Multi-sensor Corrosion Growth Modeling with Latent Variables Using Hierarchical Clustering and Vector Autoregression Model

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SUMMARY & CONCLUSIONS

Modeling corrosion growth for complex systems such as the oil refinery system is a major challenge since the corrosion process of oil and gas pipelines are inherently stochastic and depends on many factors including exposures to environmental conditions, operating conditions, and electrochemical reactions. Moreover, the number of sensors is usually limited, and sensor data are incomplete and scattering, which hinders the capability of capturing the corrosion growth behaviors. Therefore, this paper proposes Multi-sensor Corrosion Growth Model with Latent Variables to predict the corrosion growth process in oil refinery piping. The proposed model is a combination of the hierarchical clustering algorithm and the vector autoregression (VAR) model. The clustering algorithm aims to find the hidden (i.e., latent) data clusters of the measured time series data, from which the time series from the same cluster will be included in the VAR model to predict the corrosion depth from multiple sensors. The model can capture the relationship between sensor time series data and identify latent variables. A real case study of an oil refinery system, in which in-line inspection (ILI) data were collected, was utilized to validate model. Regarding corrosion growth prediction, the paper compared the prediction accuracy of VAR model with other three forms of power law model, which is widely accepted to expect the time-dependent depth of corrosion such as power function (PF), PF with initiation time of corrosion (PFIT), and PF with initiation time of corrosion and covariates (PFCOV). The results showed that VAR model has the lowest prediction error based on the mean absolute percentage error (MAPE) evaluation for test data. Finally, the proposed model is believed to be useful for dealing with a complex system that has a variety of corrosion growth behaviors, such as the oil refinery system, as well as it can be applied in other real-time applications.

1. INTRODUCTION

Corrosion growth phenomena is a major threat to oil refineries which grows over time and threatens the refinery piping's safety and reliability, which can result in loss-of-containment incidents leading to severe sequences such as human and environmental disasters and economic losses [1]. Capturing corrosion growth behavior in a complex system such as an oil refinery system is challenging since it contains a lot of pipes, and each group of pipes has different corrosion growth behavior due to exposure to different environmental conditions, operating conditions, and chemical reactions. In literature, several models have been proposed to capture corrosion growth behavior in oil and gas pipelines. Several linear models have been proposed based on either corrosion rate is equal to a single value of 0.4 mm/year which is recommended by National Association of Corrosion Engineers (NACE) [2], or based on single ILI data [2], or based on two ILIs data [3], or multiple ILIs data [4]. Linear models are widely used in practice because they are simple and capable to predict the corrosion growth process of pipelines when having limited In-line Inspection (ILI) datasets [5]. These models should be restricted to use for special cases only because the corrosion growth nature is nonlinear. Another researcher [6] suggests a model that combines linear and nonlinear by making the first phase a rapid exponential pit growth and the second phase is slow linear growth. In the research community, the power law model is widely accepted to expect time-dependent depth of corrosion and it was first postulated for atmospheric corrosion by [7]. This model is preferable to predict corrosion depth over time of pipeline because it somehow follows the corrosion growth mechanism where corrosion rate starts at a higher rate at the beginning stage and then slows down with time [8]. The de Waard-Milliams model is most commonly used in predicting internal corrosion rate which is discussed with other CO2 corrosion models in [9]. It is conducted in a comparative study in [10] among other artificial intelligent models, and it is found that de Waard-Milliams has the lowest prediction accuracy regarding corrosion rate prediction. As the corrosion process is associated with high uncertainties, Gamma process model, Monte Carlo simulation, and other probabilistic models have been discussed in [11] which have been used to predict the corrosion rate and corrosion depth of the pipeline. A Markov chain has been used to predict the external corrosion growth in underground pipelines [12]. The Weibull distribution has been used to estimate pit initiation of corrosion, and the non-homogenous Markov chain model has been used to estimate corrosion pit growth distribution [13]. An inverse Gaussian process-based model is used in [14] to predict corrosion growth of depths on underground pipelines. The second-order polynomial dynamic linear model (DLM) is used to predict the growth of corrosion depths on buried energy pipelines [15]. These models can overcome the high uncertainties inherited in corrosion growth nature because probability is considered as a primary factor in these predictive models. However, these stochastic process models could be invalidated when any change occurs in operating conditions, environment, or temperature [11]. Recently, machine learning (ML) models have become a candidate for predicting the corrosion growth process of pipelines. Several studies [16] [17] discuss Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM), and polynomial models in predicting internal corrosion rate. ML models are also used in predicting corrosion depth; for example, [18] discusses predicting time-dependent corrosion depth using Particle Swarm Optimization & Feed-Forward Artificial Neural Network (PSO-FFANN), Gradient Boosting Machine (GBM), and Deep Neural Network (DNN). [19] discusses estimating time-dependent corrosion depth of pipelines using feed-forward Subspace Clustered Neural Network (SSCN) and Particle Swarm Optimization (PSO). SVM models are widely discussed in [10] [20] [21] in predicting corrosion growth of pipelines based on the integration of SVM with meta-heuristic optimization techniques to optimize the hyperfine parameters in SVR. Isotonic regression is discussed in [22] regarding predicting corrosion depth for internal corrosion of oil refinery piping. A recent study [23] proposes a physics-informed latent variable model that identifies type of soil and predicts the corrosion depth over time in oil and gas pipelines.

