

Prediction of Pipe Wall Thinning Caused by Flow Accelerated Corrosion Using a Physics-Informed Neural Network

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1. Introduction

Flow accelerated corrosion (FAC) gradually thins the inner wall of carbon-steel piping in nuclear power plants through chemical and mechanical interactions with steam, water, and two-phase flow. Pipe ruptures caused by FAC have led to severe casualties and economic losses. The elbow rupture at Surry Unit 2 in 1986 caused four fatalities and led to the establishment of an industry-wide FAC management program, and the condensate line rupture at Mihama Unit 3 in 2004 caused five fatalities and six injuries and led to mandatory full ultrasonic inspection of secondary-side carbon-steel piping [1]. Monitoring of pipe wall thinning is therefore essential.

Efforts to predict FAC wall thinning with mathematical models have a long history. The Chexal-Horowitz model developed by EPRI, an industry standard, expresses the wear rate as a product of influence factors [2], and modified mass-transfer models and time-dependent roughness models have followed. However, the mathematical modeling remains difficult for three reasons: 1) the exact functional forms are often undisclosed or depend on assumptions, 2) some required inputs, such as chromium content and local operating conditions, cannot be measured in the field, and 3) there is no ground truth, since field inspections provide only thickness readings contaminated by measurement error.

On the other hand, a large amount of inspection experience has been accumulated in the field, and data-driven prediction methods based on such measurements have been actively studied, with artificial intelligence being the representative approach [5]. In a previous study, a virtual wall-thinning data generation code was developed for testing thinning-evaluation algorithms; it

implements a measurement-error model derived from 648 inspections of 183 elbows at four Korean nuclear power plants [3].

This generation code implements a measurement-error model built on extensive accumulated inspection experience. However, it has a limitation in that physical formulas are not incorporated: the magnitude and the spatial distribution of wall thinning are not physically linked to the operating conditions.

In this study, the data generation code is therefore improved by incorporating physical formulas, namely the FAC rate equation and an analytic local-velocity solution, so that the operating conditions physically determine both the magnitude and the spatial distribution of wall thinning. Based on the generated data, a prediction technique is then developed that overlays the formula-based thinning rate onto the pipe geometry using a physics-informed neural network (PINN) and predicts grid-wise wall-thinning rate maps. Throughout this paper the term PINN [4] is used in the broad sense of a neural network that incorporates physics knowledge.

2. Wall Thinning Data Generation

The prediction problem is defined as follows. Given the current thickness map, six operating conditions (temperature T , chromium content Cr , flow velocity V , pipe diameter D , dissolved oxygen O_2 , and pH), and an elapsed time, predict the future thickness map. The network estimates the wall-thinning rate map $r(x, \theta)$, and the thickness map follows by linear decay,

$$TH(t + \Delta t) = TH(t) - r \cdot \Delta t \quad (1)$$

The data were collected with a wall-thinning data generation code [3]. For each pipe the code converts the

operating conditions into a thinning rate through the FAC rate equation,

$$r_F = F_1(T) \cdot F_2(Cr) \cdot F_3(V, D) \cdot F_4(O_2) \cdot F_5(pH) \cdot F_6(geometry) \quad (2)$$

Each factor represents how one condition influences FAC. Temperature has an intermediate peak, because the corrosion reaction is slow when it is too low while the oxide layer becomes less soluble when it is too high. Chromium suppresses thinning by stabilizing the oxide layer. A higher flow velocity accelerates thinning by carrying dissolved iron away from the wall more quickly, whereas a larger diameter slows it. Dissolved oxygen and pH both suppress thinning, the former by promoting a more stable oxide and the latter by lowering iron solubility. Elbows thin faster than straight pipes because the flow is disturbed.

