich et al., 2002) but they help the DM to do a selective search for the best alternative through knowledge, testing, and heuristic methods (Aliseda, 2006). This paper will examine three heuristics that people use when assessing probabilities of events. These heuristics are called 'representativeness', 'availability', and 'adjustment and anchoring' (Kahneman et al., 1982). The characteristics of those three heuristics, and the biases related to these heuristics will be discussed in the following text.

Bias is defined as an "inclination or prejudice in favour of a particular person, thing, or viewpoint" online (AskOxford, 2007). So bias will sort of 'steer' the thoughts of a person towards something he/she recognizes from before or something the person tend to prefer. One example of that could be a scenario where some persons are to taste different wines and only get to know the price of the wine. People then often tend to say that they like the taste of the expensive wine better than the less expensive ones. And if the price tags are switched between the wines, people seem to focus on the price of the wines and still seem to like the taste of the wine that now is the more expensive one even though this was the wine that the person did not prefer when it was less expensive. The person is then biased to the price and thinks that the more expensive wine must taste better, and chooses accordingly. If the DM is aware of these heuristic principles and learn how to recognize them he/she can use them to avoid biases in the probability assessment.

Representativeness heuristic:

The representativeness heuristic could be explained as to how people recognize certain traits or characteristics of a person to represent a certain group or type of job (Kahneman et al., 1982). One example could be that a person is described as a 35-year-old man that is meticulously and with high motivation. He is often working long hours and is often travelling in relation with his job. According to representativeness heuristic people would say that this man is a consultant rather than a farmer for instance. People use the given information and

compare it with some characteristics that are stereotype for a member of a group. The more the person judge the information and the characteristics to be similar, the higher probability the person assign to the fact that the other person is a member of the group in discussion (Clemen and Reilly, 2001).

However, assigning probability based only on the similarities with a certain group can be dangerous because important information can be ignored and not taken into consideration, thus resulting in error and inaccuracy (Clemen and Reilly, 2001, Gilovich et al., 2002). One type of information that may be ignored is the base-rate or prior probability. This can be explained as some information that is given but often overlooked. An example is a test group that is told that a person is being drawn from a sample group consisting of 70 engineers and 30 lawyers. Then they are given certain characteristics about a man drawn from the sample group, such as: he is 30 years old, married with no children, well liked by colleagues, quite successful, motivated and so on, and the test group is then asked to assign the probability that this man is an engineer or a lawyer. The subjects in the test group assigned the probability that this person was an engineer to be 0.5. The subjects then used the representativeness heuristic and forgot the important prior probability about the sample group (Kahneman et al., 1982). Another error that representativeness heuristic can lead to is the so called ‘gamblers fallacy’. If the toss of a coin is taken into consideration, and the results of five tosses are all heads, that is, H-H-H-H-H. Then, due to the gamblers fallacy, a person that is to judge the outcome of the next toss would gamble on a tail because he/she assumes there is a bigger chance that the outcome of the next toss is a tail after five heads in succession. However, with a fair coin the probability is still 0.5 for a head or a tail (Kahneman et al., 1982, Clemen and Reilly, 2001). Conjunction fallacy is also an error often committed when judging probabilities related to the conjunction of two events. The conjunction fallacy is related to the representativeness heuristic in that people tend to assign a higher probability of a conjunction of two events than they assign a probability to either of the two events. People recognize a stronger similarity between a conjunction of two events and the stereotype characterization for a group, than similarity of one of the constituent events and the stereotype characterization, thus assign a higher probability for the conjunction of two events to be a member of a group that the probability for one of the constituent events to be a member (Matlin, 2003). I.e. the number of Norwegian petroleum engineers with a master’s degree born in Stavanger cannot be larger that the number of Norwegian petroleum engineers with a master’s degree.

Availability heuristic:

The other heuristic mentioned earlier is the availability. This is a cognitive principle that is based on how easy it is for the DM to picture a given event in his/her mind. Cognition is a mental activity that "describes the acquisition, storage, transformation, and use of knowledge" p.2, (Matlin, 2003). So when the DM assigns probability of an event according to the availability heuristic he/she will assign the probability of an event according to how frequently he/she has seen a similar event happen prior to the situation the DM now is facing (Clemen and Reilly, 2001). According to this, an event that seems more likely to happen to the DM the more available the outcome is to him/her. And other events may seem unlikely to happen to the DM because it is difficult for the him/her to explain or retrieve a picture of the event (Gilovich et al., 2002).

In relation to this it has been argued that events that seems to appear often or recently to a person, may 'contaminate' the true frequency that this event really happens. This is illustrated in Figure 12. An example of contaminants can be as follows: there has been a fire in a neighborhood and the media covering this fire discuss the dangers around fires and how often it has happened lately. So a person living in this neighborhood and watches the media will assume that there is a higher probability to experience a fire than it is to be involved in a car crash because of the recency of the fire, even though this may not be the real case.

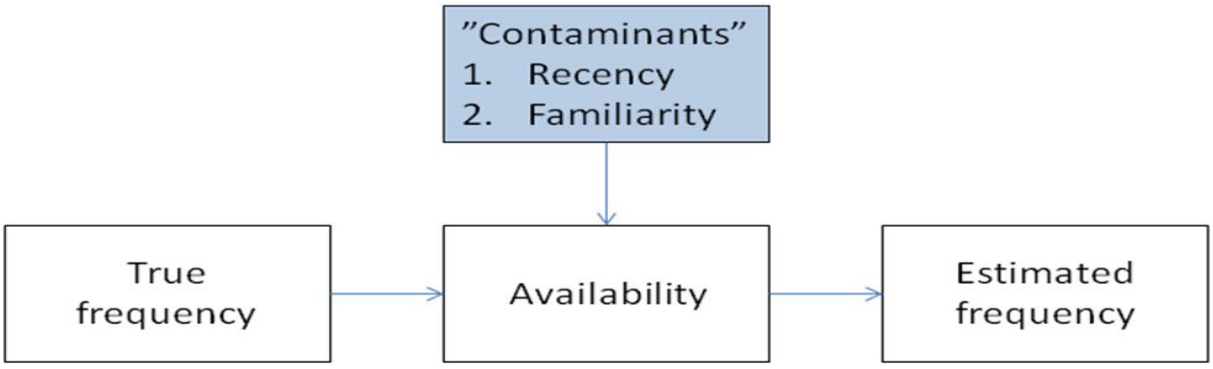

Figure 12. "The relationship between true frequency and estimated frequency, with recency and familiarity as 'contaminating' factors" p.421 (Matlin, 2003)

Adjustment and anchoring:

The third heuristic mentioned earlier is the adjustment and anchoring heuristic. When a person is estimating an event, he/she often choose one initial value, an ‘anchor’, and adjust the value because of other knowledge and information of this event. The anchor can for instance be a mean of some distribution, and the person that is estimating an event will then adjust away from this mean due to some extreme points of the same distribution (Kahneman et al., 1982, Clemen and Reilly, 2001). It is also been argued that the anchoring and adjustment heuristic will often depend upon the availability heuristic, because “highly available information is likely to serve as an anchor.” p.428, (Matlin, 2003). One example of anchoring and adjustment could be a person that is looking for a new coat and has decided an approximate price range for the coat. But the salesman starts the sale by first showing the customer a very nice but very expensive coat. If the customer then really likes this coat but think it was too expensive, he might end up buying a much more expensive coat than he contemplated when he entered the shop. This is because he used the very expensive coat he was presented with at first as an anchor, and adjusted his buying price from that instead of the price he initially wanted to pay (Matlin, 2003).

Intelligent expert system:

The DM and the organization that is embarking upon a decision analysis process should implement an intelligent expert system to minimize the risk of errors in assessing uncertainty in a problem. Figure 13 shows a simple expert system where an expert in a field related to a problem provides the system with certain rules as to how decisions should be made for a given problem. If the system is successful, the system will come to the same conclusion as the expert would make in the same situation. One rule could be related to medicine saying: "If the patient is able to stand up and is strong enough to call the doctor, give the advance 'take two aspirins and call me in the morning'" p.692, (Howard, 1988). However, this simple system has no normative power, i.e. it does not judge or reflect over whether the action it proposes is the proper action to do (Howard, 1988).

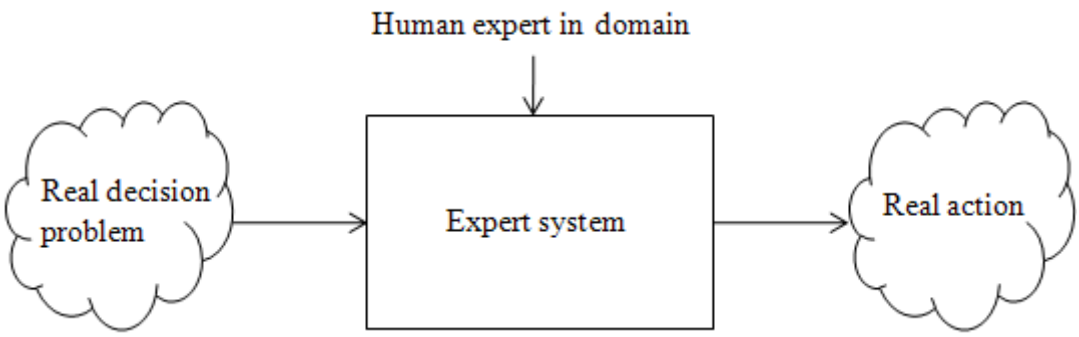

Figure 13. An expert system, p.692 (Howard, R A 1988)

In an intelligent decision expert system the DM will provide alternatives, information and preferences to the system and in return the expert in the field will provide the system with insights and recommendations to guide the decision. Figure 14 below illustrates this system. This two-way communication will provide all parties involved in the process with information and feedback to the system to create the best basis for making the best decision with the information available at the time the decision is to be made (Howard, 1988).

