

Comparison of Model Predictions and Field Data: The Case of Top of the Line Corrosion

Ussama Kaewpradap,* Marc Singer,^{†,*} Srdjan Nesic,* and Suchada Punpruk**

ABSTRACT

Top of the line corrosion (TLC) is a specific type of corrosion that occurs due to internal water condensation in wet gas lines. It is a serious concern for the oil and gas industry and has been the cause of numerous pipeline failures. Many research projects have been executed with the aim of better understanding the mechanisms and developing accurate predictive models of TLC. Irrespective of their complexity, most of the models are based on laboratory experimental data. This makes it important, even in the case of most advanced models, to compare and validate a model's predictions using field data. Data collected from sweet wet gas lines that experienced TLC issues were analyzed, processed, and then used as an input for a mechanistic TLC predictive model to simulate the evolution of temperature, pressure, water condensation rates, and TLC rate along the pipeline. The simulation results were then compared with in-line inspection (ILI) data. Challenges were encountered in the analysis of the field data due to their incompleteness, inaccuracy, and variability as well as in the processing of the ILI data. A coherent methodology for comparison with model prediction results was developed and described.

KEY WORDS: field data, magnetic flux leakage data, modeling, top of the line corrosion

INTRODUCTION

TLC is associated with numerous pipeline failures and is a growing concern for the oil and gas industry.¹⁻⁶ TLC is encountered under water condensing conditions in wet gas pipelines operated in a stratified flow regime at low gas velocity. Water, along with the light hydrocarbons, condenses on the top and the sides of the inner pipeline surface due to the temperature difference between the external and internal pipeline environments. Carbon dioxide (CO₂), hydrogen sulfide (H₂S), and volatile organic acids make this condensed water especially corrosive.⁷⁻⁸ TLC has been intensely studied over the past decade with the aim of better understanding the underlying corrosion mechanism in order to develop accurate prediction models and successful mitigation techniques.⁹⁻¹⁵ Different corrosion prediction models have been proposed with varying degrees of complexity and sophistication. In all cases, there is a wide gap between development of corrosion models in academic and research institutions and their application in the field. In order to bridge this gap, model performance must be validated with actual pipeline TLC failures in the field.

In 2010, Gunaltun, et al., presented a first attempt to compare TLC prediction model results with field data measurements.¹⁶ In theory, a top of the line environment constitutes a prime candidate for comparing field measurement and model predictions, as the chemistry of condensed water is relatively simple and is not altered by the complex brine composition encountered in the bulk liquid phase. However, a purely mathematical/statistical approach cannot be used

Submitted for publication: August 17, 2016. Revised and accepted: April 20, 2017. Preprint available online: April 21, 2017, <http://dx.doi.org/10.5006/2229>.

[†] Corresponding author. E-mail: singer@ohio.edu.

* Department of Chemical and Biomolecular Engineering, Institute for Corrosion and Multiphase Technology, Ohio University, Athens, Ohio 45701.

** PTT Exploration and Production, Bangkok 10900, Thailand.

uncritically to process large volumes of field data because this tends to lead to the inclusion of poor quality data into the analysis. TLC defects, at least in sweet environments, have been reported to be made of many large “mesa attack type” features, which are governed by uniform corrosion mechanisms.¹⁷

However, in-line inspection (ILI) data often represent defects in the form of small pits. Gunaltun’s attempt to compare field data and model predictions¹⁶ highlighted numerous challenges involved with the interpretation of the ILI data and model predictions.

The present study proposes a new methodology aimed at developing a more representative set of input parameters (based on production data) and output parameters (based on ILI data), the main objective being to identify gaps in the modeling approach. The mechanistic TLC model TOPCORP™ (referred to as the “model” in the following text), developed by the Institute of Corrosion and Multiphase Technology at Ohio University, is used. Its capabilities are validated against subsea line data from an offshore gas field in the Gulf of Thailand that has been in operation since 1992. Additional details can be found in the author thesis.¹⁸

A TOP OF THE LINE PREDICTION MODEL

The theory and implementation behind the TLC model used in the current study was developed originally by Zhang, et al.¹² This model provides a fully mechanistic description of the TLC process. The three major phenomena covered by this model are as follows:

Dropwise condensation, used for condensation rate calculation based on heat and mass transfer theory.

Chemistry of the condensed water, developed from thermodynamic arguments by using chemical equilibria.

Corrosion, where the TLC rate was predicted based on the kinetics of the electrochemical reactions.

The model was adapted to run line simulations where, in order to obtain predictions along a pipeline, only pipeline inlet parameters and pipeline physical characteristics are required, as listed in Table 1. Among

TABLE 1
List of Input Parameters to the Model

Parameter Name
Inlet temperature and total pressure
CO ₂ , H ₂ S gas content
Brine composition (especially bulk water pH and organic acid content)
Gas, water and oil/condensate flow rate in standard conditions
Pipeline diameter, roughness, section length, inclination
Thermal insulation (coating concrete ...)
Burial ratio and depth

TABLE 2

List of Model’s Output Parameters

Parameter Name
pH and chemistry of the condensed water along the line
Water condensation rate along the line
Steady state uniform top of the line corrosion rate along the line

the pipe characteristics listed, the type and thickness of insulation layers and the burial ratio and depth can have a significant influence on the condensation rate and the temperature drop along the line. For example, ensuring 100% pipe burial is a very effective way to mitigate TLC. The main output parameters are listed in Table 2.

The effect of many important factors on TLC, such as gas temperature, CO₂ partial pressure, gas velocity, condensation rate, and acetic acid concentration, were accounted for in the model.¹²

However, the effect of oil/water co-condensation was not taken into account, because the research on this topic was still ongoing at the time this study was performed. Since then, recent experimental work¹⁹ has shown that the condensation of light hydrocarbons does not seem to prevent liquid water from reaching the hydrophilic steel surface. It should be noted that the experimental work was performed with only one hydrocarbon (heptane) and that the conclusions may differ if other, heavier hydrocarbons are considered. However, the mere fact that so many wet gas lines suffer extensively from TLC is a good indication that one should not rely solely on the co-condensation of hydrocarbons for corrosion mitigation.

