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Citation	Frontiers of Structural and Civil Engineering. 2025
Version Type	VoR
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Predicting deterioration in paint-coated steel due to defects using a generative adversarial network approach

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ABSTRACT Corrosion significantly impacts the integrity of steel structures, making them more prone to damage and failure. Coating the steel surface with anti-corrosion paint is a prevalent method. Nevertheless, these coatings are susceptible to damage, and corrosion tends to initiate at and spread from the damaged points, potentially leading to severe localized deterioration. Accurately predicting the progression of corrosion and coating deterioration at these critical points is essential for effective maintenance of steel structures. This study focused on two different paint-coatings applied to SM400 steel, onto which defects of varied sizes and shapes were artificially induced to mimic real-world paint-coating damage. These specimens underwent the accelerated corrosion test (ISO 16539 Method B) to generate data on corrosion depth at various time intervals. Subsequently, a modified generative adversarial network (GAN) model was employed to develop a highly accurate prediction model for the deterioration of steel surfaces, where the inputs to the model are four sequential corrosion depth measurements, and the output is the predicted future corrosion depth distribution. The performance of the proposed model was quantitatively evaluated using the root mean square error (*RMSE*). The model demonstrated outstanding predictive accuracy across all defect scenarios presented in this study. Compared with both traditional GAN variants (Conditional GAN and Information Maximizing GAN), the proposed model demonstrated a lower *RMSE* in predictive accuracy. This finding underscores its capability for precise corrosion prediction in steel structures, even with a relatively small data set. This predictive capability holds significant potential for predictive maintenance and failure analysis in steel infrastructure. This study not only validates the use of GAN in predictive maintenance but also provides a novel approach for the early detection and management of corrosion, crucial for extending the lifespan of critical infrastructure.

KEYWORDS corrosion, generative adversarial network, paint-coated steel, coating defects, predictive maintenance, failure analysis

1 Introduction

Corrosion significantly affects the maintenance of steel structures across various industries [1]. This process entails the chemical reaction of metal with its environment, producing oxides, hydroxides, or sulphides [2]. Beyond aesthetic concerns, corrosion can diminish the load-bearing capacity of steel components, heightening the risk of structural failure [3,4].

Approximately 10% or more of total metal production is converted into rust each year, representing a substantial proportion of maintenance costs [5]. Moreover, corrosion is estimated to account for over 3% of the world's gross domestic product [6,7]. Consequently, mitigating corrosion through effective measures, such as protective coatings and periodic inspections, is critical for prolonging service life and reducing overall upkeep expenses [8].

Among corrosion prevention strategies, paint coatings remain the most commonly employed due to their cost-

effectiveness and ease of application [9]. These coatings act as physical barriers against corrosive species [10], but they are susceptible to impact or abrasion damage, which compromises the substrate's protection [11]. When defects occur, water and oxygen can penetrate the coating, triggering localized corrosion processes like pitting [12], which rapidly weakens structural elements [13,14]. Even minor coating flaws may accelerate corrosion, as the damaged area can become an anodic site in a galvanic cell, with the surrounding intact coating acting as the cathode [15,16]. Furthermore, undercutting corrosion may propagate laterally beneath seemingly intact regions of the coating [17], making early detection and accurate prediction of coating deterioration essential for scheduling maintenance and controlling repair costs [18].

The progression of corrosion is inherently complex, influenced by numerous factors. Historically, researchers have employed diverse methodologies to quantitatively evaluate and predict corrosion, acknowledging the challenges in acquiring real-time data on corrosion progression and its fluctuating elements. Consequently, it has been a common assumption that changes on corroded surfaces occur randomly, prompting a focus on understanding the probability distributions of corrosion rates tied to specific corrosion characteristics for effective modeling and prediction [19,20]. Research incorporating fractals and semi-variogram functions has been pivotal in assessing the corrosion characteristics [21,22]. Additionally, Monte Carlo simulation techniques have been utilized to envisage the corrosion trajectory, relying on probability distributions for corrosion growth rates [23]. While these methods are largely geared toward assessing and predicting general corrosion, strategies for addressing localized corrosion, such as three-dimensional (3D) cellular automata and genetic algorithms also exist, underscoring the stochastic and non-uniform nature of atmospheric corrosion, including localized effects [24]. However, there are still many limitations to methods for predicting and evaluating corrosion progression due to the limited number of target materials as well as corrosion environments for each method. Moreover, in the case of coated steels, predicting corrosion underneath steel surface coatings involves several complexities and challenges, mainly due to the insidious nature of such corrosion and the various factors that may influence its occurrence and progression. In this context, the significance of non-destructive testing and the advancements in acoustic emission technology for corrosion monitoring have been underscored, offering a promising avenue for the efficient detection of corrosion beneath coatings [25]. Nevertheless, these techniques necessitate specialized equipment and encounter limitations in quantifying corrosion extent and predicting coating degradation, highlighting the ongoing need for

innovation in corrosion detection and prediction methodologies.

