Development of an Advisory System Based on Bayesian Network to Minimize Corrosion Problems in Underbalanced Drilling

Abdullah Al-Yami, Jerome Schubert and Vikrant Wagle

Abstract: In underbalanced drilling the use of air as an injected gas sets up the potential for oxygen corrosion. Membrane nitrogen with about 5% oxygen eliminates the chance for fire or explosion, but does not solve the corrosion problem. Natural gas or cryogenic nitrogen eliminates the chance for oxygen corrosion, but does not always eliminate the chance of corrosion from other down hole acid gasses (Hydrogen Sulfide, H2S, Carbon Dioxide, and CO2). Any corrosion that occurs while drilling will be forced by some drilling fluid or drilling operational procedure such as KCl fluids, aerated mud, or floating mud cap operations.

The objective of this study is to identify some of the practical elements of corrosion encountered with underbalanced drilling and their optimum solution by development of an advisory system based on field cases and expert opinions. This advisory system is intended to be a field guide for the drilling engineer or rig supervisor. Corrosion is a matter of concern to the drilling contractor because of pitting or loss of steel in the drill pipe.

The advisory system is developed by proposing a set of guidelines for the optimal practices to minimize corrosion in underbalanced drilling operations. The optimum practices collected from data and experts’ opinions, are integrated into a Bayesian Network BN to simulate likely scenarios of its use that will honor efficient practices when dictated by varying certain parameters. These parameters are measuring corrosion, identifying corrosion types, drill pipe and corrosion, treatment methods for H2S corrosion, CO2 sources and treatment, different methods to test for corrosion, general corrosion prevention and treatment, treatment methods for formation water and makeup water, and recommended practices to minimize corrosion in underbalanced drilling operations.

To the best of the authors’ knowledge, this paper is the first study to develop an advisory system for minimizing corrosion problems. The developed software solutions on corrosion will be demonstrated such as using mechanical means to reduce O2 concentration and inhibitors for pipe coating. Finally, the advisory system list recommendations for all types of underbalanced drilling (flow, aerated, foam and mist) to minimize corrosion problems.

Index Terms— advisory system, bayesian, corrosion, drilling, underbalanced, simulation.

1 INTRODUCTION

The design of optimum underbalanced drilling operations depends mainly on previous experience and knowledge to successfully complete with a degree of confidence. Effective communication is also an important factor for successful operations. Good coordination is required between the engineer, the service company and the rig foreman. Knowledge transfer in underbalanced drilling operations is therefore fundamental for the optimal design of the job.

Long field experience is required for underbalanced drilling specialists to select optimum practices. In some instances, operation failures can occur because of the lack of knowledge or lack of knowledge transfer.

There are different methods that companies have approached to make guidelines for their engineers to save on operations cost and time. However, these methods cannot be used by other companies or experts with different opinions or with different field conditions.

(Al-Yami and Schubert, 2012) proposed several UBD expert models, using Bayesian network, such as flow, foam and aerated models. This paper is the first study to develop an advisory system to minimize corrosion problem in UBD operations.

The Bayesian paradigm can be defined as:

\[
p(\text{hypothesis}|\text{evidence}) = \left( \frac{p(\text{evidence}|\text{hypothesis}) \cdot p(\text{hypothesis})}{p(\text{evidence})} \right)
\]

Representing the probability of a hypothesis conditioned upon the availability of evidence to confirm it. This means that it is required to combine the degree to plausibility of the evidence given the hypothesis or likelihood \( p(\text{evidence}|\text{hypothesis}) \), and the degree of certainty of the hypothesis or \( p(\text{hypothesis}) \) called prior. The intersection between these two probabilities is then normalized by \( p(\text{evidence}) \) so the conditional probabilities of all hypotheses can sum up to 1.