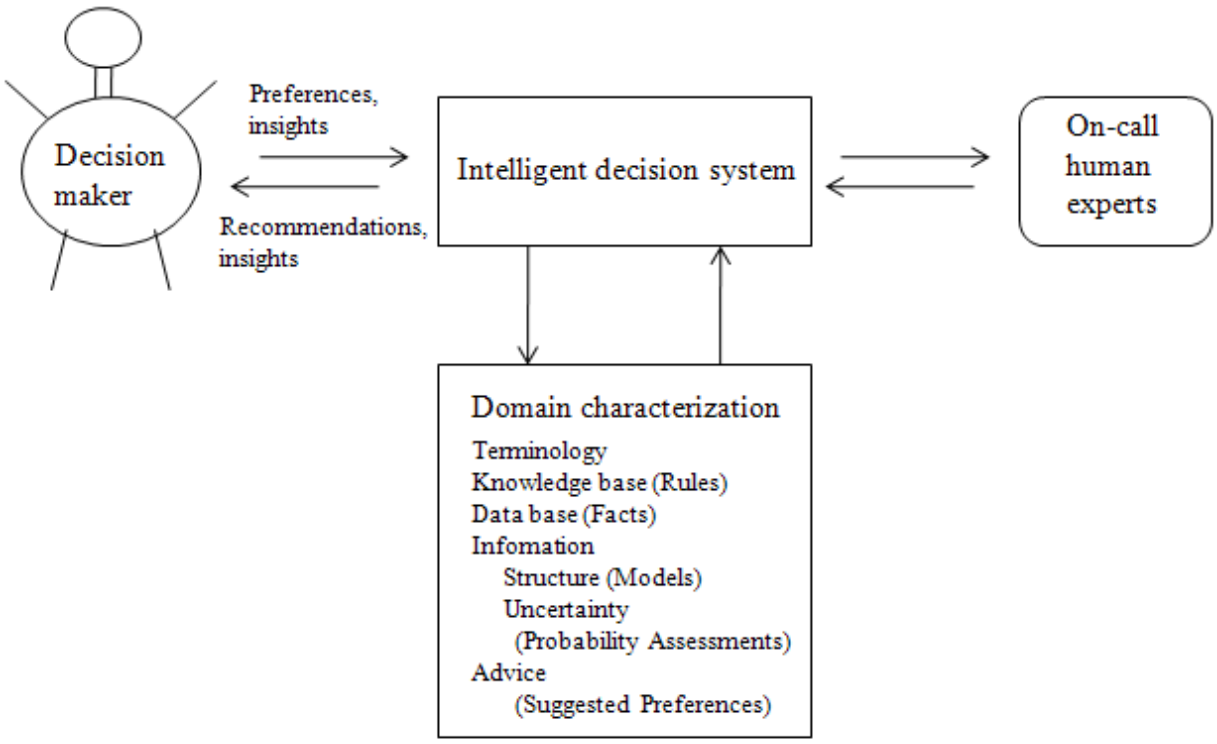

Figure 14. Intelligent Decision System Interactions. p.694 (Howard, R A. 1988)

The Tyrihans Field and the SeaBooster™ System:

The Tyrihans Field (see Figure 15) is located 40 km southeast of the Kristin Field in the southern part of Haltenbanken in the blocks 6406/3 and 6407/1.

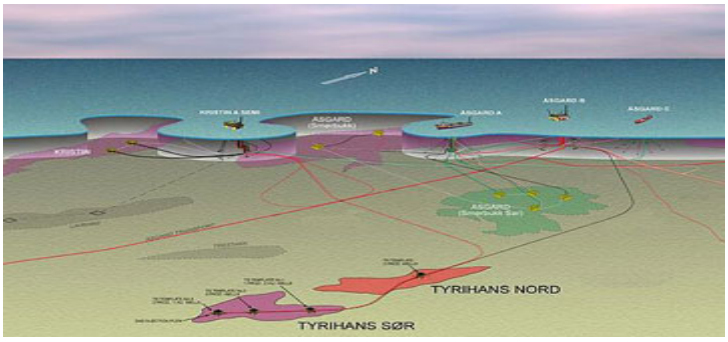

Figure 15. Tyrihansfeltet Statoil (2005).

The field consists of two parts, Tyrihans Sør and Tyrihans Nord, which are divided by a saddle filled with water. Tyrihans Sør was found in 1982 and proved an oil zone of 35m with an overlaying gas cap, while Tyrihans Nord was found in 1983 and proved an oil zone of 18 meters with an overlaying gas cap. The water depth at Tyrihans field is between 260m and 285m. The produced hydrocarbons will be transported through a subsea tie-back solution to the Kristin for processing and further transport through Åsgard Transport to Kårstø. The Tyrihans Field is planned to have 12 subsea wells divided between 5 subsea templates. One template is planned to be located at Tyrihans Nord, three templates will be located at Tyrihans Sør, and one template will be located in the saddle point between Tyrihans Nord and Tyrihans Sør. The well in the saddle point template will be an injection well that is injecting fresh seawater into the saddle by the use of Aker Kværner Subsea' SeaBooster™ (see Figure 16) (Statoil, 2005, ScandOil, 2006, Regjeringen, 2006).

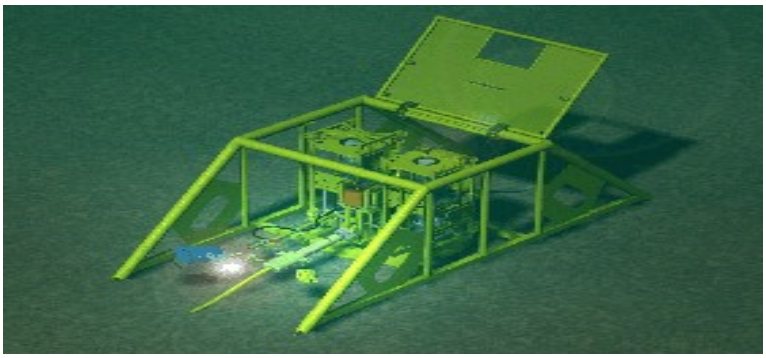

Figure 16. SeaBooster™ System

The Problem:

The operator of a subsea production field is receiving a lot of data from the control modules that measures and monitor the operations and conditions of the subsea equipment. Up until now there has been uncertainty to how this data should be interpreted to know the cause of any deviation in the readings. This work will analyze the data received from a Subsea Water Injection pump and look into what failure modes this pump may experience and how to react to any deviation in the readings of the data received from the control module.

The purpose of the Subsea Water Injection pump, WI pump from now on, is to uphold the pressure inside the reservoir so that more oil can be produced from the reservoir. It is important for the production that the pressure is not decreasing below a certain level because if so, the well will start producing gas instead of oil. If the gas is produced before the oil in the reservoir it is almost impossible to produce the oil later because the pressure in the reservoir has decreased too much, and the properties of the oil makes it much harder to produce.

At the Tyrihans field there will be used a centrifugal WI pump to inject water into the reservoir to uphold the pressure in the reservoir. The estimated life time of these kinds of pumps are said to be 5 years (Eriksson et al., 2007) because all centrifugal pumps are exposed to internal wear over time due to the liquid running through them, or some other elements that causes damage to the pump, such as failure in cooling system, lubrication and so on. These failures will be looked into in more detail later on in this paper. However, regardless of the reason for the wear of the pump, this wear will decrease the effect of the pump, causing a decrease in the reservoir pressure. Thus there is a need to monitor the condition of the WI pump to be sure that the pump can inject enough water to uphold the pressure in the reservoir.

Due to the fact that the WI pump is located on the seabed at a depth of approximately 300 meters of sea water depth some 170 km vest of the northern shore, it is way too costly to perform physical check on the WI pump. And an intervention of the WI pump at frequently scheduled times is not the optimal solution either, because an intervention of a subsea pump means that the whole pump unit is being pulled to the surface and changed with a new pump that then is being lowered and installed in the template, and the operator needs to shut down the oil production during the intervention. If the production is continued while the WI pump is pulled to surface and shipped to shore for maintenance, the pressure in the reservoir might decrease to a level where the properties of the reservoir is destroyed. Nor is it a good policy to wait until the pump is breaks down. The operator then has to stop the production to maintain

the pressure in the reservoir, and cannot start producing again until the WI pump has been fixed and reinstalled, or until a new pump has been installed. This will result in a loss of production that means loss of money.

