



A systems-based approach for modeling of microbiologically influenced corrosion implemented using static and dynamic Bayesian networks

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ABSTRACT

Microbiologically influenced corrosion (MIC) is a microbial community assisted degradation of materials affecting chemical processing and oil and gas industries. MIC has been implicated in incidents involving loss of containment of hazardous hydrocarbons which have led to fires and explosions, economic and environmental impact. The interplay between abiotic environmental factors and dynamic biotic factors in MIC are poorly understood. There is a lack of mechanistic understanding of MIC and very few models are available to predict or assess MIC threat. Here we report on the development of a model to assess the susceptibility to MIC. The high-resolution model utilizes 60 independent nodes, including operational and historical failure analysis data, and is built by combining empirical relationships between the abiotic and biotic variables impacting MIC. Both static and dynamic Bayesian-network (BN) approaches were used to combine heuristic and quantitative states of variables to ultimately yield a susceptibility measure for MIC. A confidence-in-information metric was generated to reflect the amount of data used in the estimation. A susceptibility to MIC of 45%–60% was estimated by the model for ten different scenarios simulated using case-studies from literature. The susceptibility to MIC estimated by these scenarios was further interpreted in the context of these cases. This systems-based MIC model can be utilized as an independent estimator of susceptibility or can be incorporated as a sub-model within comprehensive safety threat assessment models currently utilized in industry.

1. Introduction

Microbiologically influenced corrosion (MIC) is a phenomenon that occurs due to the interplay of microbial communities and corrosive environments at the metal surface (Little and Lee, 2014). MIC in pipelines, storage tanks and other structures can result in the loss of containment, harming people or destroying property and the environment. MIC is estimated to contribute to 40% of internal corrosion and 20–30% of external corrosion in pipelines (Wolodko et al., 2018). MIC has been suggested as a proximate cause in numerous worldwide process safety incidents. For example, the propane tank explosion at Umm Said in 1977 has been attributed to weld failure caused by MIC, which led to catastrophic failure of the tank (Chang and Lin, 2006). Similarly, the crude oil spill on the Alaskan North Slope in 2005 and the Abkatun Permanente platform fire in the Gulf of Mexico in 2015 have been

suspected to be a consequence of MIC leading to structural failures of pipelines (Kannan et al., 2018).

The microbial communities associated with MIC are diverse and comprise multiple species including sulfate-reducers, acid-producers, methanogens, and iron reducers, that form biofilms (Geissler et al., 2014). These microbial communities and their by-products interact with other corrosive compounds/ions and the metal to result in MIC. As MIC is a complex process, several mechanisms for MIC have been proposed. Though there is a lack of consensus on the MIC mechanisms, chemical microbiologically influenced corrosion/electrical microbiologically influenced corrosion (CMIC/EMIC) and biocatalytic cathodic sulfate reduction (BCSR) have been proposed as possible mechanisms for MIC (Kip and van Veen, 2015).

Currently the ability to predict MIC is hampered by knowledge gaps in the formation of biofilms associated with MIC, the underlying MIC

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mechanisms and corrosion rates, understanding of the effect of microbial growth kinetics on corrosion, and the combinatorial effect of multiple functional groups like corroding metal composition, water chemistry, and environmental conditions (Skovhus et al., 2017a,b). Nevertheless, few models like the Checworks predictive model (CW), the Union Electric Callaway MIC index (UE) model, the Lutey/Stein MIC index (L/S) have been proposed for assessing the susceptibility to MIC and quantitatively predicting the likelihood of MIC occurrence (Skovhus et al., 2017a,b). However, these models do not reflect the current state-of-the-art knowledge that MIC is mediated by the interaction of multispecies biofilms (comprising microorganisms beyond sulfate reducers and acid producers) with metal. Further, these models employ non-Bayesian approaches and cannot integrate information about microbiology, corrosion, and physical and chemical environment. Hence, comprehensive and new Bayesian models are required for predicting susceptibility to MIC. The susceptibility of MIC is interpreted statistically utilizing the descriptive statistics of mean and standard deviation of the model's output which is in the form of a distribution. Additionally, two metrics the percentage of MIC susceptibility and the confidence of information of the data utilized in the model are introduced in for the interpretation of the results based on the model developed in this work.

A Bayesian network (BN) model consists of nodes representing variables and directional edges representing dependencies. BN is commonly used to model a (acyclic) causal structure of system variables with limited data having high uncertainty. BN models are usually utilized where model validation is challenging. Credible and robust BN models are built using a logical and flexible framework combined with expert experience and system data (Chen and Pollino, 2012). Bayesian networks have been utilized in models to study sub-sea pipeline reliability and extensive fault diagnosis (Cai et al., 2016; Cai et al., 2017; Cai et al., 2020). BNs utilize Bayesian inference to update the likelihood of an event based on the aggregation of information from multiple sources about the state of the system. BN's have been used in conjunction with layer of protection analysis (LOPA), fuzzy models, fault trees, and other risk assessment techniques to handle uncertainty (Khan et al., 2015). This ability of BN to illustrate and update complex interactions allows for a powerful and versatile tool for reasoning in a complex multi-level interaction situation like in MIC (Weber et al., 2012). Bayesian networks (BN) are specifically utilized in this work since the modeling of MIC faces challenges of a complex system and lacks high-fidelity data to build a first principle model. Many of the existing decision support tools leverage only high-level heuristic observations and correlations which do not capture the causative interactions which have been observed mainly in lab-scale studies. Utilizing BN allows us to scale the results obtained from laboratory studies to industrial settings where there is a possibility to train the model with data to obtain a better insight into the system behavior.

BN models have been recently applied to the analysis of MIC. Ayello et al. utilized a BN approach for estimating internal and external corrosion in pipelines and incorporated a MIC sub-model into the framework that included the presence of sulfate reducing bacteria (SRB) and conditions promoting SRB growth (Ayello et al., 2014). Although the model leverages data from several abiotic factors for uniform and localized corrosion, the resolution of the model on the parameters impacting MIC is limited. Koch et al. used BN models to investigate the impact of corrosion on carbon steel crude flow lines by incorporating the presence of general aerobic and anaerobic bacteria and the presence of sulfides, although it is unclear how the abiotic and biotic factors are directly associated in this model (Koch et al., 2015). However, the authors validated their findings using operational data from Abu Dhabi Company for Onshore Oil Operations. Shabarchin and Tesfamariam utilized Bayesian-belief based assessment method for internal corrosion of oil and gas pipelines that included a MIC sub-model comprising of operational factors such as pigging, water conditions, use of biocides, and bacterial presence (Shabarchin and Tesfamariam, 2016). However,

this model does not account for the metabolic capabilities of microorganisms and the association between abiotic and biotic factors. Bhandari et al. utilized Bayesian belief network to model pitting corrosion as a consequence of environmental factors and presence of SRB (Bhandari et al., 2016). Although it is unclear how the presence of SRB was uniquely related with MIC, the corrosion rate predicted using this approach agreed with experimental data and thus promising.

The utility of a systems-based model is to expose the biochemical interaction in the context of the exogenous environmental factors represented by fluid flow physics, and compositional variations in the micro-environment. By utilizing a Bayesian approach in conjunction with the systems based modeling, it provides a platform to develop an algorithmic approach to model the state of MIC in a corroding system. The model itself is constituted of components (such as failure analysis history, materials property, maintenance history, and operational data) which synthesize information based on the physical understanding between the input variables. The synthesis is performed by selecting stochastic distributions in these components which approximate the interaction between the inputs to generate outputs used in the next iteration of calculation. By improving the quality of inputs (data from the system) and tuning the stochastic distributions (by observation and validation), this approach has the potential to be a 'learning system', i.e. the accuracy and precision of the model to represent the state of MIC improves over time.