This work introduces the use of Bayesian networks as a way to provide reasoning under uncertainty, using nodes representing variables either discrete or continuous. Arcs are used to show the influences among the variables (nodes). Thus, Bayesian networks can be used to predict the effect of interventions, immediate changes, and to update inferences according to new evidences.

Bayesian networks are known as directed acyclic graphs because generating cycles are not allowed. The terminology for describing a Bayesian Network follows a hierarchical parenting scheme. A node is named a parent of another node named child if we have an arc from the former to the later. The arcs will represent direct dependencies. Evidence can be introduced to the Bayesian network at any node, which is also known as probability propagation or belief updating. It
is important to define the conditional probability distributions to each node (Korb and Nicholson, 2004). In order to prove the concept and the benefits of using this approach, one simple model simulating the decision-making process of the selection of corrosion treatment is shown below.

2 MODEL FOR THE PROOF OF THE CONCEPT

In order to prove the concept and the benefits of using this approach, one simple BDN model simulating the decision-making process of the selection of corrosion minimization practices is introduced in Fig. 1. This model contains one decision node (Treatment), three uncertainty nodes (type of UBD, Reservoir pressure, and Consequences), and one value node (Corrosion Expert). In this model, our selection for treatment is affected by our selection of type of UBD and reservoir pressure.

Once the structure of the BDN is defined, it is required to define the probability states associated with each node. These are given in Table 1 through Table 5. The model is designed in a way that the engineer will select his uncertainty nodes (type of UBD and/or reservoir pressure) to get the recommended treatment (using good foaming agents or keeping mud guns submerged into drilling fluid, Table 1). Table 2 shows the probability states of Type of UBD based on treatment. Table 3 shows the probability states of reservoir pressure based on type of UBD and treatment. Table 4a and 4b defines the extent of the probability states of the consequences, which are defined as recommended and not recommended. The input utility value associated with the consequences is given in Table 5. The expected utility outcomes considering all possible cases of evidence set a minimum value of zero, which is the “not recommended” case, and a maximum value of one, which assumed to be the “recommended” case.

### Table 1: Treatment

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Use good foaming agents to form tight air emulsion</th>
<th>Keep mud guns submerged to avoid air into the drilling fluid</th>
</tr>
</thead>
</table>

### Table 2: Probability states of Type of UBD

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Flow</th>
<th>Foam</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flow</td>
<td>0.1</td>
<td>0.9</td>
</tr>
<tr>
<td>Foam</td>
<td>0.9</td>
<td>0.1</td>
</tr>
</tbody>
</table>

### Table 3: Probability states of Reservoir Pressure

<table>
<thead>
<tr>
<th>Reservoir Pressure</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of UBD</td>
<td></td>
</tr>
<tr>
<td>Flow</td>
<td></td>
</tr>
<tr>
<td>Foam</td>
<td></td>
</tr>
<tr>
<td>Treatment</td>
<td>Use good foaming agents to form tight air emulsion</td>
</tr>
<tr>
<td>Flow</td>
<td>0.1</td>
</tr>
<tr>
<td>Foam</td>
<td>0.9</td>
</tr>
</tbody>
</table>

### Table 4a: Probability states of the consequences

<table>
<thead>
<tr>
<th>Reservoir Pressure</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of UBD</td>
<td></td>
</tr>
<tr>
<td>Flow</td>
<td></td>
</tr>
<tr>
<td>Foam</td>
<td></td>
</tr>
<tr>
<td>Treatment</td>
<td>Use good foaming agents to form tight air emulsion</td>
</tr>
<tr>
<td>Flow</td>
<td>0.1</td>
</tr>
<tr>
<td>Foam</td>
<td>0.9</td>
</tr>
<tr>
<td>Recommended</td>
<td>0</td>
</tr>
<tr>
<td>Not recommended</td>
<td>1</td>
</tr>
</tbody>
</table>