A scheduled intervention can take from 24 hours up to 8 weeks dependent on the weather condition (Eriksson et al., 2007). In this paper an intervention during good weather conditions are estimated to be from 24 hours to one week, while an intervention during bad weather conditions can be up to 10 weeks (see lognormal distribution for the estimates in the 'The Decision' chapter of this paper). But this time estimate is valid if there is an intervention vessel standing by to do the intervention right away. Due to the high level of activities in the North Sea these days have there is a high demand for intervention ships so the waiting time from a vessel is ordered can be several months which may lead to enormous costs when the well has to be shut down while waiting for the vessel to be on site and do the intervention. So the situation that is sought for is to change the WI pump as few times as possible, and still be able to maintain a high production profile from the reservoir. Hence this paper will discuss methods to find the optimal time to pull the WI pump for maintenance using the decision analysis tools described earlier. The overall purpose of this work is thus to maximize NPV by maximize production while minimizing the maintenance and intervention costs.

The Objectives:

There are some objectives connected to the decision in this problem. The frequency of the interventions should be as low as possible to minimize the stop of production and the total intervention cost. It is a very costly operation to pull the pump, ship it to shore, do an overhaul of the pump, ship it back to the site, and reinstall the pump again. Included in these cost will be the cost of the intervention vessel, the cost of shipment of the pump, the overhaul cost, and the cost due to a stop of production. So it is desirable to do this operation as few times as possible.

Another objective of the decision is to keep the production rate as high as possible at all times. A reduction in production rate will be considered as a cost in this paper and it is to be desired that the pump is being pulled and serviced when the cost of loss of production is higher per day than the daily cost of intervention and overhaul for the pump.

A third objective is that it is desirable to be able to do change the pump before a possible breakdown. A breakdown may result in a paramount cost for the operator because the production has to be shut off right away, and in worst case this happens at a time where there are several months of waiting time for an intervention vessel to be available and on site ready for intervention. So the optimal situation would be to be able to have an estimate on the remaining running time of the pump, and from that be able to schedule an intervention and order a vessel to be on site during good weather condition before within the estimated remaining running time of the pump.

Assumptions:

- The pump is injecting only fresh seawater into the reservoir.
  - This means that there are no sand particles or other pollution in the water that may cause wear to the pump.
- Temperature difference of lube oil is known during a planned power increase/decrease.
  - If the operator has planned to increase/decrease the speed of the pump, or even stop the pump, the operator of the pump will know that the temperature of the lube oil will change, so this is not included in the model.
- The Temperature reading and the Head/Flow reading will change to a certain level before the operator starts analyzing the data.
  - In the uncertainty nodes it is thus assumed that the readings show either acceptable changes, or large enough changes for the operator to start analyzing the data.
- Prod rate decrease due to decreased WI is assumed to be 5% for WI total shut down.
- Vibration data can be neglected.
  - This is because of the difficulty to perform measurements of vibration on a subsea unit. The accelerometers that measures vibration on a subsea device has been encapsulated to withstand the heavy pressure from the surrounding sea water. The downside to this enforcement of the accelerometers is the sensitivity of the sensors is decreased and the measurements is not as accurate as on a topside pump (Eriksson et al., 2007). So vibration analysis is disregarded in this model to make it less complex.
- The money that is a lost due to reduced production is calculated as a cost in this analysis. This is to make the comparison with the intervention cost easier.

- For simplicity it is used a constant production profile for the lifetime of well.
  - It could of course have been estimated a production profile with a start up production, a plateau production, late production, and perhaps a tail production, included, but due to scarce information on the matter, and for the simplicity of the calculations, it has been assumed an even production profile. However, this should be taken into consideration when applying the model to achieve a more accurate number for reduced production.
- The oil price is 63 $US.
  - This oil price is taken from http://www.oil-price.net/ 25.05.07. This is done for simplicity of the task because it is assumed that the intervention time does not take more than 8 weeks. However this can be changed by a stochastic model, or updated oil price when an intervention is contemplated.
- The pump is 'designed for its purpose'.
  - This implies that the pump is designed to operate in the environment it is planned to operate, so any wear of the pump due to lack of NPSH (Net Present Suction Head) and other polluting factors are neglected.
- Head and flow is placed in the same chance node.
  - This is done because from pump theory it can be said that these two measurements are correlated because if a decrease in one of the parameters are detected, a decrease in the other is also detected (Beebe, 2001, Yates, 2002). So for the analyses in this paper these two data readings will be considered as one uncertainty, thus there is one chance node in the influence diagram called 'Head/Flow Reading'.
- No discontinuity regarding costs is calculated.
  - The time it takes for an intervention of the WI pump is assumed to be eight weeks at the most for bad weather conditions (Eriksson et al., 2007). Due to this it is assumed that the NPV (Net Present Value) will be the same during the intervention time as it is maximum 8 weeks
- Day rate cost for an intervention vessel is set to be $150000.
  - The daily rate of an intervention vessel should be changed to the price in the contract for application of the model in a real situation.

- If the calculations of the influence diagram show that a decrease in the Head/Flow Reading is caused by one of the related events it is assumed that the DM will compare the cost of intervention with the cost of lost production and thus make a decision to pull the pump to what is most likely to minimize costs.
    - It is also assumed that an expert will have knowledge to how much longer the pump may be able to run before the fault is to critical when he/she sees which one of the events ‘Bearing Worn’, ‘Motor Worn’, and ‘Int.Leakage’ are most likely to cause the decrease of the Head/Flow Reading.
- If the calculations of the influence diagram show that the temperature increase is the most likely fault and caused by algae grow, the expert should be able to give an estimate of how much longer the pump can be operated before a failure takes place.
    - If it is shown that the motor is causing the temperature increase, it should also show in the Head/Flow calculations from the influence diagram and a sensitivity analysis may be in order to see which event is more sensitive to changes. Then a comparison with the intervention cost and the cost of lost production could be made.

The Uncertainties:

The uncertainties and their alternatives respectively that have been identified to be relevant for the problem are shown in the table below, and the uncertainties are described in detail on the next page.

Uncertainties:	**Alternatives:**
- Algae Growth	- Severe Growth - Acceptable Growth
- Leaking Sealing	- Leakage too high - Acceptable Leakage
- Bearing Worn	- Yes - No
- Internal Leakage	- Yes - No
- Motor Worn	- Yes - No
- Lube Oil Level	- Acceptable - Too low
- Head/Flow readings	- Stable - Decreased
- Temperature Readings	- Stable - Increased
- Assumed Running Time	- Low - Medium - High
- Weather Condition	- Good - Bad
- Intervention Time	- Low - Medium - High
- Production rate	- Low - Medium - High
- Oil Price	- Low - Medium - High

Prior:

- Algae growth on the cooling unit, P(A);
    - One problem with subsea equipment is that since the equipment is located on the seabed and surrounded by salt water, algae will start to grow on the surface of the equipment after it has been exposed to the salt water for a while. If the algae growth is too severe the cooling system will not dispose as much heat from the pump as it is supposed to do, and the temperature of the pump will increase.
    - The uncertainty regarding this event is to identify the probability that the algae growth is so much that it will cause a high increase in the temperature reading. Algae growth on the cooling device is thus identified to be relevant to the temperature.
- Leaking sealing, P(LS);
    - The lube oil that is lubricating the pump system is purposely kept at an overpressure so that no seawater will penetrate the sealing from the outside and inward. If the seawater is allowed to penetrate the sealing it will very soon start to rust inside the housing of the pump and shorten the lifetime of the pump severely. Due to the fact that the lube oil is always kept at an overpressure it will start leaking out through the seal from the start up of the pump. Initially the consumption of lube oil due to this leakage will be of small rate, but as time goes by the wear of the pump will cause the lube oil to leak out at larger and larger amount. Hence, after some time the lube oil will leak out at such rates that it is not possible to keep the lube oil at an overpressure anymore, and the pump need to be serviced (Eriksson et al., 2007).
    - The uncertainty regarding this event is the probability that the seal may be leaking. An expert on the subject assesses this probability.

- Bearing Worn, P(BW);
    - The bearings in the pump are keeping the friction of the rotating system at a minimum. These bearings will wear out after a while, and the friction in the system will increase. An increase in the friction will have an effect on the head and flow readings.
    - The uncertainty related to the bearing is the probability that the bearing might be worn out and causing increased friction. An expert on the subject assesses this probability.
- Internal leakage, P(IL);
    - After some time in operation the impellers in the pump will be worn and causing an internal leakage in the system. Then some of the water that is to be boosted into the reservoir will circulate around inside the pump and the head reading and the flow reading will decrease (Goodacre, 1985).
    - The uncertainty in this event is the probability that the impellers are so worn that it will cause an internal leakage of the boosted water. An expert on the matter assesses this probability.
- Motor Worn, P(MW);
    - The motor that drives the pump will also be worn after many hours of operation and the efficiency will be reduced. If the motor is not operating to its full extent, the head and flow in the system will be reduced. The temperature readings from the pump may also increase as a result of an inefficient motor.
    - The uncertainty of this event is the probability that the motor is so worn that it cannot run the pump at a satisfying speed. An expert on the matter assesses this probability.