Learning systems that leverage operational data for MIC threat ranking are required, given the unpredictable nature of microorganisms and highly-variable microenvironments associated with MIC (Skovhus et al., 2017a,b). A recent paper on modeling of MIC notes the need to integrate knowledge from failure history, biotic and abiotic factors along with molecular microbiological assessment tools and inspection data to make better predictions (Wolodko et al., 2018). More recently, Mohammed et al. developed a Bayesian network model to determine the potential to MIC using factors related to operations and history, fluid chemistry, materials, settlement, corrosion mitigation and microbiology (Taleb-Berrouane et al., 2018). However, this model does not account for failure analysis history and the use of dynamic BN for estimating the susceptibility to MIC.

The objectives of this paper are to use a BN model to integrate the knowledge of failure analysis history, materials properties, operational data, and maintenance history to determine the susceptibility to MIC. First, a static BN model was used to determine the susceptibility to MIC using twelve different scenarios. Next, this model was modified to a dynamic BN (DBN) to predict susceptibility to MIC using five time-dependent parent nodes.

2. Methods

2.1. Bayesian network development

A BN consists of parent nodes (P) which are connected to child (C) nodes directly or through intermediate nodes (I). Parent nodes have unconditional probability determined either through data, or through the heuristic elucidation (Barua et al., 2016). In this paper, the systems-based approach combining abiotic and biotic factors, along with the efficacy of detection was represented by historical data is implemented in BN using the GENIE software platform (academic version, developed by Bayes Fusion LLC) (BayesFusion, 2017). Scenario assessment was performed by selection of 'states' or observations for each parent node to ultimately estimate the probabilities for each of the scenarios. This paper utilizes two distinct representations of the systems-based model: a static model which presents a snapshot of the factors influencing the final outcome of MIC likelihood, and a dynamic model which is an extended static model that is utilized to provide temporal variability.

The systems model developed in this work utilized 60 parent nodes that represent the variables and were selected based on their established

contribution and influence towards MIC (details in **Supplementary Information**). The nodes include tools used to evaluate MIC and variables measured such as temperature, pressure and concentration of gases and corrosion products from affected sites. The model architecture is based on the assumptions that the relationship of the parent nodes with the child nodes is exclusively determined by their impact on the MIC likelihood. The distributions chosen for these nodes were used to demonstrate these interactions. However, extensive field implementation of this model requires elaborate experiments and field-based data to determine the shape and domain of these stochastic functions.

All the factors affecting susceptibility to MIC were categorized into four groups-failure analysis history, materials property, maintenance history, and current system's operational data. Failure analysis history is accounted through data obtained by techniques that include microscopy, chemical, electrochemical characterization. Emphasis was given to tools relating to the biological characterization of the system. These include bug bottle tests, adenosine triphosphate (ATP) tests, polymerase chain reaction (PCR) methods, DNA sequencing and the microbial metabolites identified through mass spectrometry (MS) methods. Chemical characterization of corroded surfaces and corrosion residues are primarily represented by nodes which account for data from spectrometric and surface characterization methods. Electrochemical methods are represented by nodes of electrochemical impedance spectroscopy (EIS), linear polarization resistance (LPR), and other polarization based tools like cyclic voltammetry. The maintenance history of the corroding system is captured through nodes that account for activities such as pigging from pigging frequency and efficacy. The current operational data node is used to capture and synthesize information obtained about chemical treatment strategies used and information about biotic and abiotic variables impacting MIC. Because MIC is influenced by microbial activity, biotic node was given higher weight than chemical treatment and abiotic nodes. Abiotic node calculates the information obtained from chemical composition of the system, physical conditions of the system, information from electrochemical sensors or coupons placed in the system, in-line inspection results, composition of gas in the system, presence of corrosion products, and solids chemistry. Biocides and corrosion inhibitors are chemical treatment methods used to mitigate MIC and the effectiveness of chemical treatment methods were also included in the systems-based model. Each of the different parent nodes provide information with varying degrees of impact on the final outcome. Weights were assigned to each parent node to represent their effect on the outcome of their child nodes. The weighted averages of the parent nodes were used to calculate the mean value of the child nodes. It is noted here that attributing the weights is only performed approximately since they are based on heuristic estimates. The weights corresponding the parent nodes are listed in **Supplementary Information**.

2.2. Scenario development for static network

The results obtained by executing different scenarios in the BN provide a comparative narrative based on the availability of data and the conditions observed in the field. Due to the lack of an openly-accessible database with different MIC scenarios, the scenarios used in this paper are developed by utilizing data from papers by [Fichter et al. \(2015\)](#) and [Alabbas et al. \(2017\)](#), published on case studies related to MIC. A three-level resolution, comprising low, medium and high, was selected for all the parent and intermediate nodes. The child node, susceptibility to MIC, has five level resolution ranging from very low to very high. The specific levels selected for the parent nodes are available in **Supplementary Information**. The mean of each of these scenarios was normalized with the maximum possible value of mean to obtain percentage in MIC susceptibility. The mean of susceptibility to MIC is a value between 0 and 2 and hence, the percentage of MIC susceptibility is calculated as follows:

Percentage of MIC susceptibility = (Mean of susceptibility of MIC x 100)/2.

Additionally, to elucidate the availability of the data used for scenario development, a new variable, confidence in information was introduced. This variable is calculated as the percentage of the number of nodes used for running the scenario as compared to the total number of nodes in the model. This is to emphasize that due to the extensive scale of input variables (60), it is expected that in industrial implementation, data might not be available for some of the input nodes. This provides for the ability to compare the MIC susceptibility between scenarios which might utilize different number of input nodes. So, if all the nodes are used the parameter value will be 100%, but of course the accuracy of the answer still depends on the accuracy of the values determined and on the validity of the causal network. Hence, it is a relative metric. In other words, the confidence of information factor utilized in this work is only to capture the availability of information and not the quality of information.

Confidence in information (%) = (Number of nodes utilized for running the scenario)/Total number of nodes in the model) x 100.

2.3. Systems based model implementation using a dynamic Bayesian network

The versatile ability of a systems-based model to be time-dependent is demonstrated using a time-dependent Bayesian network. The time-dependency was introduced using a step-wise approach with five parent nodes: field PCR, iron carbonate, water cut, hydrogen sulfide concentration, and wall thickness. These nodes were selected as examples due to known dependencies with time and as observed in field studies. Additionally, they are a representation of the externalities that remain a challenge in MIC prediction. For example, the water cut is a consequence of the formation type, oil field characteristics, and method of recovery of oil and gas that is independent of any MIC related process. A time-dependent snapshot of their behavior was generated by placing arcs between the current time (T) and future time stamps of T+2 (years), T+5 (years), and T+10 (years) as depicted in [Fig. 1](#). This time-dependency was propagated to the outcome of top-event (susceptibility of MIC) outcome by providing each of the child nodes a temporal dependency, which were connected using appropriate arcs. A limitation in this implementation, is that the dynamic (parent) nodes, are dependent on the static nodes in sub-models. This was the outcome of limiting the complexity and reducing computational demand.