A METHODOLOGY FOR COMPARING MODEL PREDICTIONS WITH FIELD DATA

There are many challenges that need to be overcome when directly comparing ILI data and model predictions. They can be classified into three main groups as follows:

Issues Related to the Accuracy of Field Data

Availability, completeness, and accuracy of production data.

Significant variations in production data over time.

Availability and accuracy of topographic data, environmental conditions, and pipeline properties.

The mechanistic model used in this study is only sensitive to a set of basic input parameters such as production rates, temperature, pressure, etc. These input parameters can vary tremendously over the course of a field’s production life. The level of uncertainty and inaccuracy related to these data can be significant and represents the most difficult challenge in the analysis. For example, decades of production

history should not be averaged to get one single set of input data (i.e., one average pressure, one average temperature, one average gas flow rate, etc.). In addition, the topography (pipeline inclination), bathymetry (pipeline burial), and information about the outside environment (on/offshore, outside temperature) are essential for calculation of the condensation rate and TLC corrosion evaluation. Finally, any additional changes affecting the operating conditions, such as injection of corrosion or scaling inhibitors, commingling of flow streams, or production shut-downs, must also be taken into account.

Issues Related to the Model Predictions

Which model prediction data should be compared with the ILI data?

How should variations in production data over time be incorporated into the prediction?

How should the change in conditions and TLC rate along the pipeline be reflected in the model?

Even though the model has been developed to predict transient corrosion, it suggests that a uniform steady-state TLC rate is typically obtained in a matter of weeks or months.²⁰ While production parameters vary continuously, these variations are also only significant on a monthly basis. It is therefore more appropriate that the model's steady state corrosion rates be compared to the wall thickness (WT) loss data obtained from ILI inspections, as long as the main corrosion mechanism is uniform (large mesa type features) and not pitting (small pits influenced by galvanic coupling). Production data are often taken on a daily basis, but it is not practical to simulate every single production data entry. In order to address this issue, longer time periods showing similarities in terms of input production parameters can be selected, and time-averaged input parameters can be defined for each time period and then fed into the model. Consequently, a thorough analysis of the production data needs to be conducted, leading to the identification of these time periods. Changes in operational parameters over time can then be accounted for, provided that a thoughtful identification of the time periods has been performed.

Issues Related to the Analysis of In-Line Inspection Data

How to take into account the inherent inaccuracy of TLC feature sizing;

Whether the size or spatial distribution of the TLC features should be considered in addition to the maximum depth of attack;

How to determine the best approach to compare model predictions with complex ILI data.

Magnetic flux leakage (MFL) testing is probably the most widely-used nondestructive testing tool (NDT) for inspecting pipeline structures in the oil and gas industry.²¹⁻²³ It is crucial to point out that MFL does not

directly measure WT loss. Rather, deviations in the magnetic fluxes are translated into defect sizing by proprietary algorithms. These algorithms vary across different tools from vendor to vendor and are continuously updated and calibrated. The performance of MFL data is strongly affected by velocity of the tool, magnetization values, and presence of pipe joints. As a result, not all ILI data are of the same accuracy/quality, although a typical accuracy on the order of 10% to 20% of the nominal WT with 80% confidence is often claimed.²⁴⁻²⁵ Typically, MFL data are presented in terms of a list of defects along the pipeline. ILI tools report defects in clockwise location on the pipe, enabling the identification of TLC-specific features between the 10 o'clock and 2 o'clock positions. Each defect is associated with a specific circumferential location and a corresponding WT loss. Additional information relating to the merger of small defects into clusters may also be available. The presence of clusters is typical of a TLC attack (at least in sweet environments) and this is where most of the wall loss occurs.¹⁻⁴ Consequently, it is important to be cautious when analyzing ILI data and to consider only the most accurate and representative data before comparing them with model simulations. An effort was developed in this sense to improve the accuracy of the MFL measurements for TLC applications.²⁶ Although ILI measurements carry some degree of uncertainty, data interpretation is by far the most critical step in the analysis. For example, a comparison between two consecutive ILI runs should be made only if the inspection and analysis are performed using the same tool and the same mathematical algorithm for analysis.²⁷ If not, this exercise cannot be expected to produce meaningful data for validation of prediction models.

Methodology for Comparing Model Predictions and Field Data

The following procedure was implemented to compare model predictions with a specific set of field data, which is described later in this paper. However, this general approach is believed to be valid regardless the selected model or the field data of interest.

Field Condition Analysis — The following procedure is implemented in the current approach:

Step 1: The evolution of the operating parameters (inlet temperature and pressure, gas/liquid flow rates) for a selected line from start-up to present is divided into a number of time periods where these parameters have relatively stable values. For each of these time periods, a simple, time-averaged value is calculated for each operating parameter.

Step 2: The values determined for the main operating parameters (inlet temperature, pressure, and production flow rates) are used to calculate water condensation rates (WCR) and

temperature profiles using a heat and mass transfer line model.¹²

Step 3: Simulations are made to obtain TLC rate predictions for a number of selected points along the pipeline. The simulation at each point is executed until a steady state corrosion rate is obtained (i.e., no significant variation of the corrosion rate with time).

Step 4: WT losses are calculated for each time period by multiplying the average corrosion rate by the duration of the corresponding time period, assuming uniform corrosion. Cumulative WT loss is then calculated for the entire operating life of the field (or for any relevant duration) and compared with provided MFL data.