Since Eq. (2) gives one value per pipe, the code distributes it over the inspection grid using flow physics. The local velocity inside an elbow is obtained from a free-vortex analytic solution parameterized by the Dean number $De(V, D, T)$, and the mass-transfer relation converts it into a wear pattern $\phi(x, \theta; De)$ normalized to a maximum of one. The rate map is the product of the two,

$$r_{map}(x, \theta) = r_F \cdot \phi(x, \theta; De) \quad (3)$$

The operating conditions therefore determine both how much the wall thins and where: the elbow pattern varies with the Dean number, while straight pipes remain uniform. Each pipe is then obtained by forming the clean thickness time-series as $TH(t) = T_0 - r_{map} \cdot t$, where the initial thickness T_0 includes manufacturing tolerance, and applying a measurement-error model derived from field inspections, which consists of a location-dependent random error and an inspection-wise systematic bias. Fig. 1 shows an example.

The collected dataset consists of 6,000 training, 500 validation, and 500 test pipes, with a 50:50 ratio of straight pipes and elbows. The inspection-grid size varies from pipe to pipe. Random-seed ranges are separated so that no pipe is shared between splits. The true rate map of every pipe is stored apart from the training data and accessed only by the scoring code, which structurally prevents ground-truth leakage. All automated data audits, including reproduction of the thickness definition and verification of consistency with the FAC rate equation, were passed.

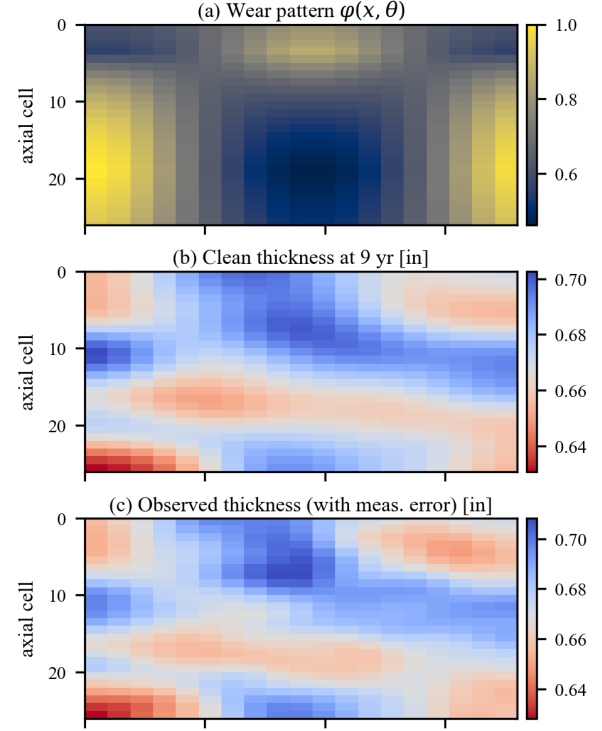


Fig. 1. Example of a generated pipe: wear pattern, clean thickness, and observed thickness with measurement error.

3. PINN-Based Prediction Model

3.1. Network architecture

The network predicts the rate map on a per-cell basis. For each grid cell, 32 input features are assembled: 14 coordinate features (circumferential $\cos k\theta$ and $\sin k\theta$ up to the fourth harmonic, and multi-scale axial features), the current observed wear ratio of the cell (the state now, distinct from the rate to be predicted), 10 pipe-level features (six operating conditions, geometry one-hot, nominal thickness, and inspection time), and 7 summary features of the observed thickness map. A multilayer perceptron with three hidden layers of width 128 and GELU activation directly outputs the wall-thinning rate of the cell through an exponential output activation

$$\hat{\rho}(x, \theta) = NN(x_p) \quad (4)$$

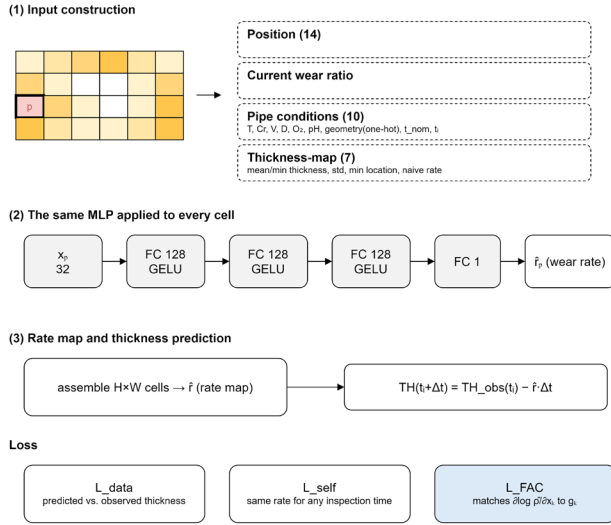


Fig. 2. Model architecture.