### Table 4b: Probability states of the consequences

<table>
<thead>
<tr>
<th>Reservoir Pressure</th>
<th>Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of UBD</td>
<td></td>
</tr>
<tr>
<td>Flow</td>
<td></td>
</tr>
<tr>
<td>Foam</td>
<td></td>
</tr>
<tr>
<td>Treatment</td>
<td>Use good foaming agents to form tight air emulsion</td>
</tr>
<tr>
<td>Flow</td>
<td>0</td>
</tr>
<tr>
<td>Foam</td>
<td>1</td>
</tr>
<tr>
<td>Recommended</td>
<td>0</td>
</tr>
<tr>
<td>Not recommended</td>
<td>1</td>
</tr>
</tbody>
</table>

### Table 5: Input utility values associated with the consequences

<table>
<thead>
<tr>
<th>Consequences</th>
<th>Recommended</th>
<th>Not recommended</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>
The main goal after the required inputs are entered into the model is to simulate the uncertainty propagation from the existing sources of evidence, which means moving the information forward starting from the treatment node. First the total probability is calculated for the type of reservoir pressure. The above model shows that our selection of reservoir pressure will affect the type of UBD and our treatment. The below equation is used:

\[
\sum_{i=1}^{n} P(B|A_i) P(A_i)
\]

The results are shown in Table 6. Tables 2 & 3 are used for this calculation. For example, given high reservoir pressure we can calculate the probability of using good foaming agents to form tight air emulsion. We have to consider the type of UBD (Flow and Foam):

\[(0.1 \times 0.1) + (0.9 \times 0.1) = 0.1\]

### Table 6: Total probability for reservoir pressure

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Use good foaming agents to form tight air emulsion</th>
<th>Keep mud guns submerged to avoid air into the drilling fluid</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>0.1</td>
<td>0.9</td>
</tr>
<tr>
<td>Low</td>
<td>0.9</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Then Bayesian equation can be used as shown below:

\[
p(hypothesis|evidence) = \left( \frac{p(evidence|hypothesis) p(hypothesis)}{p(evidence)} \right)
\]

\[
P(A_j|B) = \frac{P(B|A_j) P(A_j)}{\sum_{i=1}^{n} P(B|A_i) P(A_i)}
\]

The results are shown in Table 7. Tables 2, 3 and 6 are used for this calculation. The calculation shows the probabilities of selecting type of UBD (Flow or Foam) when having reservoir pressure (Low or High) for a particular treatment (using good foaming agents or keeping mud guns submerged into drilling fluid). The detailed calculations for using good foaming agents to form tight air emulsion are shown below:

\[p(Flow|High) = \left( \frac{p(Flow|High)p(Flow)}{p(Flow)} \right) = \left( \frac{0.1 \times 0.1}{0.1} \right) = 0.1\]

\[p(Flow|Low) = \left( \frac{p(Flow|Low)p(Flow)}{p(Flow)} \right) = \left( \frac{0.1 \times 0.9}{0.9} \right) = 0.1\]

\[p(Foam|High) = \left( \frac{p(Foam|High)p(Foam)}{p(Foam)} \right) = \left( \frac{0.9 \times 0.9}{0.9} \right) = 0.9\]

\[p(Foam|Low) = \left( \frac{p(Foam|Low)p(Foam)}{p(Foam)} \right) = \left( \frac{0.1 \times 1}{0.1} \right) = 1.0\]

For keeping the guns submerged into the drilling fluid, the calculations are:

\[p(Flow|High) = \left( \frac{p(Flow|High)p(Flow)}{p(Flow)} \right) = \left( \frac{0.9 \times 0.9}{0.9} \right) = 0.9\]

\[p(Foam|High) = \left( \frac{p(Foam|High)p(Foam)}{p(Foam)} \right) = \left( \frac{0.1 \times 0.9}{0.9} \right) = 0.1\]

\[p(Flow|Low) = \left( \frac{p(Flow|Low)p(Flow)}{p(Flow)} \right) = \left( \frac{0.9 \times 0.1}{0.1} \right) = 0.9\]

\[p(Foam|Low) = \left( \frac{p(Foam|Low)p(Foam)}{p(Foam)} \right) = \left( \frac{0.1 \times 0.1}{0.1} \right) = 0.1\]