In recent years, the versatility of deep learning has been demonstrated across a wide array of fields, finding applicability in modeling complex phenomena such as corrosion, which is influenced by a multitude of factors. Within the domain of corrosion assessment, deep learning has introduced groundbreaking methods for the detection, classification, and segmentation of corrosion in critical infrastructures, including bridges. For example, the use of convolutional neural network (CNN)-based semantic segmentation algorithms, mask region-based convolutional neural network (Mask RCNN) and you only look once version 8 (YOLOv8), has facilitated more precise quantification of corrosion areas and severity levels [26]. Nevertheless, the mere classification of corrosion falls short of addressing the comprehensive needs of steel structure maintenance. A predictive approach to corrosion progression holds greater significance. A previous study successfully leveraged a deep learning model to predict corrosion progression on uncoated steel plates, yielding promising outcomes. In this study, a new generative adversarial network (GAN) was designed to predict the surface degradation of paint coated steel [27]. This model was informed by a data set derived from two distinct types of paint coated steel, onto which various defects were intentionally introduced. The specimens underwent an accelerated corrosion test, specified by the ISO 16539 Method B, to collect the corrosion surface depth at different period [28]. The objective is to utilize GAN for predicting subsequent degradation based on the current condition of the paint coated surfaces and accurately determining the existing corrosion state. To enhance the data set's diversity and thereby refine the prediction model's accuracy, Gaussian noise and GAN techniques were employed for data augmentation. The model incorporates UNet + ViT for the generator and MobileNetV2 for the discriminator, enabling predictions of future coating degradation from current conditions [29–31]. Furthermore, it facilitates the identification of the paint coating type, defect type, and the current stage of corrosion. Comparative analysis with alternative models corroborates this model's superior accuracy in predicting the degradation of paint coated steel.

The principal contribution of this study is the proposition of a GAN-based model for the prediction of paint coating degradation, capable of predicting future degradation, where the inputs to the model are consecutive corroded surface data from four prior time points, and the output is the subsequent corrosion depth distribution. Traditional methods for corrosion prediction often rely on stochastic or deterministic models. Monte Carlo simulation, for instance, utilizes probability distributions of corrosion rates to generate a range of possible outcomes, but it may require extensive parameter

tuning and large amounts of empirical data, and it can struggle to capture complex, localized corrosion patterns. Semi-variogram and geostatistical techniques, while effective in analyzing spatial properties of corroded surfaces, are often limited by assumptions regarding stationarity or isotropy, and do not inherently provide temporal predictive capabilities. Unlike these classical approaches, the GAN paradigm employed in this study introduces a deep learning architecture that is inherently adept at learning high-dimensional distributions from relatively small or heterogeneous data sets. Earlier studies have explored deep learning for corrosion forecasting, but they typically address uncoated steel plates [22] or focus on purely discriminative tasks (e.g., identifying corroded vs. non-corroded regions). In contrast, the present work leverages GAN-based generation to predict detailed spatial progression of corrosion beneath paint coatings, an area previously underexplored. The model can predict future deterioration in the presence of various paint coating types and defects, offering a promising tool for efficient steel structure maintenance. This approach surpasses traditional methods in predicting corrosion progression, offering a faster and more precise alternative that promises significant cost and time savings in the corrosion assessment and maintenance of steel structures utilizing paint coated steel.

2 Experiment

2.1 Specimens

The specimens utilized in this study are depicted in Fig. 1, with their dimensions detailed in Fig. 2. Constructed

from SM400 steel, which is carbon steel specified by JIS G 3106. Each specimen measured 150 mm in length, 70 mm in width, and 9 mm in thickness, uniformly coated with an anti-corrosion coating. Two different coating systems were applied in this study: the A-5 (Figs. 1(a) and 1(b)) and C-5 (Figs. 1(c) and 1(d)) coating systems. The A-5 coating system, an established anti-corrosion coating prevalent in current steel structures, is detailed in Table 1, while the C-5 coating system, representing a novel coating with potential for broader application, is detailed in Table 2.

A total of 12 specimens were prepared, split evenly between the A-5 and C-5 coating systems. In general, when coating defects occurred, the degradation process of paint coated steel initiates with substrate surface corrosion at the site of coating defects, subsequently propagating into the coating and manifesting as blistering and other forms of degradation. These coating defects vary in shape and size. The most common cases are linear defects (formed by scratches from external sources) and point-like circular defects (formed by impacts from external forces). Therefore, to mimic real-world scenarios where coatings on steel structures fail due to paint coating breaches, artificial linear and circular defects were introduced. Specifically, three specimens from each coating system were introduced to include linear defects of varying widths, while another three specimens from each coating system were introduced to incorporate circular defects of differing diameters, as indicated by the brown areas in Fig. 2. Linear defects were introduced at lengths of 50 mm and widths of 1, 2, and 3 mm, respectively. Circular defects were introduced with diameters of 3, 6, and 9 mm, respectively.