In-Line Inspection Data Analysis — The following procedure is implemented in the current approach:

Step 1: Only the first few kilometers of a pipeline were considered in this study, because it is the section where the most severe TLC is typically encountered, as a result of the effect of the temperature drop along the line.

Step 2: Corrosion features in the vertical riser were not included in the analysis because they cannot be categorized as TLC.

Step 3: Only features in the upper section of the pipe (between 9 o'clock and 3 o'clock) were analyzed, because this is where TLC features are typically observed.

Step 4: ILI data obtained for features close to weld joints are notoriously noisy and thus unrepresentative. Joints were present every 12 m along the line and therefore the features located ± 0.5 m around the weld joints were eliminated from the analysis. Although it is common for the degree of attack to be more significant near weldments, this phenomenon is not TLC-specific and is not predicted by the model. It is therefore filtered out of the analysis.

Step 5: Another feature of the model is that it predicts uniform corrosion (as opposed to localized attack driven by galvanic coupling) and is therefore more representative of severe corrosion happening in the clusters than in the small pits. This is not a major limitation, as the mechanism of TLC is believed to be controlled by the chemistry of the condensed water rather than by any galvanic coupling involving corrosion products.¹⁷ Small-sized, isolated features are therefore filtered out, while large clusters are kept for the analysis. Clusters are defined as large corrosion features (where width and length are at least 3 times the un-corroded WT), following the classifications developed by the Pipeline Operators Forum (POF).²⁸ The outline of this procedure is presented in Figure 1.

Step 6: As the model has been developed to predict the most severe TLC rate, the set of data points along the line representing the maximum WT loss was retained for comparison with the simulations.

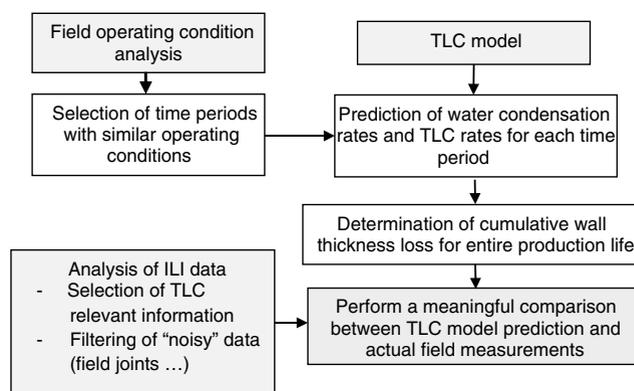


FIGURE 1. Algorithm of the selected procedure for comparison of model predictions with the TLC field data. ILI, in-line inspection; TLC, top of the line corrosion.

This set is referred to as the “maximum penetration envelope.”

COMPARISON OF MODEL PREDICTIONS WITH FIELD DATA

Part I: Detailed Analysis of Line A

Field Conditions — Field A was an offshore gas field in the Gulf of Thailand that had been in operation since 1992. Subsea lines in this field have been subjected to TLC, since production start-up, due to a highly corrosive environment. The produced gas contained 23 mol.% of CO₂ on average. The fluid temperature at the inlet of the flowline was typically higher than 80°C. With the low external environmental temperature (26°C on average), the temperature difference between the internal and external pipeline environment was quite high, leading to high condensation rate and consequently severe TLC. The field was also suspected to produce some volatile organic acid, but no water analysis was available at the time the study was performed.

The general characteristics of Line A are presented in Table 3. Changes in soil burial depth and seabed levels along the line are taken into account.

TABLE 3
Line A Characteristics

Pipeline Characteristic	Line A
Pipe length (km)	7.1
Internal diameter (m)	0.34
Pipe wall thickness (mm)	15.9
Insulation type	3LPP ^(A)
Insulation Conductivity (W/mK)	0.22
Insulation Thickness (mm)	2
Outside (sea water) temperature (°C)	26

^(A) Three-layer polypropylene coating.

TABLE 4
Brine Chemical Composition

Brine composition (mg/L)											Total acetate	Acetic acid ^(A)	pH ^(A)
K ⁺	Na ⁺	Ca ²⁺	Mg ²⁺	Ba ²⁺	Si ²⁺	Fe ²⁺	Cl ⁻	CO ₃ ²⁻	HCO ₃ ⁻	SO ₄ ²⁻	845	52	6.1
40	1958	13.4	1.6	1.4	0.4	9.8	968.1	2.4	2813.3	1.0			

^(A) Calculated values.

The fluctuations in pipeline inclination also affect predicted flow regimes. However, the flowline was fairly horizontal as the maximum elevation span was 3 m over the entire 2 km of line.

The chemical composition of the brine is shown in Table 4. A large concentration of acetate species was present in the brine (845 mg/L). However, due to the relatively high pH (6.2), only 52 mg/L of undissociated acetic acid should have remained in the brine. According to a vapor liquid equilibrium model developed in-house,⁷ only 30 mg/L to 40 mg/L of acetic acid will be present in the condensed water at the top of the line. This information was not known at the time the simulation work was performed, therefore, it does not consider any amount of acetic acid. This is not believed to have a significant effect on the corrosion prediction considering such a low concentration.

Chemical inhibition was used as the primary corrosion mitigation technique. Continuous injection and monthly batch treatment was implemented. In addition, a maintenance pig was operated before each batch treatment. For the corrosion simulations performed in this study, the effect of inhibition at the TLC is assumed to be nil.

Figure 2 shows the production variation for Line A from the start-up year (1998) to the inspection year (2005). The production data were analyzed considering the three main parameters that are believed to affect TLC: gas flow rate, inlet temperature, and inlet pressure. Three time periods of similar values were selected, although it is acknowledged that some additional fluctuations in the operating parameters still appear. The selection of each of these time periods is at the discretion of the user, who has to balance data representativeness with calculation practicality. The average values for each time period were calculated and are presented in Figure 3. They were used as inputs for the TLC model.