Most significant research efforts focus on finding suitable corrosion growth models for the upstream and midstream oil and gas industry based on a study of a single or limited number of pipelines. In addition, data scarcity is a major issue facing these researchers; therefore, most of the proposed models are built based on only one or two inspections and consider temporal cases only. In contrast, using those models to predict the corrosion growth for refinery piping (downstream) is challenging since it carries out numerous operations, and various corrosion behaviors occur due to latent variables (e.g., exposure to different environmental conditions, operating conditions, and electrochemical reactions). However, this paper proposes Multi-sensor Corrosion Growth Model with Latent Variables to predict the corrosion growth process in oil refinery piping. The model is built based on the combination of the hierarchical clustering algorithm and the Vector Autoregression (VAR) model. This paper contributes to validating the proposed model using a real-life ILI data set from oil refinery piping. For future work, we will be working on extending the work by conducting more realistic experiments using simulated data and real data.

The rest of the paper is divided into five sections; Section 2 gives a brief background of the hierarchical clustering algorithm and VAR Model. Section 3 presents the proposed model and Section 4 introduces the case study and discusses the model implementation. Finally, the paper concludes in Section 5.

2. *HIERARCHICAL CLUSTERING ALGORITHM AND VECTOR AUTOREGRESSION*

2.1 Hierarchical Clustering Algorithm

Hierarchical clustering is an algorithm used to group different objects into groups (clusters). Agglomerative hierarchical clustering process discussed in [24] is most commonly used to group objects where each object begins in its own cluster and as one moves up the hierarchy, pairs of clusters are merged based on similarity using a dendrogram, which is a tree-structured graph, to visualize the hierarchical relationship between the clusters. Several distance metrics have been developed, such as Euclidean, Chebychev, Manhattan, Correlation, and others. These distance metrics are selected to measure the similarity of two objects. Type of distance metric is usually selected based on the aim and concern of the study.

2.2 Vector Autoregression (VAR) Model

VAR model is a stochastic process model that captures the relationship between multiple variables over time and these variables are treated as endogenous variables which means that each variable changed by its relationship with other variables. A general form of VAR model that includes p-lags of variables, VAR(p), is as follows [25]:

$$\boldsymbol{Y}_t = \boldsymbol{c} + \boldsymbol{\pi}_1 \boldsymbol{Y}_{t-1} + \boldsymbol{\pi}_2 \boldsymbol{Y}_{t-2} + \cdots + \boldsymbol{\pi}_p \boldsymbol{Y}_{t-p} + \boldsymbol{\varepsilon}_t \quad (1)$$