Likelihoods:

- Lube Oil level,
    - Special lubricating oil is used for cooling down and lubricating the motor, gearbox, and the bearings. As mentioned above the lube oil is kept at an overpressure to prevent seawater from leaking into the pump system. Another event that will cause a change in the lube oil level is if the pump is shut down or operated on reduced speed. However it is assumed in these analyses that the operator knows a change in the operating speed of the pump, thus this event is not taken into account in the influence diagram drawn for the problem in this paper. This is to prevent the influence diagram to be complex for this analysis.
    - The uncertainty related to the lube oil level is whether the change in lube oil level is caused by the leakage through the seal, P(LO|LS), or if the change in level is caused by a reduction in the operating speed of the pump (N/A).
- Head pressure and flow instrument readings
    - The head pressure is the pressure that the pump is pushing the injected water with. At the Tyrihans field the operating head pressure is planned to 206 bars. The flow meter is measuring the flow of the injected water and is planned to be around 87500 barrels per day. Three events have been identified as possible faults that will result in a decrease in the head and flow readings, and these events are friction due to worn bearings P(HP|BW), internal leakage in the pump P(HP|IL), or that the motor is worn and not operating as designed P(HP|MW).
    - The uncertainties related to the head/flow reading are whether the decrease in the head/flow reading is caused by one of the failure events mentioned above.

- Temperature readings
    - There have been identified three events that may cause an increase in the temperature reading. These events are algae growing on the cooling device P(TR|AG), an inefficient motor P(TR|MW), and also a change in the operating speed of the pump (N/A). The event of the operating speed is not taken into consideration in this analysis, because this event is controlled by the operator

who will thus be aware of the occurrence of an increase of the operating speed. So this is not considered an uncertainty as it is a decision variable.

- The uncertainties related to the temperature reading are identified as the algae grow on the cooling device and a worn motor in the pump system.

At the time of the writing of this paper there was neither time nor any available personnel to come up with the subjective probabilities for the analysis, so the random function that is built into Excel® was used to create random probabilities for the different events. This was done to be able to continue creating the decision model for the problem. But in a 'real life' analysis these probabilities must of course be changed with subjective probabilities provided by the experts.

Influence Diagram:

So by using the information from the previous section, an influence diagram is constructed to illustrate the problem in an easy and transparent manner. The influence diagram for the problem in this paper is shown in Figure 17:

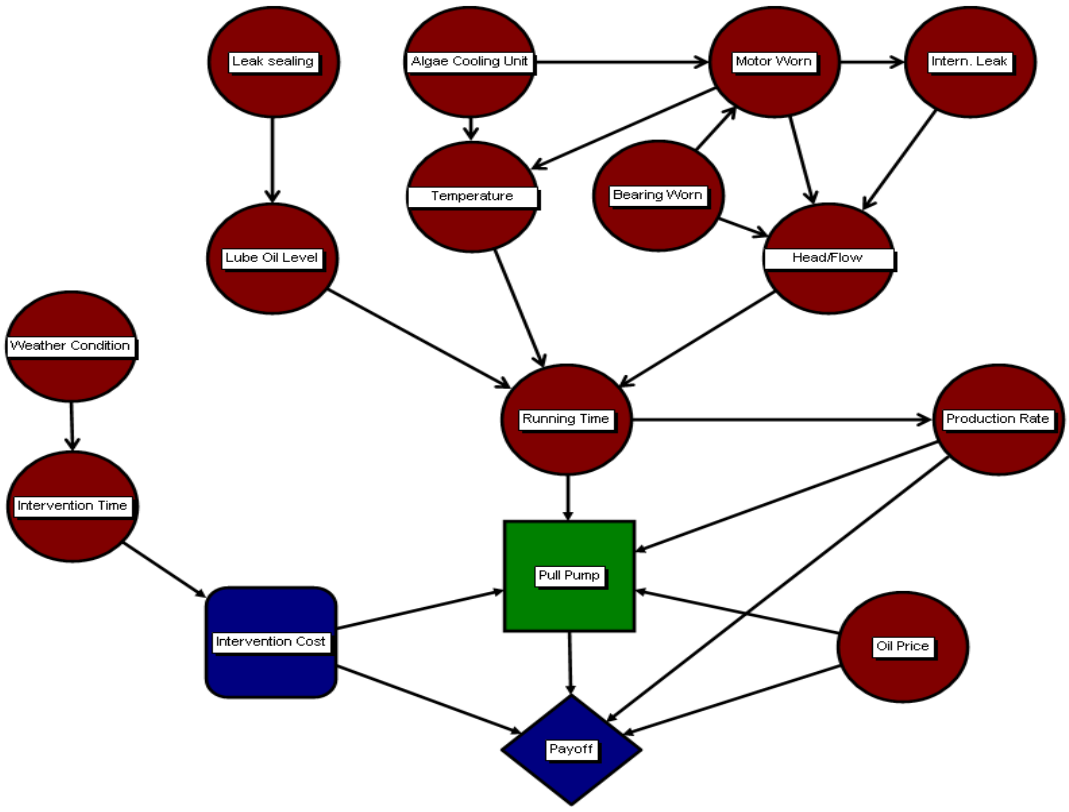

Figure 17. Influence Diagram for WI pump problem.

Decision Tree:

According to Howard (1988) there is no use for decision trees to do a sound decision analysis when the influence diagram is properly defined. However, during the process of computing the model described in this paper, the author found that it was much easier to 'see' how to compute the Bayesian formulas applied in the calculations later in this paper. The decision tree visualized the 'paths' for each event so that it was easier to place the conditional probabilities, and also to pick the relevant joint probabilities for the Bayesian formulas. Before a decision tree was drawn it was difficult to see all the relevance arrows that should be drawn in the influence diagram to illustrate a more correct picture of the situation the influence diagram is describing. It was found that there should be relevance arrows between the events relevant to the 'Temp.Reading' node, and the events relevant to the 'Head/Flow Reading' node to obtain the correct joint probabilities between these events. It is acceptable to draw relevance arrows between these events even though they may not be relevant to each other, because as described earlier in this paper, relevance arrows implies that there may be relevance between the two nodes.

As stated before, no arrows between the nodes is the strongest statement, as this implies that there is no relevance whatsoever between the two nodes. The relevance/influence arrows between the 'Bearing Worn' node and the 'Motor Worn' node, and between the 'Motor Worn' node and the 'Int.Leakage' node are the ones that are drawn to get the correct joint probabilities for the 'Head/Flow Reading' uncertainty. It is worth noticing that the order of the nodes is indifferent for the conditional probabilities, i.e. the subjective probabilities assigned by the experts, of this set of nodes. That is, it doesn't matter for the resulting joint probabilities whether the 'Bearing Worn' node or the 'Internal Leakage' node is placed first in the influence diagram, as long as the conditional probabilities that follows in the decision tree is assigned correctly according to what these probabilities are conditional to. Thus, in a 'real life' example the order of the nodes should be so that the experts find it easiest to come up with the subjective probabilities e.g. the expert may find it easier to assign the probability for P(BW|MW) than P(MW|BW). As it can be seen from the tree example (Figure 18) there is one prior subjective probability P(BW), and several conditional subjective probabilities in different varieties of the following chance nodes. See Figure 18 for examples of conditional subjective probabilities.