### Table 7: Using Bayesian equation for the proposed model

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Use good foaming agents to form tight air emulsion</th>
<th>Keep mud guns submerged to avoid air into the drilling fluid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of UBD</td>
<td>Updated values</td>
<td>Updated values</td>
</tr>
<tr>
<td>Flow</td>
<td>0.1</td>
<td>0.9</td>
</tr>
<tr>
<td>Foam</td>
<td>0.9</td>
<td>0.1</td>
</tr>
<tr>
<td>Reservoir Pressure</td>
<td>Updated values</td>
<td>Updated values</td>
</tr>
<tr>
<td>High</td>
<td>Selected by user</td>
<td>Selected by user</td>
</tr>
<tr>
<td>Low</td>
<td>Selected by user</td>
<td>Selected by user</td>
</tr>
</tbody>
</table>

Now, once the Bayesian calculations are completed, there are two approaches for the engineers to use this model. The first approach is to specify the reservoir pressure (high or low) and this will determine the suitable decision in this model which is the suitable treatment. For example if we have low reservoir pressure, then the probabilities of treatment (consequences) in Table 7 and probability states of the consequences in Table 4. The results are shown in Table 8. Below is an example calculation:

**Use good foaming agents to form tight air emulsion**

**Recommended**

\[0 \times 0.1 + 1 \times 0.9 = 0.9\]

**Not Recommended**

\[(0.1 \times 1 + 0 \times 0.9) = 0.1\]
Keep mud guns submerged to avoid air into the drilling fluid

Recommended

\[ (0.9 \times 0 + 0.1 \times 0) = 0 \]

Not Recommended

\[ (0.9 \times 1 + 0.1 \times 0) = 1.0 \]

Table 8: Consequences when selecting low reservoir pressure from Table 7 and Table 4

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Use good foaming agents to form tight air emulsion</th>
<th>Keep mud guns submerged to avoid air into the drilling fluid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recommended</td>
<td>0.9</td>
<td>0</td>
</tr>
<tr>
<td>Not recommended</td>
<td>0.1</td>
<td>1</td>
</tr>
</tbody>
</table>

The utility is finally calculated using below equation from Table 8 and Table 5:
For using good foaming agents to form tight air emulsion it is:

\[ \text{Expected utility} = \sum \text{consequence result} \times \text{input believe} \]
\[ = 0.9 \times 1 + 1 \times 0 = 0.9 \]

For keeping the guns submerged into the drilling fluid it is:

\[ \text{Expected utility} = \sum \text{consequence result} \times \text{input believe} \]
\[ = 0 \times 1 + 1 \times 0 = 0 \]

Table 9: Expected utility values (first approach)

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Use good foaming agents to form tight air emulsion</th>
<th>Keep mud guns submerged to avoid air into the drilling fluid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected utility</td>
<td>0.9</td>
<td>0</td>
</tr>
</tbody>
</table>

For this study, Graphical Network Interface was used for calculations of the uncertainty propagation to build up the expert system. Fig.2 shows the results for the first approach example (selecting low reservoir pressure) which agrees with the calculation above. Figs.3 shows the results for the second approach example (selecting high reservoir pressure and flow UBD) which also agrees with the calculation above.

Using Bayesian intelligence allows the design of expert systems that can be used in different fields and/or by different experts with different opinions. The system can be updated easily with the new opinions by changing the probability states shown above (Tables 2-4) and the model will update the calculation to show the recommended treatment.

The objective of this paper is to propose a set of guidelines for the optimal practices to minimize corrosion in underbalanced drilling operations, by integrating current best practices through a decision-making system based on Artificial Bayesian Intelligence.