In-line inspection Analysis — The raw MFL data reported many defects mostly located in the first 1.5 km, as illustrated in Figure 4(a). Following the procedure described above, representative ILI data were obtained by filtering the raw data. Only features located at the 10 o'clock to 2 o'clock position were retained, and any defect located at ± 1 m of a pipe joint was automatically discarded. In addition, uniformly corroded clusters were identified following the classifications developed by the POF.²⁸ Those features are believed to be the most representative of a TLC attack and are thought to be comparable to the model

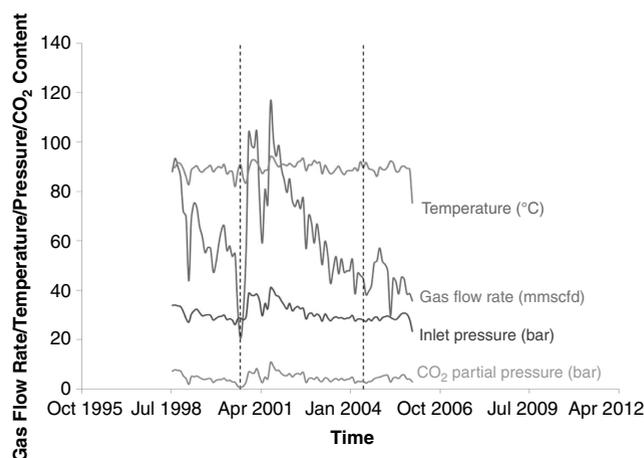


FIGURE 2. Input parameter variation over time for the inlet of flowline A.

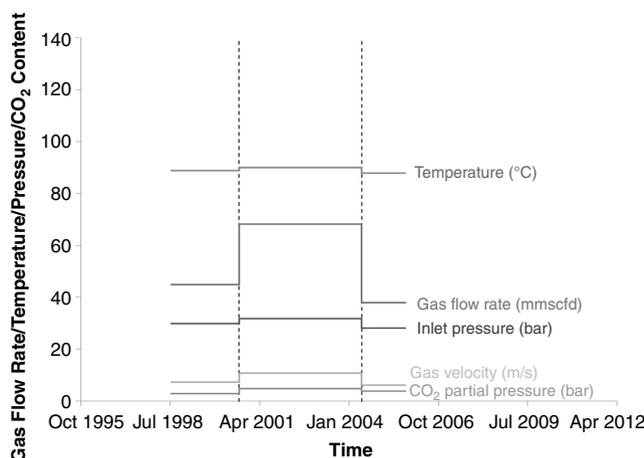


FIGURE 3. Averaged input parameters for the inlet of flowline A using three time periods.

prediction's output (Figure 4(b)). The maximum measured WT loss was also captured by drawing a maximum penetration envelope, as shown in Figure 4(b) (an arbitrary continuous line passing through the maximum WT loss points). The uniform TLC features identified as clusters coincide with the maximum penetration envelope.

Simulation Results — Figure 5 shows the predicted WCR and temperature profile along the line. While the inlet temperature was taken directly from production history, the profile of temperature along the line was calculated using the heat transfer module in the model.

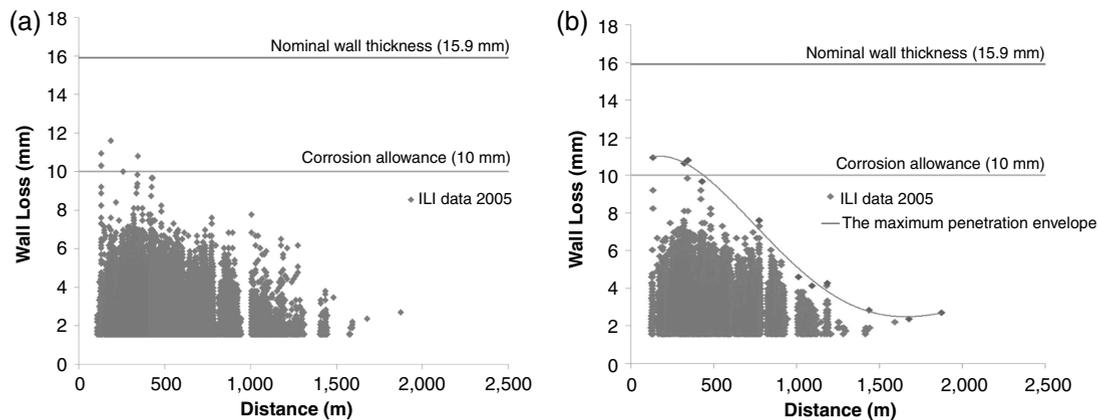


FIGURE 4. ILI data filtering for Line A: (a) all ILI corrosion features, (b) a subset showing only TLC clusters (uniform corrosion data) along with the maximum penetration envelope. (non-TLC features and noisy measurements close to pipe joints are filtered out).

The analysis was broken down into three time periods (period #1, period #2, and period #3) wherein it was found that the operating parameters were reasonably stable, and, therefore, time averages could be used. The majority of the flow regimes predicted by the model¹² for Line A were stratified, indicating a TLC possibility.

For the first time period, high values of WCR were calculated at the beginning of the pipeline as a result of the higher temperature gradient between the inside and outside of the pipe wall. The predicted WCR values were naturally lower when the pipeline was buried and decreased along the pipeline because of the reduction of internal fluid temperature.

For the second time period, the values of WCR were higher than for the first time period at the same locations; however, on many other locations the increase in gas velocity led to a change in flow regime prediction to nonstratified, thus eliminating the risk from TLC. This change in flow regime only affected some sections, not the entire line.

For the third time period, the predicted WCR is clearly lower than for the first two time periods, mostly because of the lower fluid temperature and lower heat exchange between the pipeline fluids and the environment.

In summary, the inlet temperature appeared to be the main parameter affecting WCR in this case. It is therefore crucial to obtain accurate inlet temperature data in order to maximize the accuracy of the predictions.