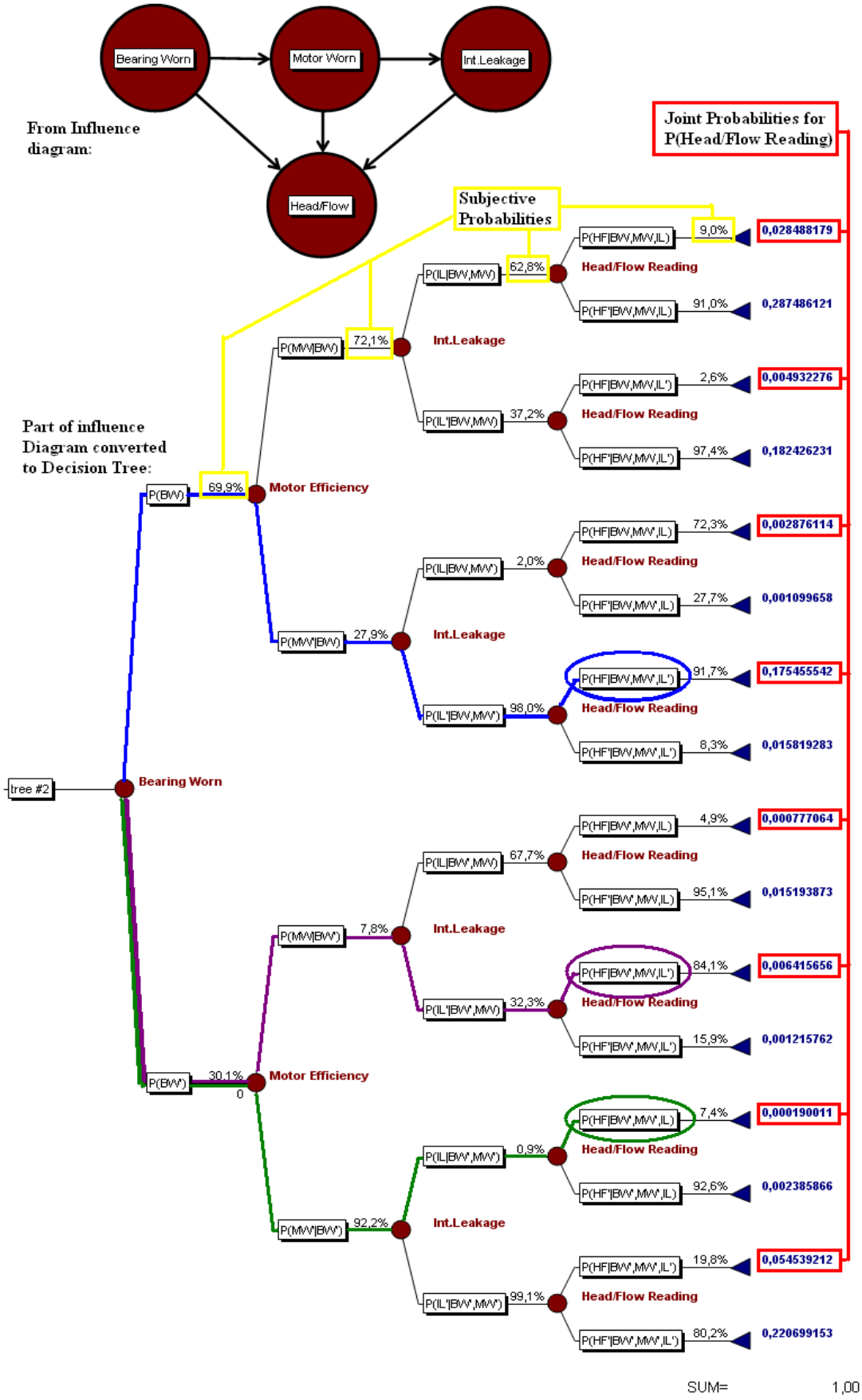

Figure 18. Precision Tree Example showing a part of the Influence Diagram converted into a decision tree.

Bayesian Formulas:

From the assessed probabilities given in the influence diagram the following formulas are given:

$P(Lube\ oil\ level | Leaking\ Seal)$

$P(Temp.Reading | Algae\ Grow, \overline{Motor\ Worn})$

$P(Temp.Reading | Motor\ Worn, \overline{Algae\ Grow})$

$P(Head/Flow\ Reading | Bearing\ Worn, \overline{Motor\ Worn}, \overline{IntLeak})$

$P(Head/Flow\ Reading | Motor\ Worn, \overline{IntLeak}, \overline{Bearing\ Worn})$

$P(Head/Flow\ Reading | IntLeak, \overline{Bearing\ Worn}, \overline{Motor\ Worn})$

In the formulas given below, the following abbreviations apply:

- Lube Oil Level = LO
- Leaking Seal = LS
- Temp.Reading = TR
- Algae Growth = AG
- Motor Worn = MW
- Head/Flow Reading = HF
- Bearing Worn = BW
- Internal Leakage = IL

From the previously shown precision tree it can be seen that the formulas applicable for the problem presented in this paper can be 'flipped' into the more useful inferential form using Bayes' Theorem will then look as follows:

$$P(LS|LO) = \frac{P(LO|LS) \cdot P(LS)}{P(LO)}$$

$$P(AG|TR, \overline{MW}) = \frac{[P(TR|AG, \overline{MW}) \cdot P(\overline{MW}|AG) \cdot P(AG)]}{P(TR)}$$

$$P(MW|TR,\overline{AG}) = \frac{\{P(TR|MW\,\overline{AG}) \cdot P(MW|\overline{AG}) \cdot P(\overline{AG})\}}{P(TR)}$$

$$P(BW|HF) = \frac{\{P(HF|BW,\overline{MW},\overline{IL}) \cdot P(BW,\overline{MW},\overline{IL}) \cdot P(BW|\overline{MW}) \cdot P(BW)\}}{P(HF)}$$

$$P(MW|HF) = \frac{\{P(HF|MW,\overline{BW},\overline{IL}) \cdot P(\overline{IL}|MW,\overline{BW}) \cdot P(MW|\overline{BW}) \cdot P(\overline{BW})\}}{P(HF)}$$

$$P(IL|HF) = \frac{\{P(HF|IL,\overline{BW},\overline{MW}) \cdot P(IL|\overline{BW},\overline{MW}) \cdot P(\overline{BW},|\overline{MW}) \cdot P(\overline{BW})\}}{P(HF)}$$

Then all the different possibilities for ‘Lube Oil level’, ‘Temp.Reading’, and ‘Head/Flow Reading’ are identified. This is done by the same principle as in the example with the Venn diagram shown in Figure 9 and the example tree shown in Figure 18:

$$P(LO) = \{P(LO|LS) \cdot P(LS) + P(LO|\overline{LS}) \cdot P(\overline{LS})\}$$

$$P(Temp.Reading) = \left\{ \begin{array}{l} P(TR,AG,MW) + P(TR,AG,\overline{MW}) \\ +P(TR,\overline{AG},MW) + P(TR,\overline{AG},\overline{MW}) \end{array} \right\}$$

$$P(HF) = \left\{ \begin{array}{c} P(HF,BW,MW,IL) + P(HF,BW,MW,\overline{IL}) + P(HF,BW,\overline{MW},IL) \\ +P(HF,\overline{BW},MW,IL) + P(HF,BW,\overline{MW},\overline{IL}) + P(HF,\overline{BW},MW,\overline{IL}) \\ +P(HF,\overline{BW},\overline{MW},IL) + P(HF,\overline{BW},\overline{MW},\overline{IL}) \end{array} \right\}$$

Then, by inserting the identified different possibilities for ‘Lube Oil level’, ‘Temp.Reading’, and ‘Head/Flow Reading’ into their respective denominator in the ‘flipped’ Bayes’ formulas given above, the complete formulas in the decision analysis model is given as follows:

$$P(LS|LO) = \frac{\{P(LO|LS)\cdot P(LS)\}}{\{P(LO|LS)\cdot P(LS) + P(LO|\overline{LS})\cdot P(\overline{LS})\}}$$

$$P(AG|TR) = \frac{\left\{\begin{array}{c} P(TR|AG,\overline{MW}) \\ \cdot P(\overline{MW}|AG)\cdot P(AG) \end{array}\right\}}{\left\{\begin{array}{c} P(TR,AG,MW) + P(TR,AG,\overline{MW}) \\ +P(TR,\overline{AG},MW) + P(TR,\overline{AG},\overline{MW}) \end{array}\right\}}$$

$$P(MW|TR) = \frac{\left\{\begin{array}{c} P(TR|MW,\overline{AG}) \\ \cdot P(MW|\overline{AG})\cdot P(\overline{AG}) \end{array}\right\}}{\left\{\begin{array}{c} P(TR,AG,MW) + P(TR,AG,\overline{MW}) \\ +P(TR,\overline{AG},MW) + P(TR,\overline{AG},\overline{MW}) \end{array}\right\}}$$

$$P(BW|HF) = \frac{\left\{\begin{array}{c} P(HF|BW,\overline{MW},\overline{IL}) \\ \cdot P(BW,\overline{MW},\overline{IL}) \\ \cdot P(BW|\overline{MW})\cdot P(BW) \end{array}\right\}}{\left\{\begin{array}{c} P(HF,BW,MW,IL) + P(HF,BW,MW,\overline{IL}) + P(HF,BW,\overline{MW},IL) \\ +P(HF,\overline{BW},MW,IL) + P(HF,BW,\overline{MW},\overline{IL}) + P(HF,\overline{BW},MW,\overline{IL}) \\ +P(HF,\overline{BW},\overline{MW},IL) + P(HF,\overline{BW},\overline{MW},\overline{IL}) \end{array}\right\}}$$

$$P(MW|HF) = \frac{\left\{\begin{array}{c} P(HF|MW,\overline{BW},\overline{IL}) \\ \cdot P(\overline{IL}|MW,\overline{BW}) \\ \cdot P(MW|\overline{BW})\cdot P(\overline{BW}) \end{array}\right\}}{\left\{\begin{array}{c} P(HF,BW,MW,IL) + P(HF,BW,MW,\overline{IL}) + P(HF,BW,\overline{MW},IL) \\ +P(HF,\overline{BW},MW,IL) + P(HF,BW,\overline{MW},\overline{IL}) + P(HF,\overline{BW},MW,\overline{IL}) \\ +P(HF,\overline{BW},\overline{MW},IL) + P(HF,\overline{BW},\overline{MW},\overline{IL}) \end{array}\right\}}$$

$$P(IL|HF) = \frac{\left\{\begin{array}{c} P(HF|IL,\overline{BW},\overline{MW}) \\ \cdot P(IL|\overline{BW},\overline{MW}) \\ \cdot P(\overline{BW},|\overline{MW})\cdot P(\overline{BW}) \end{array}\right\}}{\left\{\begin{array}{c} P(HF,BW,MW,IL) + P(HF,BW,MW,\overline{IL}) + P(HF,BW,\overline{MW},IL) \\ +P(HF,\overline{BW},MW,IL) + P(HF,BW,\overline{MW},\overline{IL}) + P(HF,\overline{BW},MW,\overline{IL}) \\ +P(HF,\overline{BW},\overline{MW},IL) + P(HF,\overline{BW},\overline{MW},\overline{IL}) \end{array}\right\}}$$

After these formulas are used with the influence diagram and the available conditional probabilities, the DM can see what fault is most likely with the information given and make a decision to pull the pump or not. See Figure 19 below for an illustration of the path chosen. It is not in the intention of this work trying to optimize the assessment of the probabilities. Hence a sample random number generator has been used to draw the probabilities. In a 'real life' analysis the experts will give the subjective probabilities based on the data they receive from the subsea control module and their knowledge, i.e. an expert will not give a high probability for the event 'Lube Oil Level decreased' if the data from the control module shows otherwise.