3 UBD CORROSION EXPERT MODEL

The calculation shown above was performed for a small model with limited options. To develop a model that can be used to assist in minimizing corrosion problems related to underbalanced drilling operations, a more comprehensive model is needed. Literature review and corrosion experts’ opinions were used as evidence to build this model using the proposed Bayesian Network. Variable nodes allow the user to input desired conditions that allows for generating the corresponding best practices.

Eighteen uncertainty and consequences nodes are defined for this model to determine best practices in nine decision nodes, Fig.4. The model is divided into nine parts or decisions. Each decision has uncertainties and consequences nodes. The consequences node combines the uncertainty nodes where corrosion expert opinions were used to assign and define the conditional probability distribution. The model then calculates the optimum practices decision.

The first uncertainty node is named measuring corrosion, Fig.5. It has 5 possible measurement methods which are visual...
inspection, measurement of mud properties, drill pipe ring, corrosion coupons, and electrical resistance probe. Once the engineer selects his uncertainty the optimum practices to measure corrosion will be shown in the decision node.

The second uncertainty node is identifying corrosion types, Fig.6. It has 6 possible corrosion types which are red rust, pitting and red rust, black coating on the pipe, magnetite, barnacles or black scale bubbles, and stray electrical currents. Once the engineer selects his uncertainty the optimum recommendation to identify corrosion type will be shown in the decision node.

The third uncertainty node is named drill pipe and corrosion, Fig.7. It shows the two possible scenarios of using corrosion resistant alloys and aluminum drill pipe. The decision node will show the optimum conditions of using both drill pipes.

The fourth uncertainty lists potential treatment methods for H2S corrosion, Fig.8. Once the user selects his uncertainty from the list the decision node will provide the recommended practices for that treatment.

The fifth uncertainty enables the user either to select potential CO2 sources or a description of its corrosion, Fig.9.

The sixth uncertainty shows different methods to test for corrosion such as oxygen content, iron concentration, pH level, alkalinity, phosphonate level at the flow line to control phosphate inhibitor addition, total hardness and H2S level, Fig.10. Once the user selects his uncertainty (the test of interest) from the list the decision node will provide the recommended testing procedure.

The seventh uncertainty shows general corrosion prevention and treatment such as pH control, Oxygen, use of emulsifiers and oil and commercial inhibitors, Fig.11.

The 8th uncertainty shows two probability states. The user will select treatment methods for either formation water or makeup water, Fig.12.

Finally, the 9th uncertainty enables the engineer to select the recommended practices to minimize corrosion in underbalanced drilling operations such as general UBD, flow drilling, aerated or gaseated mud, foam and mist, Fig.13.

4 DISCUSSION

This section shows the use of this model in the different scenarios where the user select his conditions. To view the results once the model is executed can be done by obtaining the optimum results from each section separately.

Fig.14 shows that the engineer wants to know the optimum practice to measure corrosion through the selection of measurement mud properties. The model recommends to measure fluid properties relative to corrosion at both the suction and flow line. This includes:

- pH,
- oxygen content,
- total hardness,
- bicarbonates,
- iron concentration,
- residual volumes of the inhibitor.

A comparison of the properties, in and out, will tell if corrosion is occurring, (increased iron and/or significantly decreased pH), and if there is enough inhibitor in the system to carry over to the flow line. This may be taken a step further and pH and hardness tests run on the rig water to predict potential induced problems, Rehm et al. (2012).

Fig.15 shows the user how to identify corrosion type by observation of red rust from the uncertainty and its identification from the decision node.

The simplest and the most common early identification of oxygen corrosion is red rust on the drill pipe. This is an indication that downhole conditions are conducive to oxygen corrosion. Rust is hematite (Fe2O3). It forms rapidly over a few hours and the coating will be red and soft. Uniform rust is probably the result of a pH below 7 or oxygen/salt-water attack at the surface, Rehm et al. (2012).