The choice of the distribution should ideally capture the behavior of the variable in the environment and should be a consequence of the physics of system. A Weibull distribution was chosen for the parent nodes to be a proximate representative. It should be noted that the distribution chosen here is to demonstrate the model, and other distributions such as normal, uniform, multi-parametric distributions may also be implemented if they are found to be representative of the input variables behavior. The Weibull distribution with its shape and scale parameters demonstrates sub-exponential behavior which is advantageous to capture heavy-tailed distribution by modifying the parameters of the stochastic function. This property is attractive to capture low-likelihood events (events in the tails) commonly seen with MIC failures. The domain of the distribution was between [0, 2]. Two levels of evidence in the fixed domain of the parent nodes were utilized, a low-level of evidence of 0.2 and a higher level of evidence of 1.8. These were chosen to capture the behavior of the function on 10% and 90%, hence close to the limits imposed by the domain of the function. The model was simulated using Monte Carlo simulations with 10,000 iterations for every point of external evidence (point of observation).

3. Results

3.1. Bayesian network structure

The overall goal of this work was to develop a model that can be used for deriving a quantitative measure of MIC susceptibility of a system

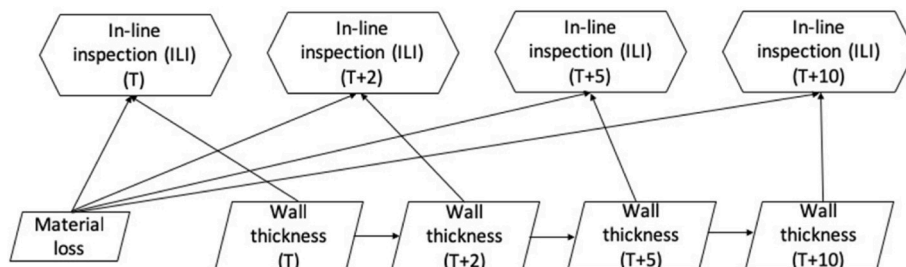


Fig. 1. Schematic of time dependency incorporated for the wall thickness parent node in the MIC model. The node shape does not indicate the type of the node.

(Fig. 2). All the factors affecting MIC susceptibility were categorized into four groups: failure analysis history (Fig. 3), material properties and maintenance history (Fig. 4), and current system operational data (Figs. 5–7).

3.2. Static Bayesian network

A total of 12 scenarios were generated based on cases obtained from literature. The state of the observables was determined based on author's knowledge and expertise (details in **Supplementary Information**) and utilized to generate susceptibility measures for MIC. These were then interpreted in the context of the actual field observations reported for these scenarios. A summary of the model simulation results is given in Table 1.

Scenario 1 corresponds to samples collected from sour gas wells. Because of the extreme conditions associated with the system and no microbial growth, the system was assumed to be corroding with abiotic mechanisms. Using the available information, 60% MIC susceptibility was obtained with 23% confidence. Scenario 2 represents observation from samples collected from an oil and gas production system. This system had reported minimal issues with MIC but had multiple false-positives for microorganism growth with culture-based tests. The model predicted 51% MIC susceptibility with 13% confidence. Scenario 3 was generated from data from a produced water system. This system reported high growth of SRB due to mixing with fresh water containing high sulfate levels. The model estimated 54% MIC susceptibility and was obtained with 12% confidence. The observed value of MIC susceptibility is not as low for scenarios 2 and 3 because the system could still have potential to develop corrosion issues in the future based on the variables measured. Also, the confidence in information is very low, indicating that further testing and assessment should be conducted to better

evaluate and track MIC.

Scenarios 4 and 5 correspond to all the parent nodes given observations of high and low respectively to establish the bounds for the mean of the distribution corresponding to the susceptibility of MIC. Because all the nodes were used, the confidence in information is 100% as expected.

Scenario 6 was developed based on a major leak caused by deep localized pitting on the outlet of high-pressure production traps seen at gas oil separation plant. This was reported to be due to the under-deposit corrosion and MIC. A 58% MIC susceptibility was obtained with 28% confidence. Scenario 7 provides insights to failures of heat exchangers caused by deep pits in a refinery's seawater cooling system. When the results from the assessment tools were used in the MIC model, 47% MIC susceptibility was obtained with 17% confidence. Scenario 8 corresponds to failure of a nozzle in fire hydrant system caused by stress corrosion cracking (SCC) accelerated by microbial activities. The model estimated 50% MIC susceptibility with 8% confidence. Scenario 9 is from an instance of failure of a diesel shipping line due to deep localized pits possibly because of MIC. A MIC susceptibility of 54% was obtained with 17% confidence. Scenario 10 is related to samples collected from a failed heater treater fire tube in an oil shale field. This system reported MIC even though the tube was exposed to extreme conditions. Again, 54% MIC susceptibility was obtained with 18% confidence. In scenario 11, samples collected from oil-based muds from a drilling rig were analyzed for MIC related indicators. A 56% MIC susceptibility was obtained with 15% confidence. Water-based muds from a drilling rig were gathered and their composition was investigated resulting in the development of scenario 12. A 53% MIC susceptibility was estimated with 15% confidence. The slightly higher MIC susceptibility for oil-based muds than water-based muds is a direct consequence of the abundances of the microbial species associated with MIC.

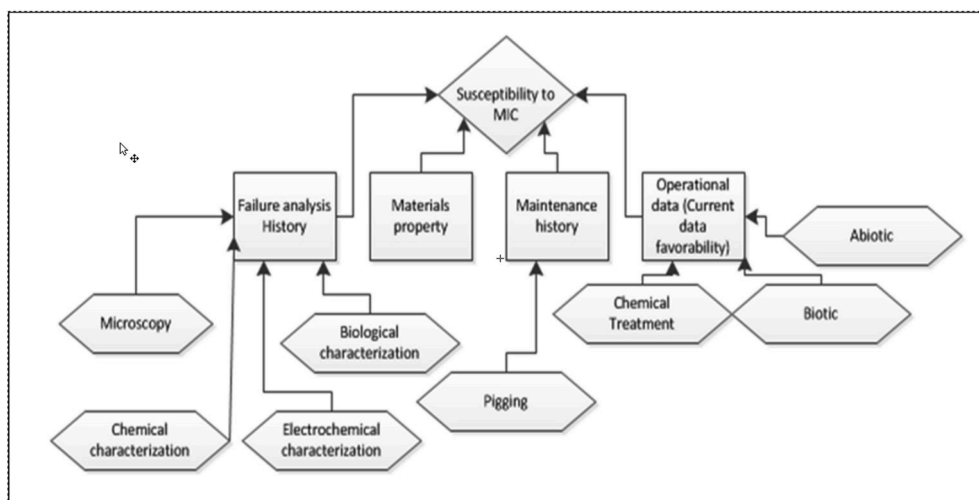


Fig. 2. Schematic of the model for prediction of susceptibility of MIC combining historical and operational data implemented with a Bayesian network. The node shape does not indicate the type of the node.