3.2. Loss functions

The training loss consists of three terms. The data term compares predicted and observed thickness changes between inspection pairs, weighted according to the known measurement-error model; its shape component is constructed so that the inspection-wise systematic bias cancels out. The self-consistency term requires the same rate map regardless of which inspection is used as input, reflecting the fact that the thinning rate does not depend on the inspection time. The physics term is the physics-coupling point with the predicted rate to each operating condition, $\partial \log \hat{p} / \partial x_k$, to the corresponding known gradient g_k of the FAC rate equation.

4. Results and Discussion

The two cases were trained on the 6,000 training pipes for 600 epochs. Fig. 3 compares their training and validation loss curves. The Data + Physics loss case starts from a markedly lower loss and stays below the Data loss case throughout training. At the very first epoch its validation loss is already lower than the level the Data loss case reaches only after several tens of epochs, and within about 20 epochs it reaches the validation level that the Data loss case attains only at 600 epochs.

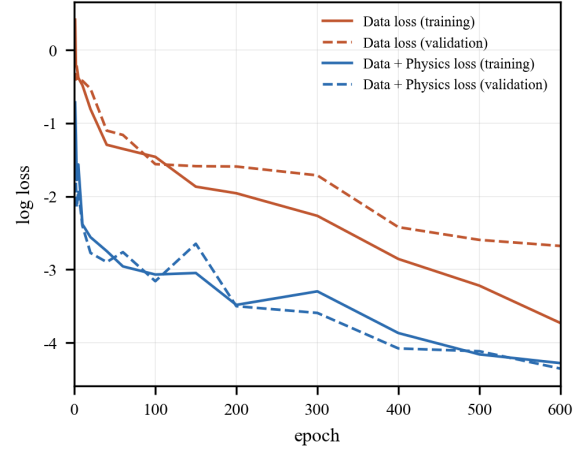


Fig. 3. Training and validation loss curves: Data loss versus Data + Physics loss.

Since the generated data provide the true rate maps, the two cases are evaluated by the median relative error of the predicted rate map with respect to the truth on the 500 unseen test pipes. Table II summarizes the results as the mean and standard deviation over the five seeds. Physics coupling reduces the error from 0.0495 to 0.0147, less than one third of the Data loss case. The validation and test errors are almost identical, indicating no overfitting. Fig. 4 compares a predicted rate map with the truth for a test elbow.

Fig. 4 compares the true and the predicted wall-thinning rate maps for one test elbow. The pipe was chosen as the median-error case among the 250 test elbows, not as a best case. The predicted map reproduces the spatial pattern of the true map: the cell-wise relative error of this pipe is 3.2 % in median, and the predicted location of the maximum thinning rate coincides with the true one.

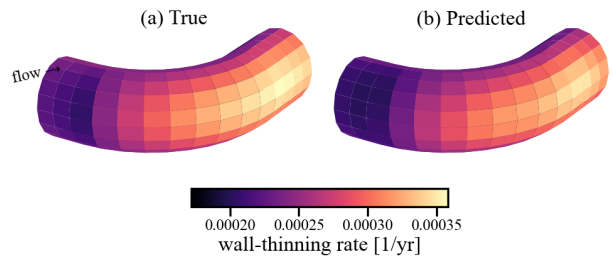


Fig. 4. The same rate maps rendered on the elbow geometry (bend radius 1.5 D): true (a) and predicted (b).

5. Conclusion

In this study, a PINN-based technique was developed to predict grid-wise wall-thinning rate maps of nuclear power plant piping. The network takes an inspection record and predicts the wall-thinning rate of each grid cell directly, while the FAC rate equation is coupled through the loss function. By combining the physical formula with the network in this way, the technique indicates not only how fast the wall thins but also where it thins. As a future step, this technique will be developed into a monitoring aid of the digital-twin type, in which the predicted rate and the remaining thickness computed from it are rendered on the three-dimensional pipe geometry.

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