Selecting aluminum drill pipe (Fig.16) might be an option to minimize corrosion in underbalanced drilling operations. Aluminum drill pipe is not normally influenced by the materials that cause problems with steel pipe. This includes oxygen, hydrogen sulfide and carbon dioxide products. Any oxygen available combines with the aluminum to form an aluminum oxide coating on the pipe which resists further corrosion. Upon visual inspection, the drill pipe will have a dull aluminum colored coating, which is the oxide. The model recommends that the pipe should not be exposed to pH below 7 or above 10 for long periods of time. The aluminum oxide coating degrades in the high and low pH range. With a loss of coating, the raw aluminum is exposed and “chemically milled” off the pipe. With invert oil mud, the pH of the water should be kept in the range of 8-10. Chloride above 180,000 ppm tends to destabilize the coating. With high chlorides the pH should be kept in range of 7.5 to 9, Rehm et al. (2012).

In case of hydrogen sulfide corrosion, the engineer decides on using iron sponge for treatment (Fig.17). Iron sponge is made of a very finely divided iron oxide (hematite). It preferentially absorbs the sulfide into insoluble iron sulfide. Various service companies use mixtures of different iron oxides which improve the absorption of H2S such as iron (II) oxalate and iron sulfate. For drilling fluids a pretreatment is common in the range 20 lbs/bbl (50kG/m3). The material is also very commonly used to clean H2S from gas streams. The Iron reaction is slower in a very high pH environment. In high pH environment, Ferrous gluconate (organic iron chelating agent) is stable at high pH level up to 11.5, Rehm et al. (2012).

The model can aid in identifying potential carbon dioxide (Fig.18) in UBD drilling operations. The model suggests that corrosion from CO2 in its various forms does not require oxygen in the drilling or packer fluid, so it is most commonly seen in production tubing and casing. It can be introduced from the makeup water, from gas in the formation, treatment of cement, or decay or organic additives, Rehm et al. (2012).

In case commercial inhibitors are selected (Fig. 19), recommendation will be given about their use such as their proper environment and limitations. Commercial inhibitors limit corrosion by forming a film on the steel. Acids or an acid environment will tend to weaken or destroy the various films. The films are also subject to erosion from high velocity fluids and particles, so a continuous flow of inhibitor is required to limit...
corrosion by isolating the steel drill pipe or casing from any local electrical cells. The corrosion agent should be checked for concentration at both the suction and the flow line, Rehm et al. (2012).

If the formation water is to be used in the underbalanced drilling operations (Fig.20) then the model recommends different treatment for different water conditions. Most of these conditions can be treated before use. The simplest treatment is the use of caustic soda (NaOH) to raise the pH above 9. Soda Ash (Na₂CO₃) can be used in the place of caustic soda, but it runs the possible risk of scaling in workover or production operations, and it is probably not a good choice for hot wells. Some of these water conditions are, Rehm et al. (2012):
- Acid formation water with a pH below 6 is usually black, treat with caustic soda (NaOH) to raise the pH above 9.
- High bicarb (HCO₃⁻) content above 1000 ppm, treat with caustic soda (NaOH) to raise the pH above 8.3 with high bicarbs it may take an excessive amount of caustic to get the pH to 9
- Carbon dioxide (CO₂), treat with caustic soda and/or soda ash to raise the pH above 9
- Various sulfate or sulfide ions, raise the pH above 10 with potassium hydroxide (KOH) or caustic soda (NaOH)
- Hydrogen sulfide gas, (H₂S), (for small or trace amounts), keep the pH above 10 with caustic soda and lime and use one of the commercial iron sequestering agents. Pre-treat the drill water with zinc carbonate at about 0.3 lb/bbl (0.6 kg/m³) Iron Sponge at 10lb/bbl (30kg/m³), or a commercial agent.
- Saline or salt water. Best not used with air injection fluids. Keep the pH above 7 if possible. It is probably better to use saturated salt water.
- KCl water, not a bad short term corrosion problem if the pH is kept above 9. If it is not completely displaced out of the well there will be significant long term corrosion problems with tubing and casing.