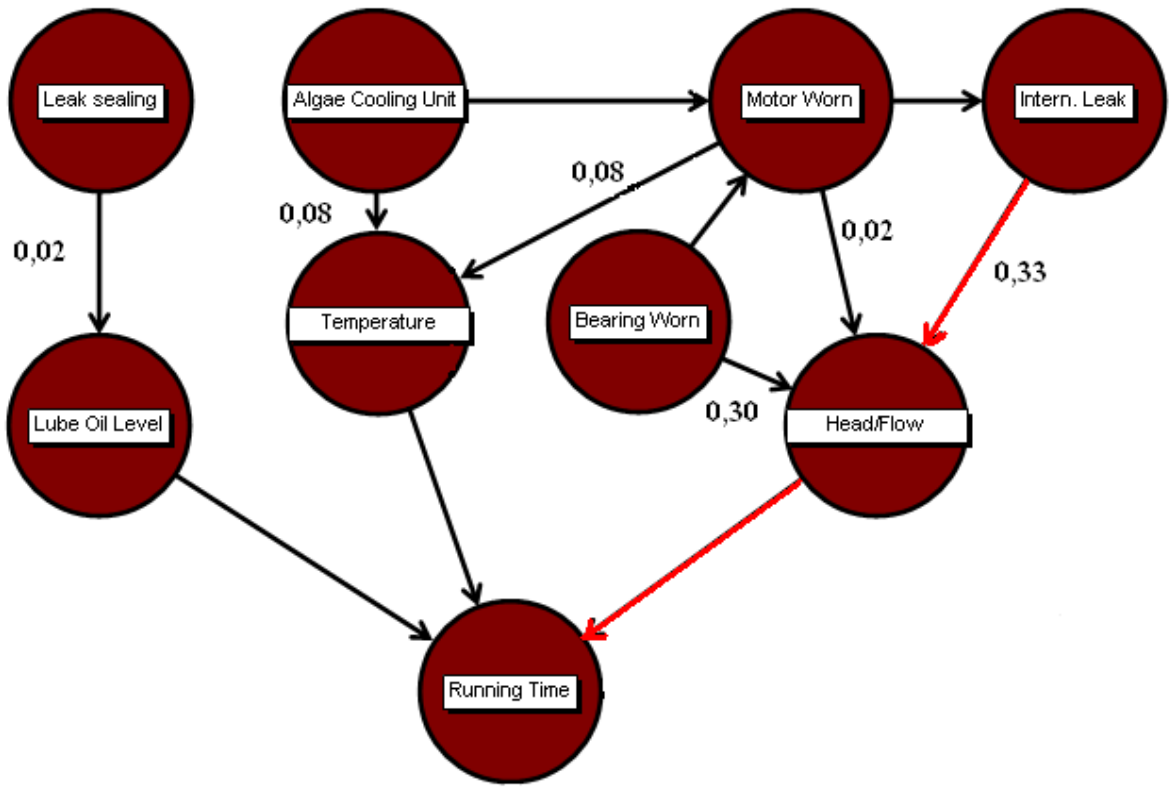

Figure 19. Example of path chosen after conditional probabilities are calculated

Sensitivity analysis:

From Figure 19 it can be seen that the probability for an internal leakage P(IL|HF) and a worn bearing P(BW|HF) are not that far from each other 33% and 30 % respectively. Therefore it is recommended to do a sensitivity analysis of these probabilities to see if any of the events are sensitive to small changes.

A sensitivity analysis is not supposed to replace the probabilities found in the Bayesian calculations, but rather complementing the probabilistic approach to the problem and is helpful for learning more about what event is most sensitive to changes (Benaroya, 2004). By varying one of the subjective probabilities from 0 to 1 while keeping the other constant, a plot of the results can show how the probabilities relate to each other and for what subjective probabilities the 'Internal Leakage' and the 'Bearing Worn' are most likely to happen. In Figure 20 the subjective probability P(HF|IL,MW',BW') is varied from 0,1 to 1,0 and its appurtenant probability is varied by 1 - P(HF|IL,MW',BW') so that these two always sum to 1. This is to follow the rule that they have to be collectively exhaustive and mutually exclusive, as mentioned previously. The other subjective probabilities are kept constant. P(HF|IL,MW',BW') is then plotted against the inferential probabilities P(BW|HF) and P(IL|HF). This procedure is followed for the subjective probability as well, and Figure 21 shows a plot of varying P(HF|BW,MW',IL') against inferential probabilities P(BW|HF) and P(IL|HF). Figure 22 shows both of these plots in one plot to see similarities between the graphs in Figure 20 and Figure 21.

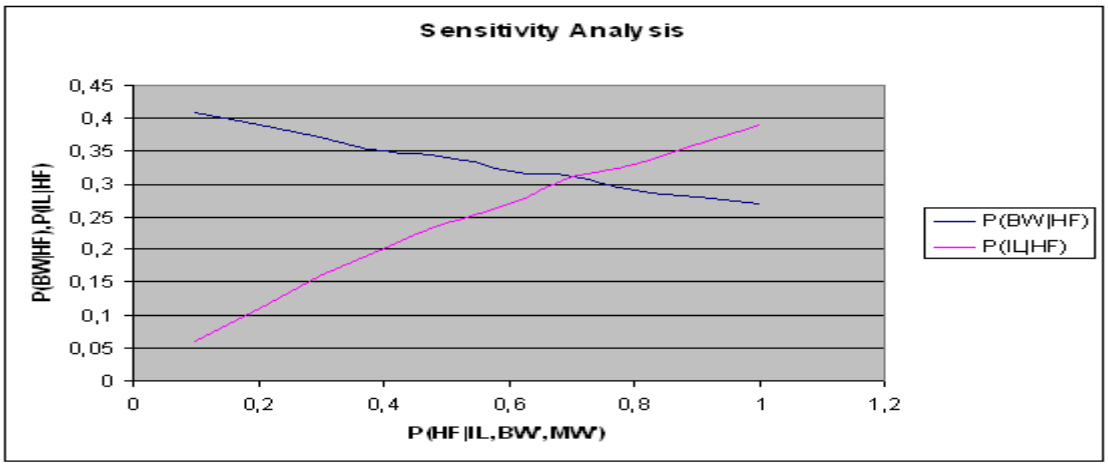

Figure 20. Sensitivity Analysis.

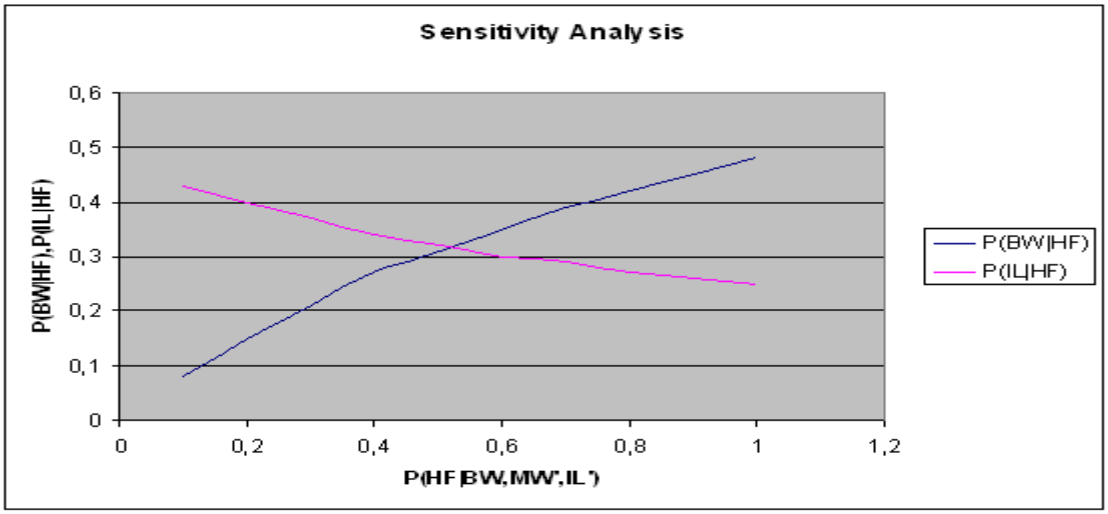

Figure 21. Sensitivity Analysis.