where $t = 1, \dots, T$ and $\boldsymbol{Y}_t = \left(y_{1,t}\, , y_{2,t}\, , \dots, y_{n,t}\right)'$ denotes $(n \times 1)$ vector of time series variables at time t and $\boldsymbol{c}$ denotes intercept where $\boldsymbol{c} = (c_1, c_2, \dots, c_{\mathrm{n}})'$, and $\boldsymbol{\pi}_i$ are $(n \times n)$ coefficient matrices for each i^{th} lag as follow:

$$\boldsymbol{\pi}_i = \begin{bmatrix} \pi_{11} & \pi_{12} & \cdots & \pi_{1n} \\ \pi_{21} & \pi_{22} & \cdots & \pi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{n1} & \pi_{n2} & \cdots & \pi_{nn} \end{bmatrix} \quad (2)$$

where $i = 1, \dots, p$ and $\boldsymbol{Y}_{t-1} = \left(y_{1,t-1}\, , y_{2,t-1}\, , \dots, y_{n,t-1}\right)'$ and similarly for $\boldsymbol{Y}_{t-2}$ and $\boldsymbol{Y}_{t-\mathrm{p}}$. $\boldsymbol{\varepsilon}_t = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n)'$ represents $(n \times 1)$ unobservable zero mean white noise vector process.

3. *MULTI-SENSOR CORROSION GROWTH MODEL WITH LATENT VARIABLES*

This section discusses the proposed model, which is called the Multi-sensor Corrosion Growth Model with Latent Variables. The model is built based on the combination of the hierarchical clustering algorithm to identify latent variables and the Vector Autoregression (VAR) model to predict the corrosion growth process of piping, as discussed in detail below in Section 3.1. and 3.2.

3.1 Sensor Grouping of the Refinery System using Hierarchical Clustering

Hierarchical clustering is used to identify latent variables by grouping sensors with similar corrosion growth behaviors in one cluster, believing those sensors are exposed to similar environmental conditions, operating conditions, and electrochemical reactions. The hyperparameter tuning process in the hierarchical clustering algorithm can be challenging since we have to pre-define various hyperparameters such as the number of clusters, distance threshold, and distance metric. One possibility is to use a validation data set and domain knowledge to fine-tune the hyperparameters. In hierarchical clustering, the correlation-based distance which is donated by c is selected as a dissimilarity measure because it fits the aim of the study, which is grouping sensors based on the similarity of corrosion growth behavior of sensors even though the time series values between sensors are far in terms of geometrical distance and the criteria of similarity of corrosion growth behavior indicates that sensors within a cluster are exposed to similar environmental conditions, operating conditions, and electrochemical reactions . Correlation-based distance metric (c) measures distance between two time series, $\left(\{D_{i,t}\}_{t=1}^{T}, \{D_{j,t}\}_{t=1}^{T}\right)$ which represent the corrosion depth at time t for the i^{th} and j^{th} time series where $t = 1, \dots, T$ and $i = 1, \dots, n$ and $j = 1, \dots, n$ and c is calculated using the following equation:

$$c = 1 - \rho_{D_i,D_j} \tag{3}$$

where ρ_{D_i,D_j} is Pearson correlation coefficient which measures the correlation of two (i^{th} and j^{th}) time series $\left(\{D_{i,t}\}_{t=1}^{T}, \{D_{j,t}\}_{t=1}^{T}\right)$ using the following formula:

$$\rho_{D_i,D_j} = \frac{\sum_{t=1}^{T}(D_{i,t}-\bar{D}_i)(D_{j,t}-\bar{D}_j)}{\sqrt{\sum_{t=1}^{T}(D_{i,t}-\bar{D}_i)^2 \sum_{t=1}^{T}(D_{j,t}-\bar{D}_j)^2}} \tag{4}$$

where $D_{i,t}$ and $D_{j,t}$ represents value of corrosion depth at time t in the i^{th} time series and the j^{th} time series, respectively. $\bar{D}_i$ is average of D_i.