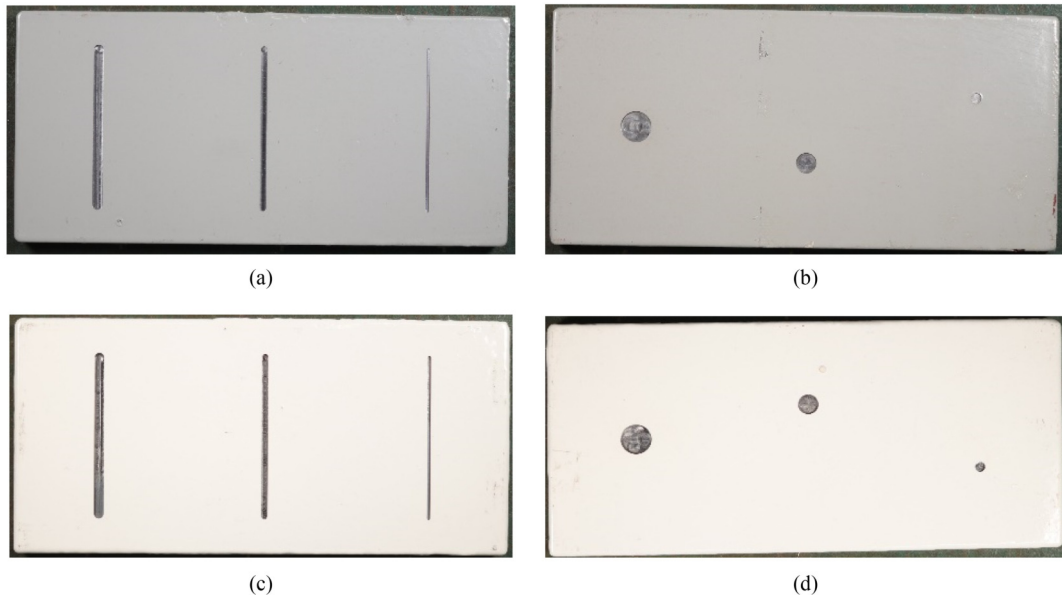


Fig. 1 Appearance of specimen: (a) A-5 coating with linear defects; (b) A-5 coating with circular defects; (c) C-5 coating with linear defects; (d) C-5 coating with circular defects.

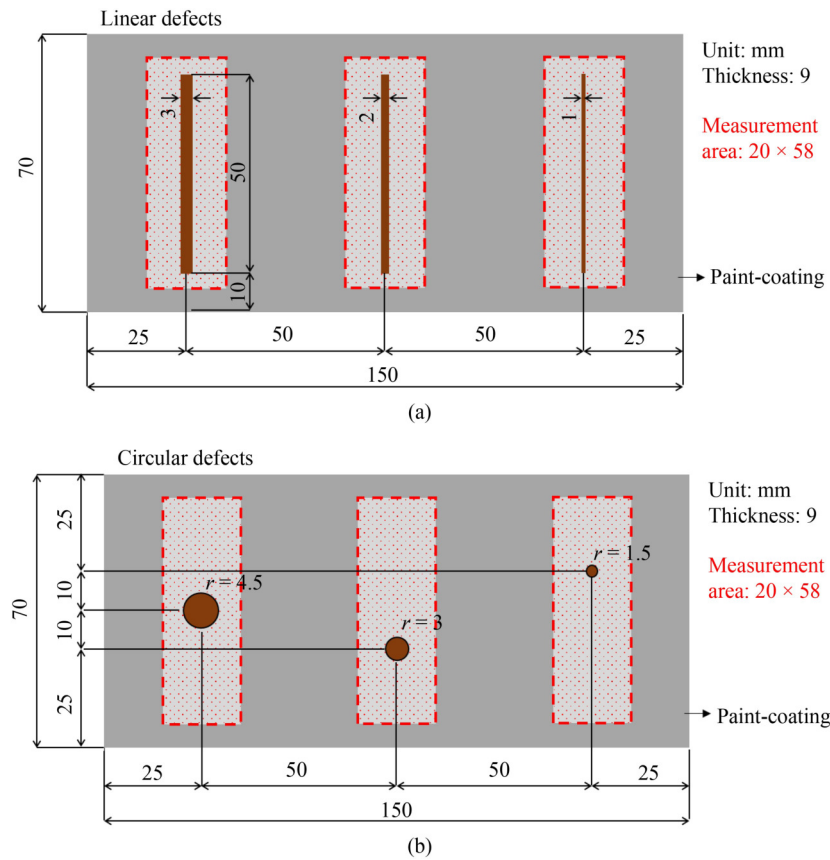


Fig. 2 Dimensions of specimen: (a) paint coating with linear defects; (b) paint coating with circular defects.