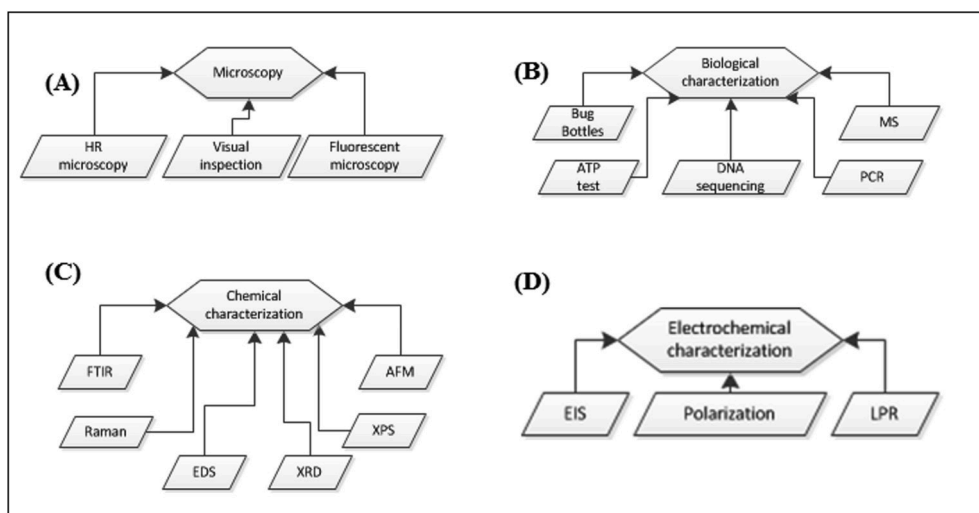


Fig. 3. Schematic of the sub-model with parent nodes for data from past failure analysis. The node shape does not indicate the type of the node.

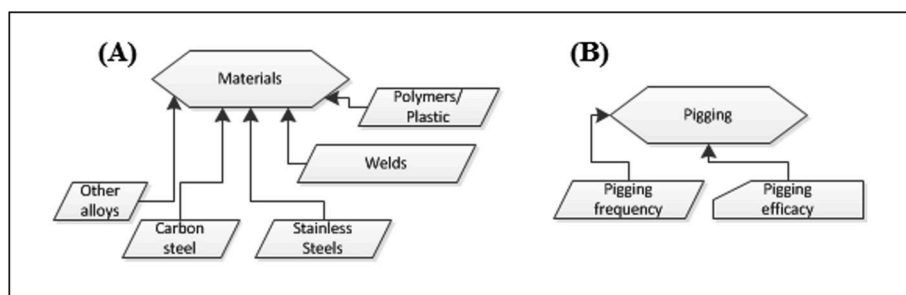


Fig. 4. Schematic of the sub-model for materials and maintenance. The node shape does not indicate the type of the node.

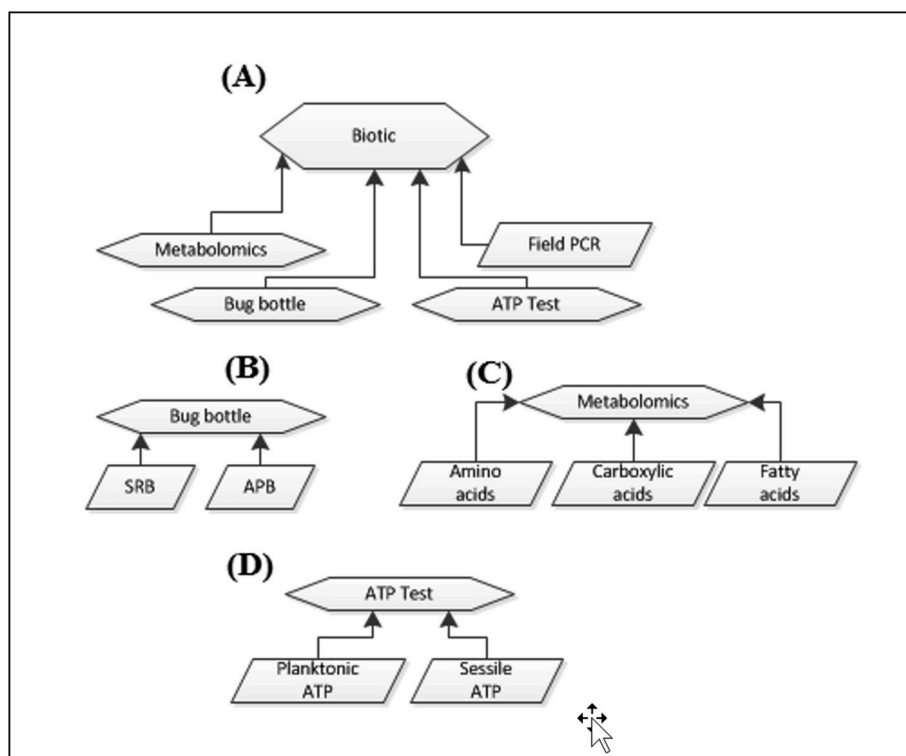


Fig. 5. Schematic of the sub-models for the biotic node utilized for the favorability of current data. The node shape does not indicate the type of node.

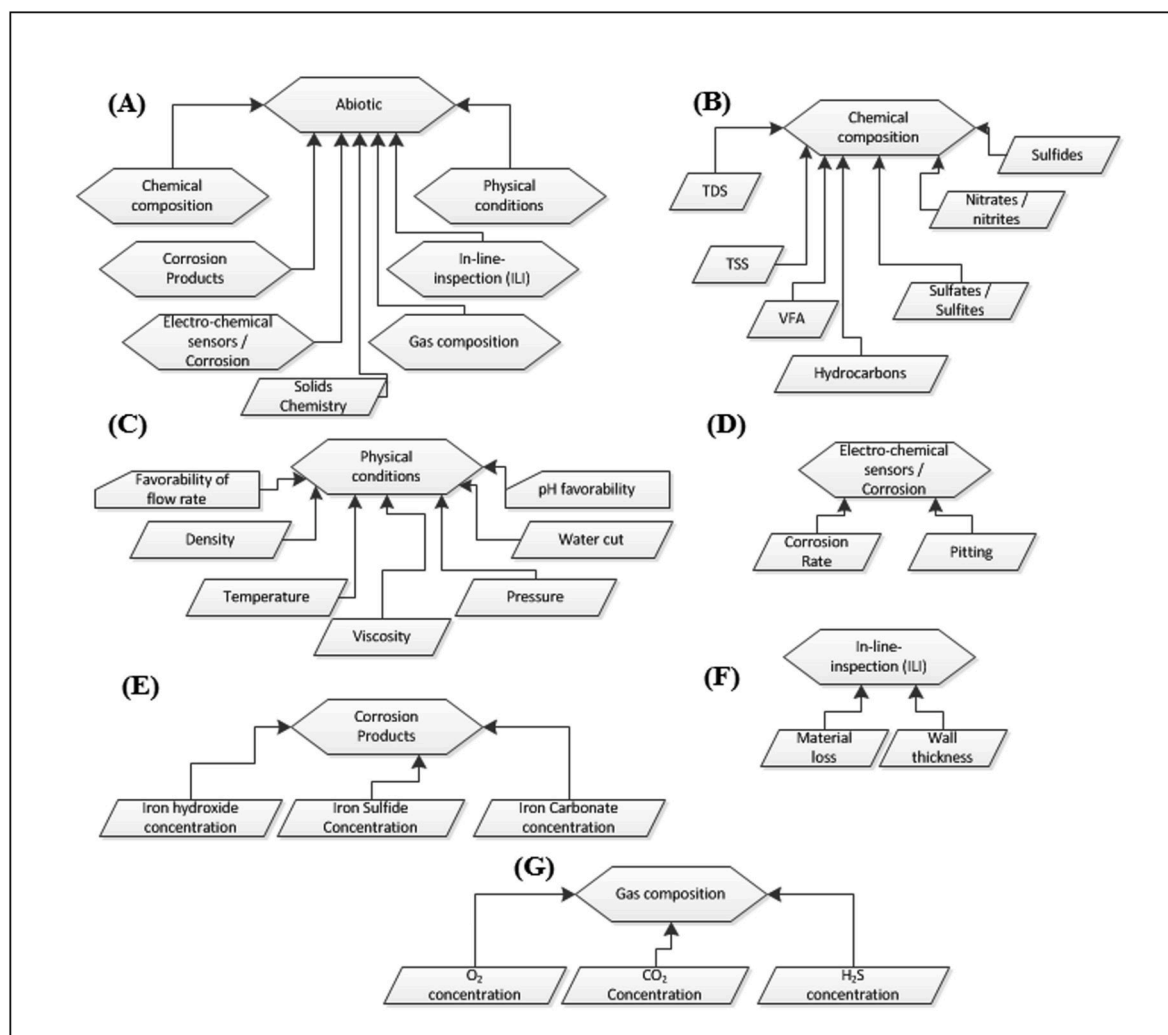


Fig. 6. Schematic of the sub-model for the abiotic node utilized for the favorability of current data prediction. The node shape does not indicate the type of node.