3.2 Estimating Time-Dependent Corrosion Depth using the VAR Model.

The VAR(p) model is selected because it is capable of describing and forecasting the dynamic behavior of corrosion growth for multiple time series variables using the following equation:

$$\begin{gathered} D_{1,t} = \alpha_1 + \beta_{11,1}D_{1,t-1} + \cdots + \beta_{1n,p}D_{n,t-p} + \varepsilon_1 \\ \vdots \\ D_{n,t} = \alpha_n + \beta_{n1,1}D_{1,t-1} + \cdots + \beta_{nn,p}D_{n,t-p} + \varepsilon_n \end{gathered} \tag{5}$$

where $D_{n,t}$ denotes the forecasted corrosion depth (the reference sensor data) and n is the number of sensors in one cluster. α_n denotes intercept and $\boldsymbol{\beta}_i$ are $(n \times n)$ coefficient matrices as follow:

$$\boldsymbol{\beta}_i = \begin{bmatrix} \beta_{11,i} & \beta_{12,i} & \cdots & \beta_{1n,i} \\ \beta_{21,i} & \beta_{22,i} & \cdots & \beta_{2n,i} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{n1,i} & \beta_{n2,i} & \cdots & \beta_{nn,i} \end{bmatrix} \tag{6}$$

where $i = 1, \dots, p$ represents p-lages of variables included in the model.

4. *REAL-LIFE CASE STUDY OF OIL REFINERY SYSTEM*

4.1 Overview of Case Study

In this study, the degradation data were obtained from 404 sensors attached to oil refinery piping. The oil refinery consists of three processing units (PUs) and each PU contains several groups. Each group has multiple sensors measuring operating condition parameters such as corrosion rate (CR), basic sediment and water (BS&W), temperature (temp), salt, pressure (P), and flow rate (FR). Cross-correlation was used to see if there is any relationship between the target parameter (CR) with other parameters, as shown in Figure 1. The corrosion rate data were converted to corrosion depth using the following equation:

$$D_{i,t+1} = D_{i,t} + CR_{i,t}(\Delta t) \tag{7}$$

where $D_{i,t+1}$ denotes the corrosion depth in the i^{th} time series at time $t+1$ for $t = 1,2, \dots, T$. $CR_{i,t}$ represents the corrosion rate in the i^{th} time series at time t, and Δt denotes the time interval between two data points. In hierarchical clustering, dendrogram graph was used to visualize the hierarchical relationship between sensors, as shown in Figure 2(a) and Figure 3(a). Regarding the corrosion growth prediction process, four corrosion growth models were conducted in the comparative study, such as PF, PFIT, PFCOV, and the VAR model. Mean absolute percentage error (MAPE) was used to measure the prediction performance for each model using the following equation:

$$MAPE_i = \frac{100\%}{T_{test}} \sum_{t=1}^{T_{test}} \left| \frac{D_{i,t} - \hat{D}_{i,t}}{D_{i,t}} \right| \tag{8}$$

where $D_{i,t}$ is the actual corrosion depth in the i^{th} time series at time t and $\hat{D}_{i,t}$ denotes the forecasted corrosion depth in the i^{th} time series at time t and T_{test} is the length of testing data.

4.2 Cross-correlation between CR and Other Operating Conditions Parameters

Correlation between operating conditions parameters and the corrosion rate, which is the target variable, was studied in the corrosion growth modeling process using cross-correlation of two time series signals as shown in Figure 1 to see if these features are leading factors that contribute to the corrosion growth process. As shown in Figure 1, no relationship between CR and the other parameters was captured based on a range of lags between -10 to 10. For example, Table 1 shows cross-correlation values at lag $zero$. Based on ccf values at lag zero in Table 1, it can be noticed that there is no significant relationship between CR and other operating condition parameters. Therefore, this paper neglected these parameters in corrosion growth modeling and focused on predicting corrosion depth based on CR sensor data using the VAR model.