Figure 6 shows the predicted TLC rate. High severity of TLC was predicted for the second time period on sections of pipe experiencing stratified flow. This time period experienced the most severe combination of high inlet temperature and high inlet pressure. These parameters all contributed to making the environment very corrosive. Cumulative WT loss data are presented in Figure 7 and indicate a high overall risk for

TLC in this pipeline. These cumulative values are back-calculated from the predicted corrosion rates and durations obtained for each period.

Comparison between the Model Prediction and Field Data—In Figure 8, the analyzed ILI data (including error bars equivalent to $\pm 10\%$ WT stemming from instrument accuracy), are compared with the cumulative WT loss predicted by the TLC model. Overall, the predicted TLC is in good agreement with the maximum WT loss ILI data (i.e., the maximum penetration envelope). It is worth stressing that these model predictions do not consider chemical inhibition while the line itself was batch treated on a monthly basis. The reasonable agreement of the predictions and the ILI measurements is most likely an indication of a fairly ineffective TLC mitigation method, as the model has been successfully validated for a number of other uninhibited environments.¹²

Over-prediction is noted at the beginning of the line (first 200 m), but the remainder of the predicted results follows the trend outlined by the maximum penetration envelope and is within the margin of error of the ILI measurements. The discrepancy encountered at the beginning of the line is a recurrent feature of comparison between the model and field data. The current understanding of the mechanisms indicates that TLC should be more severe when the fluid temperature and the condensation rate are higher. This is the case at the beginning of the line. The reason the TLC rate does not exactly follow that trend in the first few hundred meters of line is not entirely clear. This discrepancy represents a gap in the understanding of the TLC mechanisms and influential factors, as it appears quite consistently, and the model is only a faithful reflection of the current understanding. Although no definitive answer can be given at this stage, the effect of co-condensation of hydrocarbons, which should be quite important at the beginning of the line, could influence the TLC rates. This is despite recent

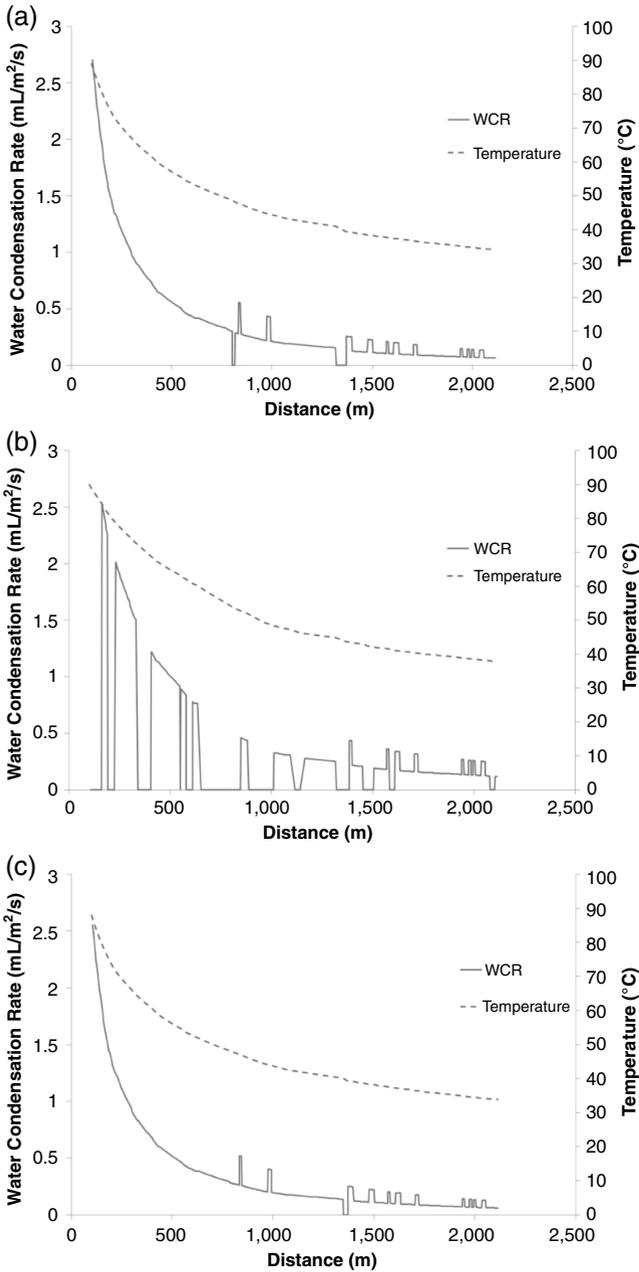


FIGURE 5. WCR and temperature profile along the length of the pipeline predicted from heat and mass transfer line model simulation: (a) First time period, (b) Second time period, (c) Third time period. WCR, water condensation rates.

experimental data that seem to suggest otherwise.¹⁹ Partial transport of inhibitor through droplets that are atomized in the highly turbulent section of pipe following the dogleg could play a role as well.

Part II: Analysis of Other Lines

In order to determine the validity of the newly-developed methodology and the accuracy of the TLC model, a similar analysis was done for another seven lines for which complete data sets were available. A summary of that work is presented in Figure 9. In all

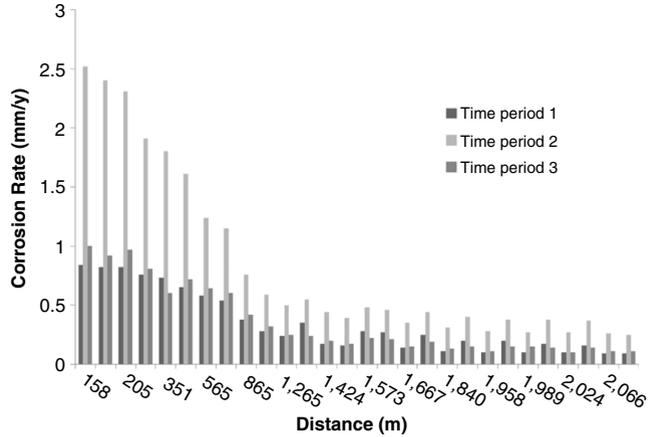


FIGURE 6. Predicted TLC rate for Line A.