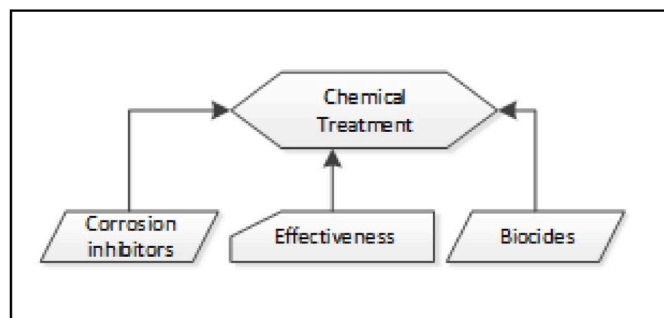


Fig. 7. Schematic of the sub-model for the chemical treatment node utilized for favorability of current data prediction. The node shape does not indicate the type of node.

3.3. Dynamic Bayesian network

As mentioned earlier, the distributions and the weights chosen in the implementation of the model are based only on heuristics and a general demonstration basis. To evaluate the propagation of *evidence* (which in field implementation would be an observation or a data point), two levels of *evidence* in the fixed domain of the parent nodes were utilized (a low-level of evidence of 0.2 and a higher level of evidence of 1.8). The X-axis in all the outputs represents the domain of the function utilized to

Table 1

Predictions of MIC scenarios utilizing MIC-Model implemented in BN.

SCENARIOS #	Susceptibility to MIC		Percentage of MIC susceptibility (%)	Confidence in information (%)
	Mean	Standard deviation		
1	1.201	0.173	60.05	23.33
2	1.027	0.198	51.35	13.33
3	1.083	0.196	54.15	11.66
4	2.000	0.119	100.0	100.0
5	0.001	0.117	0.050	100.0
6	1.153	0.192	57.59	28.33
7	0.939	0.191	46.93	16.67
8	1.005	0.201	50.24	8.333
9	1.078	0.200	53.92	16.67
10	1.077	0.195	53.83	18.33
11	1.126	0.198	56.30	15.00
12	1.067	0.199	53.33	15.00

model the node in the BN network. The height of the histogram represents the outcomes/outputs of the simulation to estimate the effect of the evidence over the domain, and they are binned into 5 discrete intervals for the sake of clarity. The Y-Axis signifies the percentage of the outputs (of the Monte-Carlo iterations) that are present in each discrete interval.

The simulations revealed a complex interdependency with MIC susceptibility as seen in Figs. 8–12. The mean of the distribution of the overall outcome (MIC susceptibility) follows a descending trend with

increasing time, uniformly for both the lower and higher level of evidence. However, this is a probable artifact of the choice of distributions (which as explained earlier are not based on specific physical models). Interestingly, we observe that there is a perceptible but nominal skewness towards the tail, observed for the top event distribution with time. This would be a behavior expected in corrosive systems with time, as the degradation activity has the ability to act as a self – accelerating reaction. For example, as the wall-thickness decreases with time, the MIC failure susceptibility will increase with time. Also, to be noted here, is that the simulations were performed with the change of each node tested independently. Hence, interdependencies between the time-dependent behavior is not captured.

4. Discussion and conclusions

The BN model presents a cohesive structure to account for three challenges faced with traditional MIC models by accounting for quality and source of historical MIC data, providing a structure to incorporate first-principle models of physics and biochemical interactions, and providing a method to account for time-dependent changes to enhance the accuracy and precision of the model. The time-based dependency of BN was captured using a modified systems based model, which enabled

the ability to discretely store and capture the state (value) of selected variables over a period of time. The MIC model developed here addresses several gaps associated with currently used MIC models by enabling a comprehensive and clear association between the abiotic and biotic components of MIC. Further, this model focusses not only on the data generated by the tools used to detect and assess MIC, but also on the tools used for MIC analysis. This is equally important because molecular microbiological methods such as sequencing and PCR can provide more detailed information than traditional assessment methods like culturing (Wolodko et al., 2018).

The BN model allows for better visualization of the interdependencies in the variables affecting the presence of propagation MIC especially because there is no single mechanistic model that captures all the biochemical interactions in the corroding micro-environment. The data from off-site tools generated by independent laboratory analysis are also integrated with pressure, temperature and metal composition, thus removing siloed assessments of the different variables used to evaluate the susceptibility of MIC. In this work, these were integrated into both the current operational data and the failure history sub-models, which allows users to input historical archived, recorded instrument, and routine maintenance data. Hence, this allows the MIC model to account for the diverse data resources by providing