Testing for iron (Fig.21) shows a recommendation of where to sample for testing. There should be a measure of the iron at the shaker and iron in the suction water. An increase in iron at the flow line means the corrosion is occurring. The best policy is that the makeup water should be clear of iron to avoid masking the increase in iron at the flow line. However an increase in iron in workover or re-entry may only mean that corrosion products are being knocked off the casing. In this case, the workover string needs to be examined within a day of operations. Magnetite on the shaker is a sure sign of casing corrosion and not works string corrosion. The typical iron test reduces the ferrous iron to ferric by heating or boiling the test solution and titrating the results. There are some iron test strips available that are much simpler to use and give adequate results, Rehm et al. (2012).

In case the engineer wants to select UB flow drilling (Fig.22), the model will suggest the following, Rehm et al. (2012):
- Do not use 3-10 wt% KCl or NaCl and try use higher concentration to slow down the corrosion rate. For shale inhibition, use synthetic shale inhibitor.
- Avoid mixing air into the mud system.
- Maintain pH above 9
- Add inhibitors if corrosion signs appeared.

5 CONCLUSIONS

The UBD corrosion model developed for this paper can provide recommendations for the following:
- Measuring corrosion
- Identifying corrosion types
- Drill pipe and corrosion
- Potential treatment methods for H₂S corrosion
- Potential CO₂ sources or a description of its corrosion
- Different methods to test for corrosion
- General corrosion prevention and treatment
- Treatment methods for either formation water or makeup water
- The recommended practices to minimize corrosion in underbalanced drilling operations

In case new practices or different experts’ opinions are presented then all we need to do is simply change the states of probabilities. In case that the above model is missing other factors then we can also update the model and its corresponding states of probabilities. The flexibility of Bayesian network in terms of updating the structure model and its beliefs makes this method the first systematic approach to build experts systems. This advisory system is intended to be a field guide for the drilling engineer or rig supervisor.

6 REFERENCES


ABBREVIATIONS

BHST : Bottom hole static temperature
BWOC: By weight of cement
Gps : Gallons per sack
Hp : Horse power
Ibpg : bounds per gallon
SI METRIC CONVERSION FACTORS

in. × 2.54E−02 = m
(°F-32) / 1.8E+00 = °C
ft × 3.048E−01 = m
gal × 3.785 412E−03 = m³
lbm × 4.535 924E−01 = kg
psi × 6.894 757E−03 = Mpa
lbm/gal × 1.198 26E−01 = S.G
bbl × 1.58987E−01 = m³

*Conversion factor is exact
Fig. 1: BDN model for the proof of the concept

Fig. 2: Model for the proof of concept (first approach)
**Fig. 3:** Model for the proof of concept (second approach)

**Fig. 4:** Overall model of corrosion
Fig. 5: Measuring corrosion options

Fig. 6: Identifying corrosion types
Fig. 7: Drill pipe and corrosion options

Fig. 8: Treatment options for H₂S
Fig. 9: Carbon Dioxide options (sources and corrosion description)

Fig. 10: Corrosion tests options
Fig. 11: General corrosion prevention options

Fig. 12: Water solution options
Fig. 13: UBD corrosion options

Fig. 14: Selecting measurement of mud properties option
Fig. 15: Selection of red rust

Fig. 16: Selection of aluminum drill pipe
**Fig. 17:** Selection of hydrogen sulfide treatment with iron sponge

**Fig. 18:** Selection of sources of carbon dioxide
Fig. 19: Selection of commercial inhibitors to prevent and treat corrosion

Fig. 20: Selection of formation water quick solution
Fig. 21: Selection for iron corrosion testing

Fig. 22: Selection of flow UBD