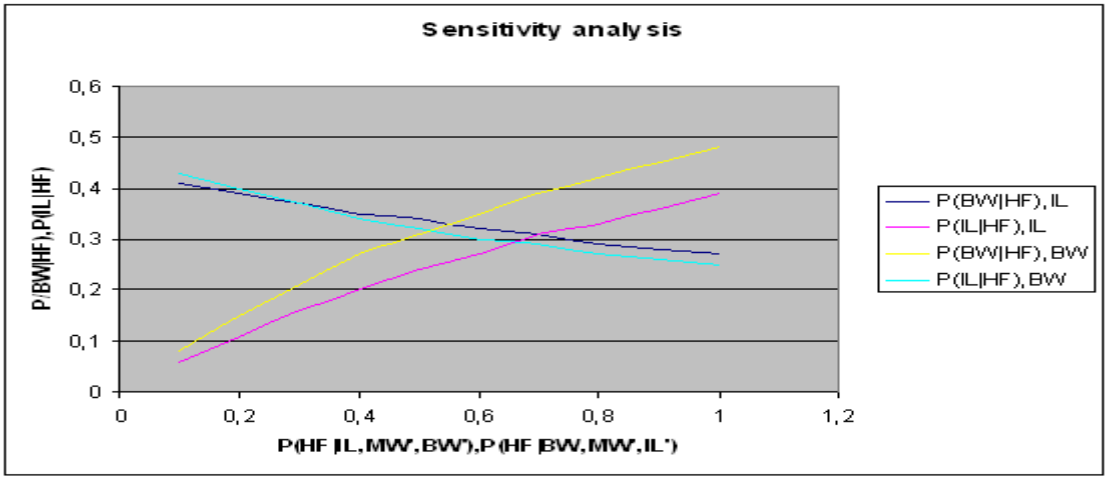

Figure 22. Sensitivity Analysis.

From Figure 20 it can be seen that ‘Bearing Worn’ is more likely to be the cause of a decreased ‘Head/Flow’ reading for P(HF|IL,MW’,BW’)<0,7, while from Figure 21 it shows that 'Worn Bearing' is more likely to be the cause of a decreased ‘Head/Flow’ reading for P(HF|BW,MW’,IL’)>0,5. Thus it can be argued that a ‘Bearing Worn’ is more likely to cause the ‘Head/Flow’ reading to decrease than the ‘Internal Leakage’ for these subjective probabilities. Again, the reader should bear in mind that all these subjective probabilities are random numbers and not ‘real case’ probabilities provided by the experts, hence the sensitivity analysis may look different in a practical problem. However, for this example it is concluded with the ‘Bearing Worn’ to be more likely to cause the decrease in the ‘Head/Flow’ reading.

The Decision:

The main decision is whether to pull the pump or not when some irregular readings are shown on the instrument panel. These readings may indicate more or less critical failures in the system. With all the uncertainties regarding this problem, the decision analysis model suggested in this paper should provide some insight to when this is most efficient to do.

So, assuming that it is the worn bearing that is causing the 'Head/Flow' reading to decrease, the following three scenarios are calculated to see what the 'best' decision for different weather conditions for given problem may be. In these scenarios it is assumed that the intervention vessel is on standby for the Tyrihans Field and will start the intervention the moment the DM decides to pull the pump. Another assumption is that the DM starts the analysis and decides on what to do as soon as some irregularities in the data readings have occurred. The three scenarios are;

- Pull the pump in good weather conditions
- Wait 5 months for good weather conditions and then pull the pump
- Pull the pump in good weather conditions.

Lognormal distribution:

The uncertainties regarding production rate, oil price, intervention cost, and intervention time are estimated using a lognormal distribution in @Risk and the extended Swanson-Megill method where the P10 and P90 each have the probability of 30% and the P50-median has the probability of 40% (Clemen and Reilly, 2001). The assumed recoverable oil reserves are 180 mill. bbl. (Regjeringen, 2006) and in this paper it is assumed an constant production profile over the lifetime of the field. This gives an estimated daily production of 30000 bbl/d. It is then assumed that if the pump efficiency is reduced to 25% it will cause a reduction in the production rate. The reason for the low number is because the WI pump is over dimensioned for its purpose (Falk, 2007).

Production:

Another assumption regarding the relationship between the WI pump and the production rate is that with a total shut down of the WI pump a 5% reduction in production, that is 1500 bbl/d, is assumed to take place when the pump is shut off, and this is the relationship that is used in these estimates. Thus the lognormal distribution of the production rate for the 25% efficiency of the WI pump, with an estimated production of 30000 bbl/d, standard deviation of 6000 barrels, and a production loss of 1125 bbl/d ((1-0,25)*1500) due to the reduced WI pump efficiency, will be as shown in Figure 23.

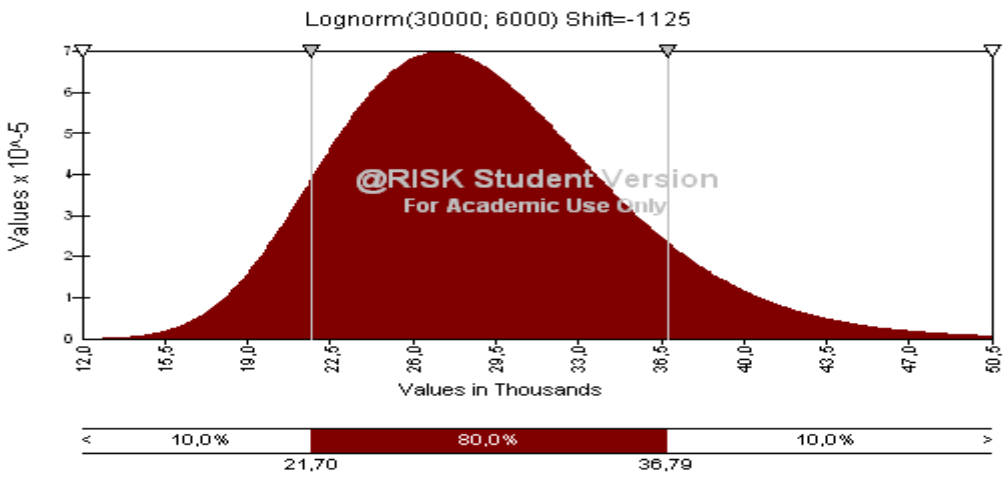

Figure 23. Lognormal distribution with 25% WI pump efficiency

Hence, with the Swanson-Megill method the change in the production rate due to the reduced efficiency of the WI pump may be:

Low:	30%	-8302	bbl/d
Med:	40%	-1134	bbl/d
High:	30%	+6790	bbl/d

As it can be seen from the estimate the well may still produce 6790 bbl/d more than assumed, but is more likely to produce 1134 bbl/d less than estimated due to the reduction in efficiency of the WI pump. The same method is used to estimate profiles for the oil price, estimated running time remaining of the pump after deviations in the data readings, and for intervention cost.

Oil Price:

For the oil price it is assumed 63 $US and a standard deviation 10 $US which gave the distribution of:

Low:	30%	50,83 $US
Med:	40%	62,21 $US
High:	30%	76,08 $US

Running Time:

For the assumed remaining running time it is assumed that the expert foretells the remaining running time to be 180 days with a standard deviation of 90 days, which gives the distribution:

Low:	30%	88 days
Med:	40%	161 days
High:	50%	292 days

Intervention Time:

For the intervention time two distribution profiles are estimated, one for good weather conditions, and one for bad weather conditions. It is assumed that the operator must pay for the whole day, so the time is adjusted to full days.

Good weather conditions with mean time 4 days and standard deviation 2 days:

Low:	30%	2 days	2 full days
Med:	40%	3,5 days	4 full days
High:	30%	6,5 days	7 full days

Bad weather conditions with mean time 7 weeks and standard deviation 2,5 weeks:

Low:	30%	4 weeks	28 full days
Med:	40%	6,5 weeks	46 full days
High:	30%	10 weeks	70 full days

Intervention Cost:

The intervention cost is set to 150000 $US per day. It is assumed that a fixed price is agreed upon when a possible intervention is to take place.

Cost of lost production:

Further it is assumed that the production from the wells is totally shut down during the intervention to maintain the reservoir pressure. In the calculations that follows the median oil price from the lognormal distribution of the oil price is used together with the median production rate per day from the lognormal distribution of the oil production rate with a 25% efficiency of the WI pump. The median is used to simplify the calculations. It is assumed that if the well continues to produce after the reduction is noticed, it will produce with the daily rate of the distribution where the WI pump is operating with 25% capacity, thus this is lost cost during a shut down.

Another assumption taken is a worst-case scenario regarding lost production due to reduced capacity of the WI pump. That is, the largest reduction of production is multiplied with the highest estimated oil price to get the worst-case cost of lost production.

By using the lognormal distributions above, the three scenarios can be calculated to see the relationship between lost production and intervention cost. Hence the estimated daily cost due to reduced production is as follows:

Highest cost:	631616 $US/d
Med cost:	70546 $US/d
Lowest cost:	-2415950 $US/d

With these numbers it is possible to look at three scenarios for the production rate and the intervention cost.