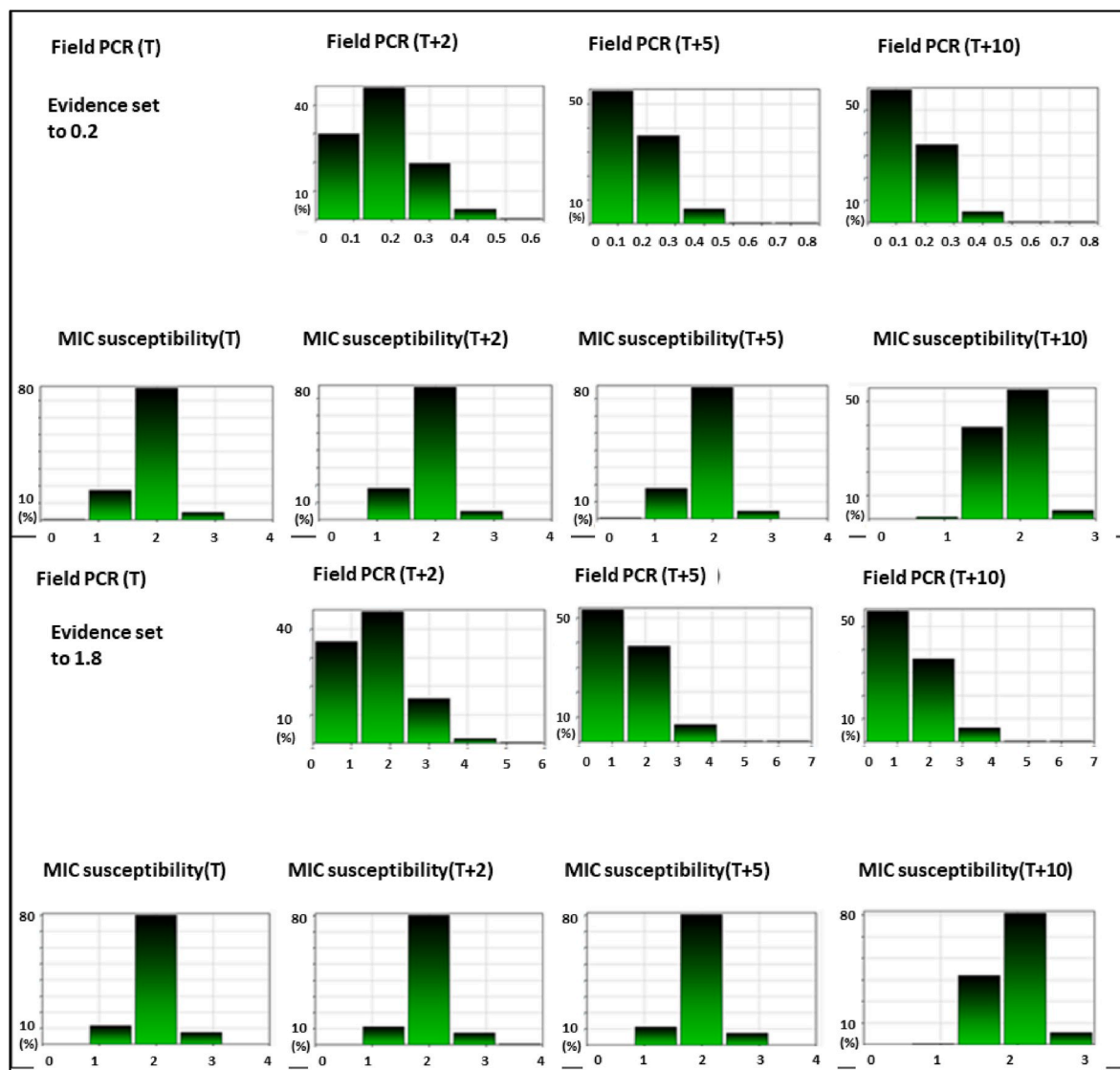


Fig. 8. Temporal changes to field PCR and MIC susceptibility nodes predicted with dynamic BN when a certain evidence is set for field PCR (T).

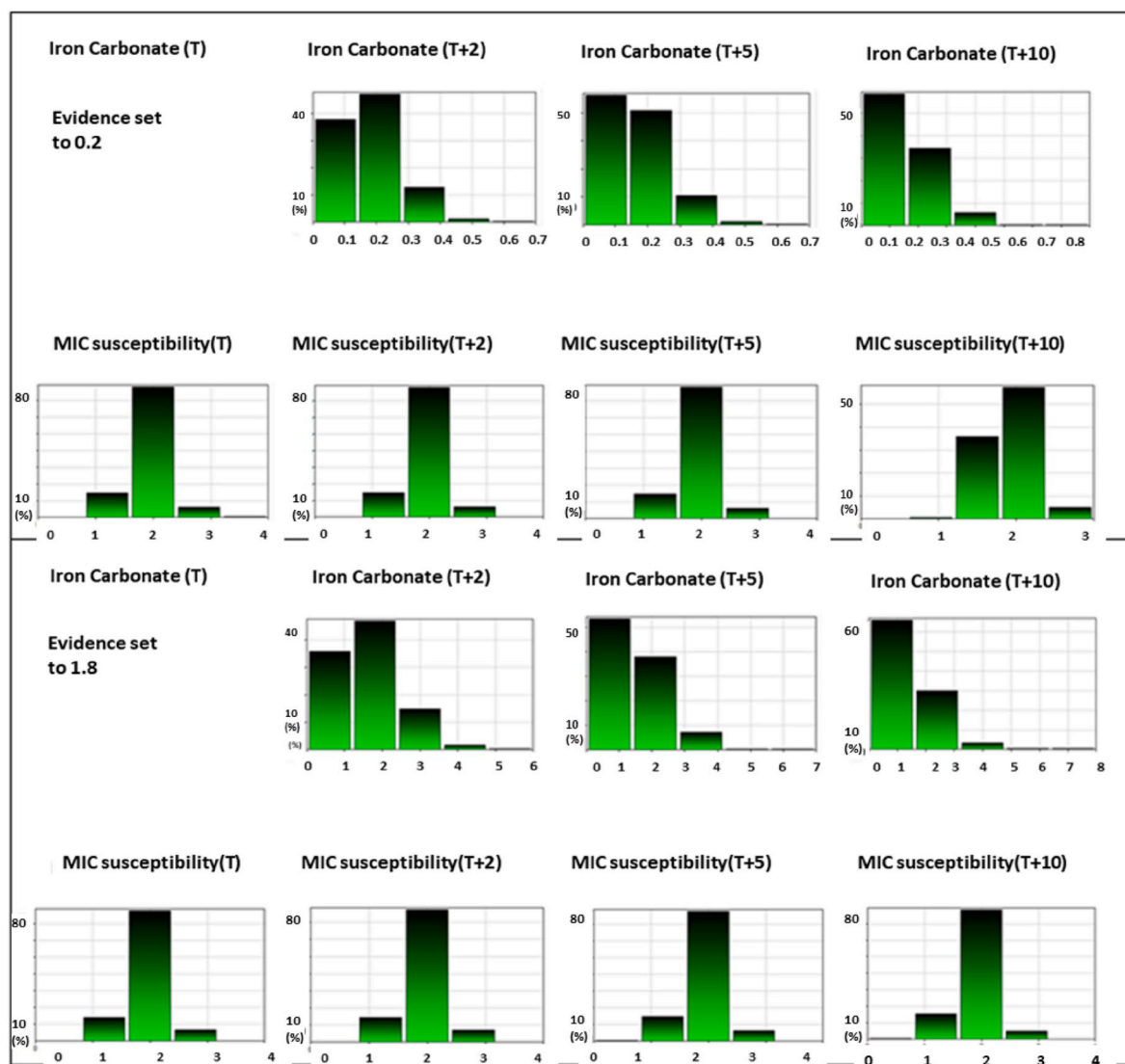


Fig. 9. Temporal changes to iron carbonate and MIC susceptibility nodes predicted with dynamic BN when a certain evidence is set for iron carbonate (T).