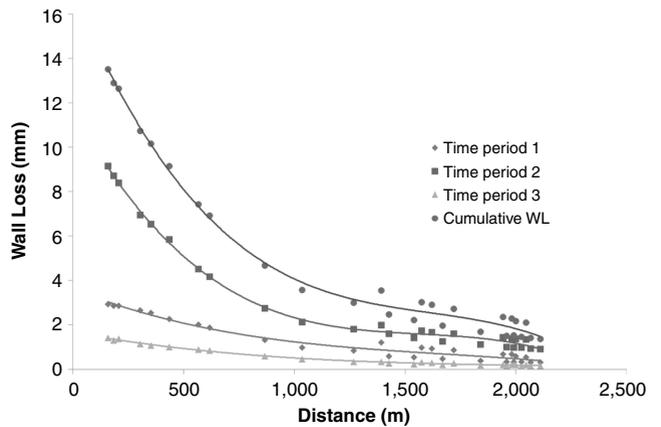


FIGURE 7. Calculated WT loss values for the three time periods and the total cumulative WT loss value.

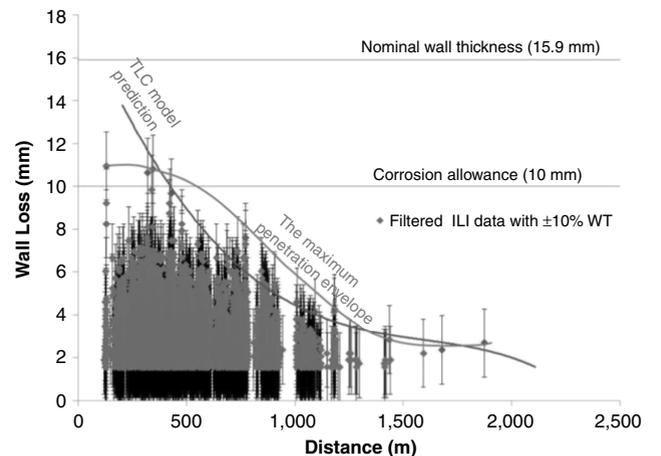


FIGURE 8. Comparison between filtered MFL data (with error bars equivalent to $\pm 10\%$ WT due to instrument accuracy) and the TLC model predictions.