Scenario 1:

Scenario 1 assumes that the Head/Flow fault is noticed during good weather, and that the DM decides to change the WI pump right away while there are good weather conditions. In the calculations that follows the median oil price and the median lost production is used and plotted against the low, med, and high intervention time to see a comparison of the cost of intervention and the cost of lost production. This is shown in Figure 24:

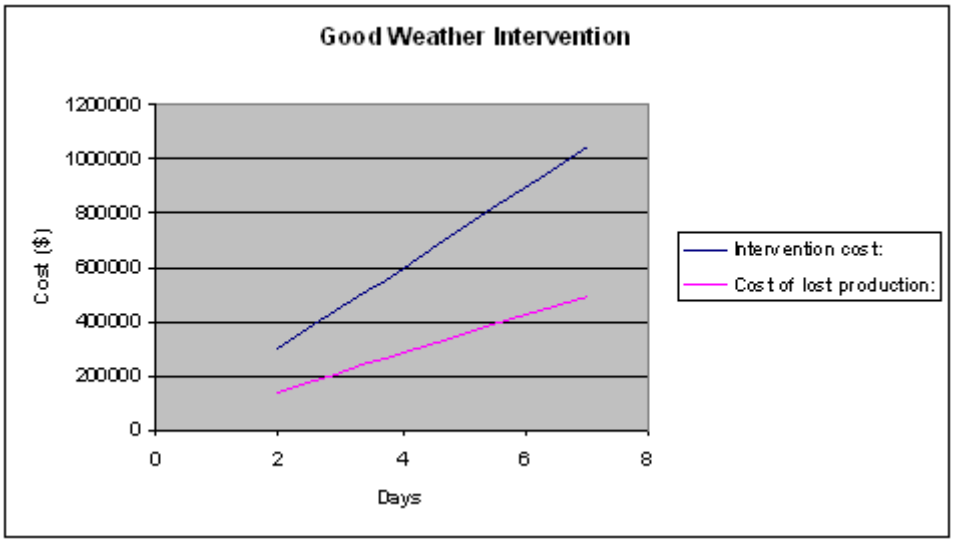

Figure 24. Comparison of intervention cost and cost of lost production during good weather condition.

From Figure 24 it can be seen that the intervention cost will always be higher than the cost of lost production during the same time, so from this estimate an intervention during good weather conditions is not the optimum decision. However, these are mere estimates, and there are good chances for the costs to go both ways. So for scenario 1 it is most likely to be more expensive to do an intervention right away than continue producing with a decreased rate, but the DM should consult weather forecasts for the future, and the experts on how much longer the pump may run before any final decision regarding intervention in good weather is made.

Scenario 2:

Scenario 2 illustrates the situation where the irregular readings are recorded and analyzed during bad weather conditions and the DM decides to pull the pump right away. Figure 25 shows the median intervention cost and the median cost of lost production plotted against low, med, and high estimates for intervention time during bad weather conditions. It shows the same trend as for good weather intervention, i.e. higher cost for the intervention than the cost of lost production during the same time. Hence this is not an optimum decision either.

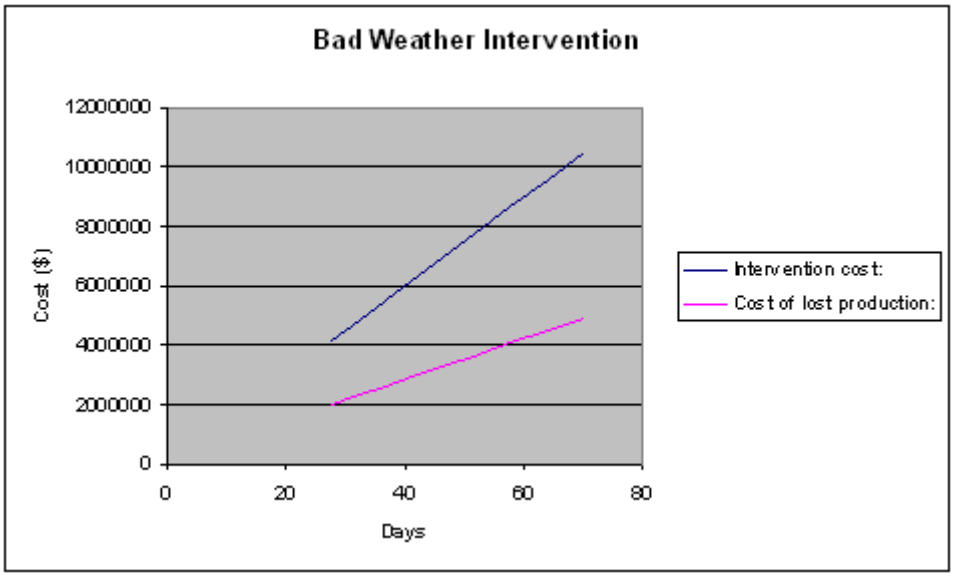

Figure 25. Comparison of intervention cost and cost of lost production during bad weather.

However, it is assumed that the weather condition stays bad during the whole intervention time and that the intervention vessel is on site and ready to start the intervention from day one, though this may not be true for a 'real life' situation. The DM must look at weather forecast and consult with the experts regarding the remaining running time of the pump to make the decision on whether to do the intervention or not.

Scenario 3:

For the scenario 3 where the Head/Flow failure is identified during bad weather conditions, and the DM wait for better weather to do the intervention, the median cost for bad weather intervention is used as a fixed cost for 16 weeks forward. This is done to simplify the comparison between intervention cost during bad weather, and the cost of lost production due to wear of the WI pump. Another assumption regarding this is that it is forecasted bad weather condition for 4-5 months from the time of analysis. Thus, by using the median cost of bad weather intervention, and the median cost of daily-lost production, a plot of the cost may look as in Figure 26:

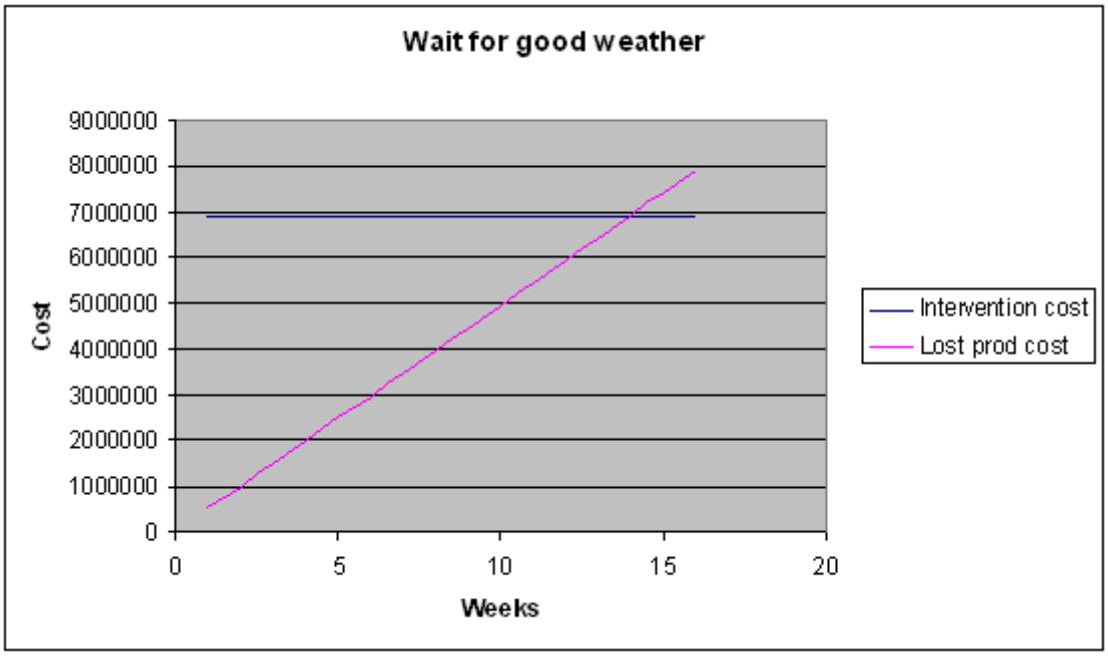

Figure 26. Plot of bad weather intervention cost vs. lost production cost

From Figure 26 it can be seen that it is justifiable to wait for better weather for at least14 weeks, as the intervention cost is higher than the cost of lost production during bad weather condition. In addition to these numbers it is of course a bigger loss not taken into the calculations, and that is the cost of the total shutdown during the intervention. If the intervention takes 46 days in bad weather condition, which is the median time from the lognormal distribution, the loss of production during intervention is considerable higher than if the intervention is estimated to take 4 days in good weather.

Conclusion:

In this work we have looked at how to use a decision analytic and Bayesian formulation to investigate the optimal time to replace a subsea water injection pump. To our knowledge, this is a new and novel approach to this problem and it is clear that this formulation can provide significant insight to the decision situation.

The approach requires the decision maker(s) and analysis team to have conversations about and determine which parameters have the largest effect on pump efficiency. In this work, it is assumed that algae growth, motor worn, worn bearings, internal leakage, and leaking sealing were the most important and structured the problem accordingly. The resulting influence diagram, even without numbers, provides great insight into the problem and creates the transparency required to understand and optimize the decision situation.

Then the influence diagram was populated with the necessary probabilities, costs, and payoffs that allowed us to identify an optimal strategy for when to pull the pump given the weather conditions at the time when the irregular data readings were detected.

Given the uncertainties associated with the key parameters, there is no one optimal strategy for all situations. If the intervention is started the same day that the decision to do an intervention is made, regardless of good or bad weather, this work shows that the intervention cost is always higher than the cost of lost production during the same time period, so this is not an optimum decision. If the intervention is postponed until the next period of good weather assumed that the expert estimates the pump to run that long, this work shows that this is an optimum solution with the assumptions made.

Clearly, the decision analytical framework applied provides new and important insights into this problem and we believe it would be a very useful and valuable tool for real world decisions of this kind.

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