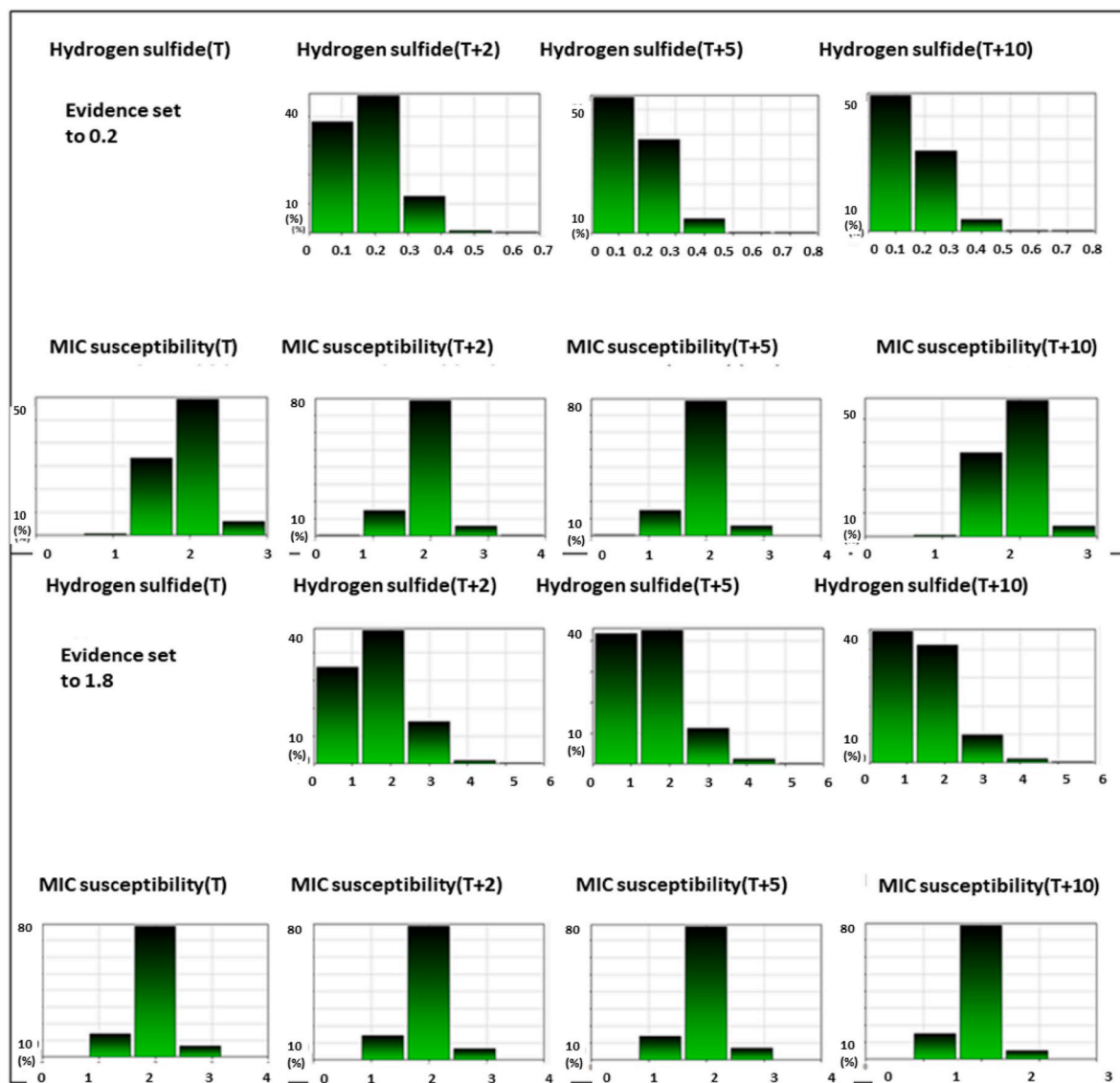


Fig. 10. Temporal changes to hydrogen sulfide and MIC susceptibility nodes predicted with dynamic BN when a certain evidence is set for hydrogen sulfide (T).

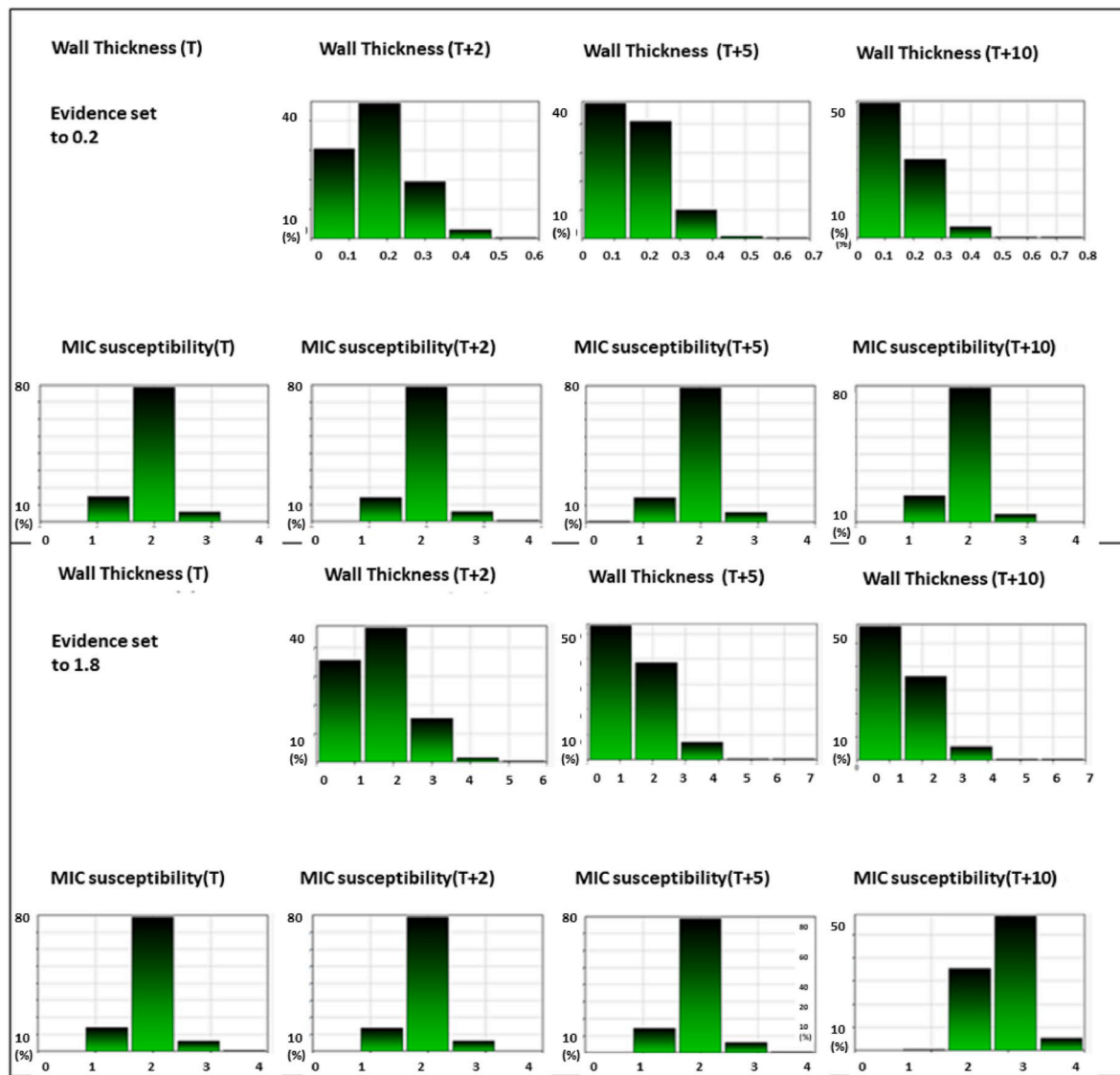


Fig. 11. Temporal changes to wall thickness and MIC susceptibility nodes predicted with dynamic BN when a certain evidence is set for wall thickness (T).

users with 60 independent data sources which are integrated ultimately to assess the susceptibility of MIC in the system. This model is based on the current understanding of causal and proximate factors allowing wider flexibility compared to the other existing models (Ayello et al., 2014; Koch et al., 2015). The next iteration of the model needs to focus on improving the synthesis of information which currently rely on approximate stochastic functions to more reliable experimentally determined causative equations. This model provides a highly granular view, to allow for the experimental investigation of the independent variables affecting MIC. Manipulating the physical micro-environment, microbial community, and the materials of construction will yield more accurate correlations which can then be incorporated in future iterations of this model. Alternatively, the model can be improved by parametric testing of the distributions and validation from field observations in systems impacted with MIC.