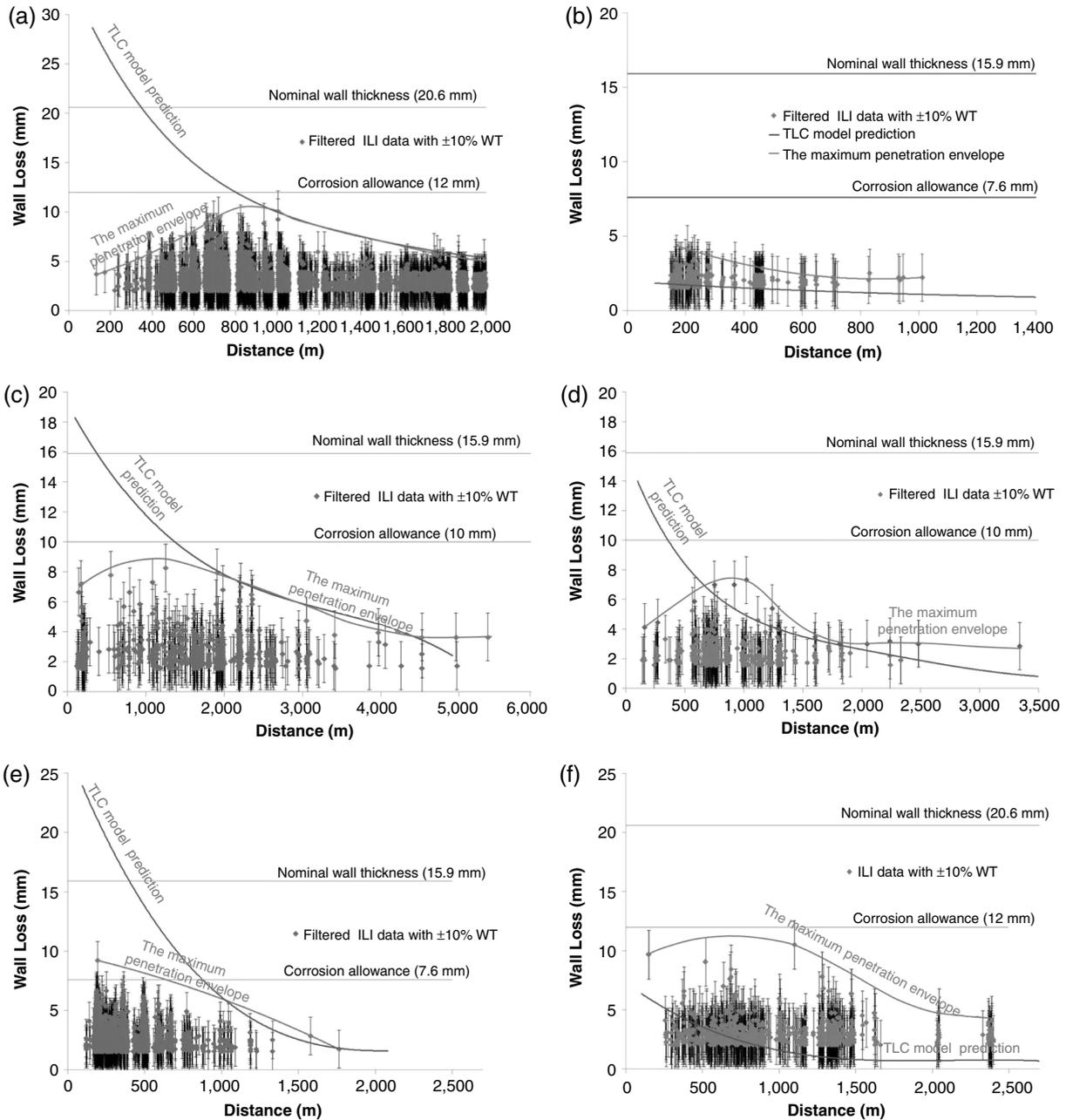


FIGURE 9. Comparison between TLC model prediction and representative corrosion features filtered from MFL data. (a) Line B, (b) Line C, (c) Line D, (d) Line E, (e) Line F, and (f) Line G.

cases, the maximum penetration envelope for the ILI data agrees well with the clustered data (representing uniform TLC), suggesting that the mode of corrosion was not the typical pitting mode but rather representative of a situation where fairly large local spots on the metal surface are suffering from uniform corrosion. The performance of the TLC model can be considered reasonable for Lines B, D, E, and F. Those predictions agree well with the maximum penetration envelope, with the exception of the first few hundred meters of line where TLC rates are over-predicted. This discrepancy relates to the same gap in understanding

highlighted in the previous section, which is important because the first sections of the line are commonly a major concern in terms of TLC. For Lines C and G, the model slightly under-predicts the rate of TLC attack along the entire line. However, when error bars are taken into account, this difference does not seem to be statistically significant. This is summarized in Figure 10, where a parity plot is shown for all seven lines that were analyzed. Each line was divided into 300 m sections, and the maximum WT loss ILI data for each section was used here and compared with the prediction for the same locations in the line. The first

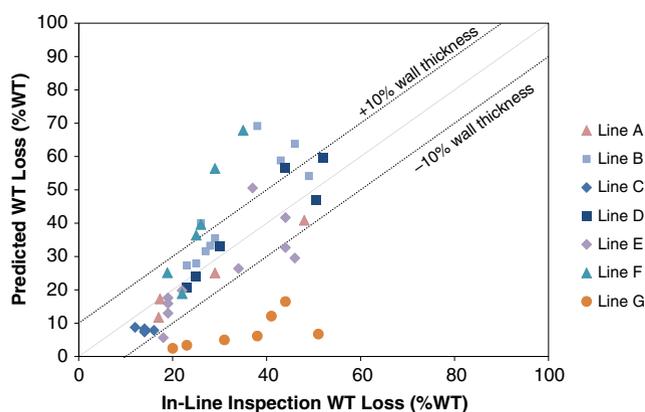


FIGURE 10. Parity plot between maximum WT loss obtained from the ILI data and the predicted TLC data for seven different lines.

500 m of each line were not considered in the analysis, as a known discrepancy exists here. A reasonable agreement was obtained in six of the seven cases, for which the results were mostly within the margins of measurement error. Only Line G showed consistent under-prediction of the ILI data as the error was more than $\pm 10\%$.

DISCUSSION

The purpose of this paper was in part to validate a mechanistic TLC model, but even more to propose a procedure that takes into account the intricacy of field data for an effective comparison with model predictions. In this sense, the steps proposed for performing a thorough analysis of the operating conditions and ILI results constitute a clear improvement compared to what has been done in the past.¹⁶

It is crucial to ensure that the input parameters “fed” to any model are, as much as possible, an accurate representation of the changing conditions (temperature, pressure, flow rate) encountered in the field.

ILI data should also be thoroughly analyzed in order to extract relevant data that the model was designed to predict.

Overall, in this exercise, the mechanistic TLC model predictions show a reasonably good agreement with the ILI data. However, the comparisons are obviously not “spot-on”, nor should they be expected to be. The procedure cannot fully account for all of the inherent complexities of field measurement or account for any lack of understanding in the modeling approach. As the TLC prediction model used in this study is mechanistic, it is only a reflection of the current knowledge and cannot predict phenomena which are not yet understood. A clear gap between model prediction and ILI results exists in the first few hundred meters of line. The model predicts the highest TLC rates at the inlet of the line (as a result of high temperature and WCR), while the ILI data consistently

show a maximum in TLC rates a few hundred meters from the inlet. The reason for this specific behavior of the TLC rate at the inlet of the pipe is unknown and should be subject to further investigation in order to verify whether this represents a TLC-specific mechanism or something else (co-condensation, inhibited droplet deposition, protectiveness of corrosion product layer, etc.).

In any case, results of model simulation, when carefully used in conjunction with field experience, significantly improve our ability to understand the main causes of corrosion and implement suitable methods to mitigate them in the future. In the case of the mechanistic TLC model used in the study, the results show that it can be used to evaluate the risk levels for TLC in various pipelines and to prioritize TLC mitigation programs and pipeline corrosion inspection strategies.

CONCLUSIONS

- ❖ An effective methodology was developed to analyze and validate the field data prior to any comparison with model predication.
- ❖ This included the processing of key operating parameters (inlet temperature, pressure, flow rate), which are known to vary over time, as well as line topography and ILI data, which are inherently complicated and not always reliable. These steps are considered to be crucial for enabling an effective comparison with model predictions.
- ❖ The mechanistic TLC prediction model used in this study showed a reasonable agreement with the ILI data for most of the lines analyzed, and predicted results within the margins of ILI measurement error.
- ❖ Faults in model performance caused by gaps in the current understanding were nevertheless identified, especially pertaining to the first few hundred meters of line, where the difference between predictions and ILI data was the greatest.