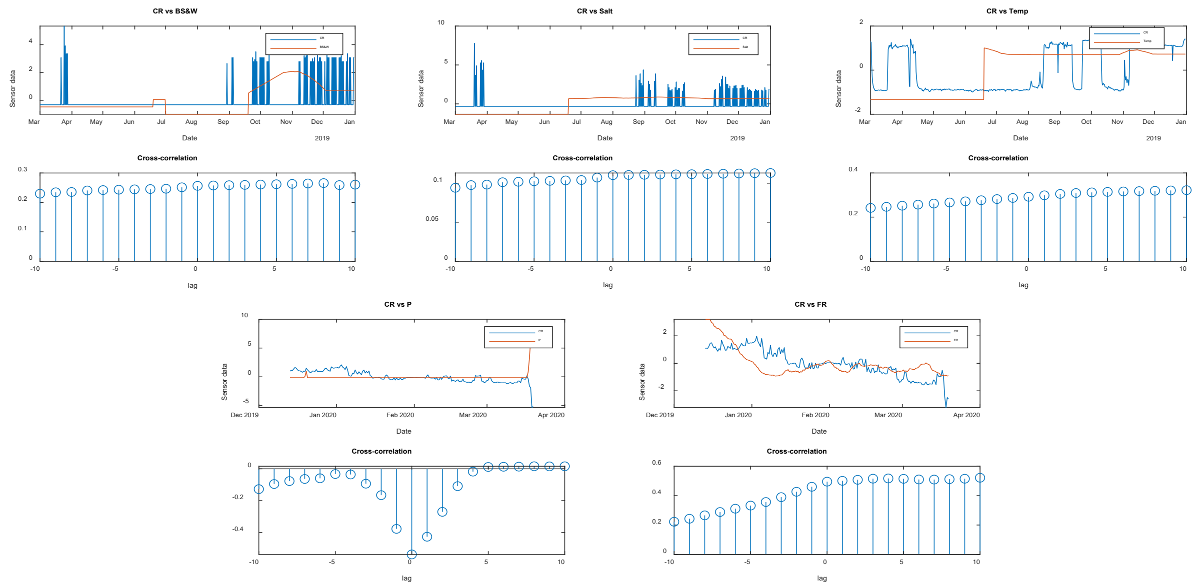

Figure 1 - Sensor data visualization & cross-correlation between CR vs other operating condition parameters

Table 1 - Cross-correlation (ccf) between CR and other parameters

Parameters	ccf values at zero time lag
CR vs. BS&W	0.26
CR vs. Salt	0.11
CR vs. temp	0.29
CR vs. P	-0.54
CR vs. FR	0.50

4.3 Model Implementation

Before the corrosion growth prediction process, hierarchical clustering was performed to identify the latent variables using dendrogram as shown in Figure 2 and Figure 3. Figure 2 shows that hierarchical clustering of sensors were implemented for 11 sensors from group A at 1st PU. Multiple sensors were grouped in different clusters. For example, time series signals for sensor #1 and #2 are visualized in Figure 2(b) where they both have similar corrosion growth behavior that was captured from clustering based on correlation-based metric using Equation (3). Similarly, hierarchical clustering was implemented in Group C at 1st PU. In Figure 3, 30 sensors were grouped in different clusters, and based on specifying cluster distance; the sensors can be grouped in clusters. For example, sensor #28 and sensor #29 were grouped in a cluster when looking for high correlated sensors where they both have similar corrosion growth behavior as shown in Figure 3(b). After implementing the hierarchical clustering process, corrosion growth prediction can be implemented using a suitable corrosion growth model for each cluster of sensors as they have similar corrosion growth behavior. Therefore, the selection of an appropriate model becomes much easier after sensors clustering because latent variables can be identified.

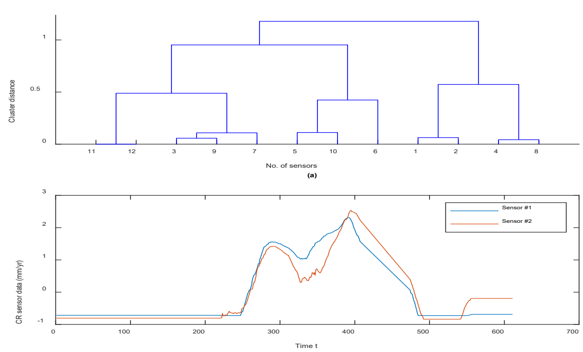

Figure 2 - (a) Hierarchical clustering of sensors in Group A using dendrogram, & (b) Corrosion growth behaviors of sensor #1 and #2 using correlation-based metric