By utilizing the ability of the network to update the conditional probabilities as a consequence of the interaction between the various factors, users can get insights into the evolution of the system from a multi-dimensional perspective, as compared to unidimensional data, such as either presence of SRB or higher flow rate. The current model can be implemented as a standalone MIC threat assessment tool for

pipelines and tanks. However, a broader use for this framework is envisioned as a sub-model in comprehensive threat assessment models which extends to other forms of corrosion and non-corrosion threats. Additionally, it should be noted that the current model is built on reviewed and empirical studies, and although it integrates multiple causal factors, the arcs of influence are built on the explicit understanding of their impact. Hence, the inter-network complexity is limited in this network, but with improved understanding of mechanisms these relationships can be introduced. The current model also provides an additional insight into the susceptibility of MIC predictions by providing confidence in the information parameter, which assess the magnitude of utilization of the data to generate the probability estimates. This provides a useful metric especially for operators who may have access to multiple data streams to implement methods to integrate it into the threat assessment model.

The Bayesian network-based modeling described here can be used by operators to determine the susceptibility of their assets to MIC. Based on the calculated value of percentage of MIC susceptibility, appropriate actions should be taken. For a moderate to high value of percentage of MIC susceptibility, appropriate mitigation should be considered and implemented to reduce the MIC threat. For a low value of percentage of

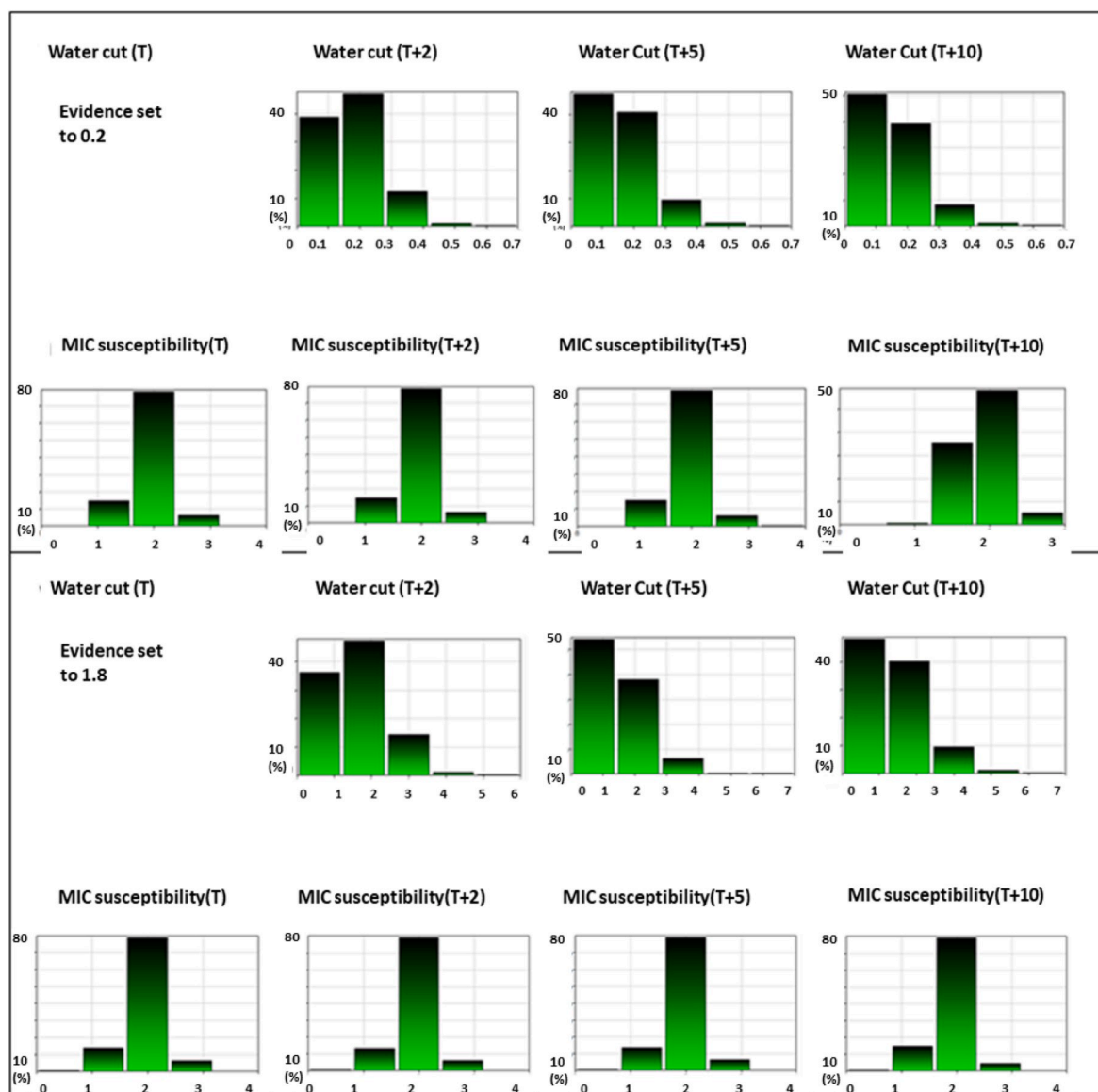


Fig. 12. Temporal changes to water cut and MIC susceptibility nodes predicted with dynamic BN when a certain evidence is set for water cut (T).

MIC susceptibility, the susceptibility of MIC should be monitored periodically to ensure that MIC threat has not changed.

As this model is limited by the lack of open-source operational data for validation, case studies based on existing reports of MIC in oil and gas systems were utilized for validation. Further validation and calibration of this model can be executed with available data. The weights used for determining the relationships between the parent nodes and the dependent nodes are based on the heuristic understanding of the relative impact of the parent nodes. There are further opportunities to improve the weightage scheme with access to operational and historical data by utilizing regression tools to improve the quality of the estimates.

The implementation of the MIC model using the dynamic Bayesian network provides a unique platform to capture temporal dependencies in parent nodes. The changes in the skewness observed time (future prediction for time points T+2, T+5, T+10) demonstrate the ability to capture typical temporal changes as manifested by the change in the distributions. This is important since MIC as a phenomenon is highly influenced by environmental perturbations. Any prediction of MIC likelihood based on the discrete evidence at fixed time-points have likely limitations due to the lack of fidelity and non-representational nature

with actual conditions. Additionally, the threat of artifacts generated by decisions related to distribution selection for the nodes (normal, Weibull or any other) and heuristic understanding are observed, and the improvement of the model is dependent on incorporating physics and bio-chemical first principle models as the basis for distribution selection. These first principle models are typically obtained using experimental approaches that are segmented independent studies of the dependencies and hence allowing them to be incorporated with limited heuristic bias going forward. Furthermore, operational data can be used for improving the connection between the nodes and for utilization of dynamic Bayesian approaches to alleviate the limitations of the acyclic graphs and to enable implementation of this model into abiotic corrosion threat models.

Declaration of competing interest

We have no conflicts of interest.

CRedit authorship contribution statement

Pranav Kannan: Formal analysis, Writing - original draft. **Susmitha Purnima Kotu:** Formal analysis, Writing - original draft. **Hans Pasman:** Writing - review & editing. **Sreeram Vaddiraju:** Supervision. **Arul Jayaraman:** Supervision. **M. Sam Mannan:** Conceptualization.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jlp.2020.104108>.

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