ACKNOWLEDGMENTS

The authors would like to acknowledge the technical guidance and financial support provided by the sponsoring companies of the Top of the Line Corrosion Joint Industry Project at Ohio University: BP, ConocoPhillips, Chevron, ENI, Occidental Oil Company, PTTEP, Saudi Aramco, and Total.

REFERENCES

1. Y. Gunaltun, D. Supriyatman, J. Achmad, *Oil Gas J.* 28, 1 (1999): p. 64-71.
2. Y. Gunaltun, D. Larrey, *Oil Gas J.* 98, 28 (2000): p. 58-63.
3. Y. Gunaltun, D. Larrey, *Oil Gas J.* 98, 29 (2000): p. 68-71.
4. M. Thammachart, Y. Gunaltun, S. Punpruk, “The Use of Inspection Results for the Evaluation of Batch Treatment Efficiency and the Remaining Life of the Pipelines Subjected to Top of Line Corrosion,” CORROSION 2008, paper no. 8471 (New Orleans, LA: NACE, 2008).

5. Y. Gunaltun, S. Punpruk, M. Thammachart, T. Pornthep, "Worst-Case TLC: Cold Spot Corrosion," CORROSION 2010, paper no. 10097 (San Antonio, TX: NACE, 2010).
6. M. Joosten, D. Owens, A. Hobbs, H. Sun, M. Achour, D. Lanktree, "Top-of-Line Corrosion—A Field Failure," EUROCORR 2010, paper no. 9524 (Moscow, Russia: European Federation of Corrosion, 2010).
7. D. Hinkson, Z. Zhang, M. Singer, S. Nescic, *Corrosion* 66, 4 (2010): p. 045002-045002-8.
8. M. Singer, A. Camacho, B. Brown, S. Nescic, *Corrosion* 67, 8 (2011): p. 085003-1-085003-16.
9. C. de Waard, U. Lotz, D.E. Milliams, *Corrosion* 47, 12 (1991): p. 976-985.
10. F. Vitse, S. Nescic, Y. Gunaltun, D. Larrey de Torreben, P. Duchet-Suchaux, *Corrosion* 59, 12 (2003): p. 1075-1084.
11. R. Nyborg, A. Dugstad, "Top of the Line Corrosion and Water Condensation Rates in Wet Gas Pipelines," Corrosion 2007, paper no. 7555 (Nashville, TN: NACE, 2007).
12. Z. Zhang, D. Hinkson, M. Singer, H. Wang, S. Nescic, *Corrosion* 63, 11 (2007): p. 1051-1062.
13. S.L. Asher, W. Sun, R.A. Ojifinni, S. Ling, C. Li, J.L. Pacheco, J.L. Nelson, "Top of the Line Corrosion Modeling in Wet Gas Pipelines," 18th International Corrosion Congress 2011, paper no. 303 (Perth, Australia: Australasian Corrosion Association, 2011).
14. J. Amri, E. Gulbrandsen, R.P. Nogueira, *Corrosion* 66, 3 (2010): p. 035001-035001-7.
15. Y. Sun, T. Hong, C. Bosch, *Corrosion* 59, 8 (2003): p. 733-740.
16. Y. Gunaltun, U. Kaewpradap, M. Singer, S. Nescic, S. Punpruk, M. Thammachart, "Progress in the Prediction of Top of the Line Corrosion and Challenges to Predict Corrosion Rates Measured in Gas Pipelines," CORROSION 2010, paper no. 10093 (San Antonio, TX: NACE, 2010).
17. M. Singer, "Study and Modeling of the Localized Nature of Top of the Line Corrosion" (Ph.D. diss., Ohio University, 2013).
18. U. Kaewpradap, "Validation of Top of the Line Corrosion Prediction Model Using Laboratory and Field Measurements" (MS Thesis, Ohio University, 2012).
19. T. Pojtanabuntoeng, M. Singer, S. Nescic, "Influence of Water/Hydrocarbons Co-condensation on Top-of-the-Line Corrosion" (Ph.D. diss., Ohio University, 2013).
20. M. Singer, D. Hinkson, Z. Zhang, H. Wang, S. Nescic, *Corrosion* 69, 7 (2013): p. 719.
21. L. Smart, B. Engle, L. Bond, J. MacKenzie, G. Morris, "Material Characterization of Pipeline Steels: Inspection Techniques Review and Potential Property Relationships," 11th International Pipeline Conference 2016, paper no. 64157 (Calgary, Canada: ASME, 2016).
22. B. Eiber, "Overview of Integrity Assessment Methods for Pipelines," Washington Cities and Counties Pipeline Safety Consortium, 2003.
23. H.A. Kishawy, H.A. Gabbar, *Int. J. Press. Vessels Pip.* 87, 7 (2010), p. 373-380.
24. R. Hall, M. McMahon, "Report on the Use of In-line Inspection Tools for the Assessment of Pipeline Integrity," US Department of Transportation, report no. DTRS56-96-C-0002-008, 2002.
25. M. Ellinger, T. Bubenik, P. Moreno, "ILI-to-Field Data Comparisons: What Accuracy Can You Expect?," 11th International Pipeline Conference 2016, paper no. 64526 (Calgary, Canada: ASME, 2016).
26. L. Huysse, A. van Roodselaar, J. Onderdonk, "Improvements in the Accurate Estimation of Top of the Line Internal Corrosion of Subsea Pipelines on the Basis of In-line Inspection Data," 8th International Pipeline Conference 2010, paper no. 31038 (Calgary, Canada: ASME, 2010).
27. P. Moreno, M. Ellinger, T. Bubenik, "ILI to ILI Comparisons: Quantifying the Impact of Multiple Inspections," 11th International Pipeline Conference 2016, paper no. 64547 (Calgary, Canada, 2016).
28. Pipeline Operators Forum (POF) document, "Specifications and Requirements for Intelligent Pig Inspection of Pipelines" 2009.