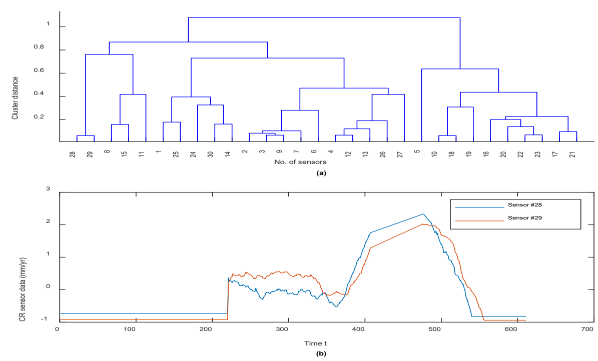

Figure 3 - (a) Hierarchical clustering of sensors in Group C using dendrogram, & (b) Corrosion growth behaviors of sensor #28 and #29 using correlation-based metric

As shown in Figure 4, the pipeline corrosion rate mechanism starts with a high rate at the beginning of the corrosion growth process, then it slows down over time because the stainless pipeline produces a passive film, which helps to mitigate the corrosion damage. In this study, the VAR model was selected to predict the corrosion growth process for all sensors in oil refinery piping as it is suitable for analyzing multivariate time series. The VAR model performance was compared with the power law model which is the most widely accepted model in predicting corrosion depth over time using three forms of power law model such as PF, PFIT, and PFCOV. In Figure 2, sensor #1 in Group A was used as a reference and sensor #2 in Group A was used as a predictor for both models: PFCOV and VAR models. The effectiveness of the VAR model is demonstrated in Figure 4 where the VAR model has lowest prediction error based on MAPE evaluation for test data and it is also better for long-term prediction compared to the other power law models. Finally, the proposed model was found a useful for modeling corrosion growth in a complex system such as the oil refinery system where it can capture the relationship between sensors based on corrosion growth behavior and identifying the latent variable. It was also able to include a nearby sensor in a cluster as a predictor to predict corrosion depth over time for other sensors within the same cluster.

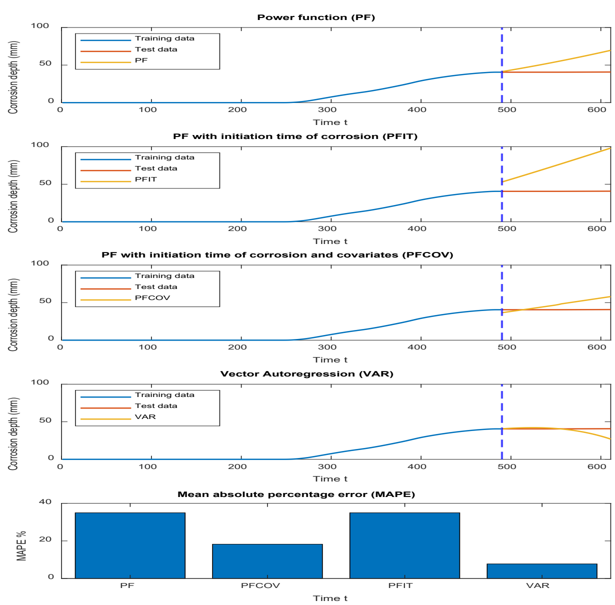

Figure 4 - Evaluation of prediction accuracy of each model using MAPE of test data

5. CONCLUSION

The paper proposes Multi-sensor Corrosion Growth Model with Latent Variables to predict the corrosion growth process in oil refinery piping. The proposed model is built based on collaboration between the hierarchical clustering algorithm and Vector Autoregression (VAR) model. The paper finds the model is capable of capturing the relationship between sensors based on corrosion growth behavior and identifying the latent variable. It is also able to include a nearby sensor in a cluster as a predictor to predict corrosion depth over time for other sensors within the same cluster. A real case study of degradation data from an oil refinery is used. Regarding corrosion growth prediction, the paper compares the prediction accuracy of VAR model with other three forms of power law model such as PF, PFIT, and PFCOV. The results show that VAR model has the lowest prediction error based on MAPE evaluation for test data.

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