Table 1 A-5 coating system material specifications (artificial)

Layer	Material	Thickness (μm)
Top layer	pure/crosslinked polyimide	35
Middle layer	electrolytic copper foil standard electrodeposition	30
Base layer	electrolytic copper foil standard electrodeposition	25
Adhesive	—	125

Table 2 C-5 coating system material specifications (artificial)

Layer	Material	Thickness (μm)
Reinforced top layer	semi-cured crosslinked polyimide	75
Sheet layer	glass fabric base material	—
Top layer	glass fabric base material	120
Middle layer	electrolytic copper foil standard electrodeposition	30
Base layer	electrolytic copper foil standard electrodeposition	25
Adhesive	—	250

2.2 Accelerated corrosion test ISO 16539 Method B

The accelerated corrosion test ISO 16539 Method B was employed for the specimen corrosion. This method is recognized for its effectiveness in replicating real atmospheric corrosion environments, enabling the specimens to develop corroded surfaces that closely mimic those found in natural corrosive environments

[28]. Consequently, it is particularly advantageous for the swift collection of corrosion data across various stages of the corrosion process.

Figure 3 illustrates the test procedure for the accelerated corrosion test ISO 16539 Method B [28]. The test conditions mimic the corrosion behavior observed in metal-coated steels across diverse real-world environments, particularly those influenced by electrical

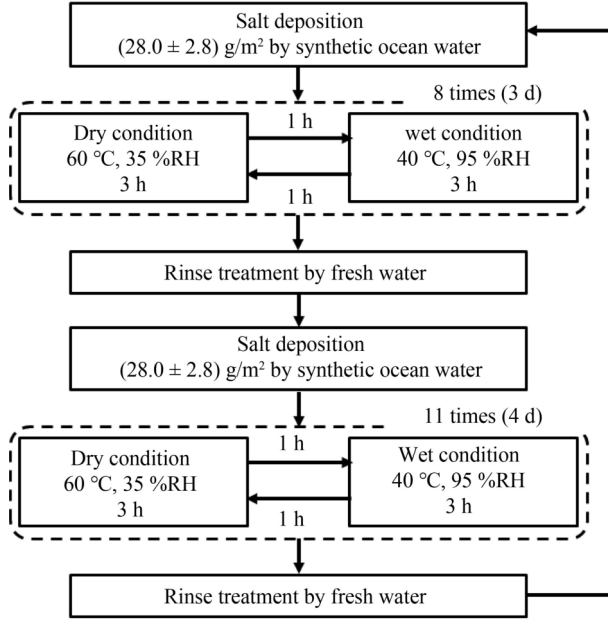


Fig. 3 Procedure for accelerated corrosion test ISO 16539 Method B.

conductivity. A key focus of the analysis was the regulation of large salt deposits and establishing a correlation between the quantity of salt deposited and the corrosion rate. It was determined that the cycle of dry and wet conditions could be controlled through adjustments in temperature and humidity, maintaining constant absolute humidity [32]. The test apparatus comprised two primary components: a synthetic seawater spray device and a test chamber, where temperature and humidity were kept constant. The procedure initiated with spraying the specimens with a 3.5% salinity synthetic seawater solution, aiming for a salt deposition target of (28.0 ± 2.8) g/m² per specimen. This was followed by cycles of drying at 60 °C with 35% relative humidity (RH) and wetting at 40 °C with 95% RH, repeating every three hours, including a one-hour transition phase. Each cycle, encompassing drying, transitioning, and wetting phases, spanned 8 h and was completed eight times before rinsing the specimen surfaces with water. Subsequently, the specimens were sprayed with synthetic seawater again, and the drying and wetting cycle was extended for an additional 11 cycles, spanning a total of 7 d.

Throughout the accelerated corrosion test ISO 16539 Method B, the surface condition of each steel plate specimen was measured at various periods.

2.3 Corroded surface measurement and data set

To collect time-series depth data on the steel plate coatings, a laser displacement meter with a resolution of 0.1 μm was employed, providing high-precision 3D (x , y , z) corrosion depth measurements. This instrument was used to scan each specimen both before the accelerated

corrosion test and at 1, 3, 4, and 5 months thereafter. The designated measurement area, highlighted in red in Fig. 2, encompassed a 20 mm × 58 mm region centered on the initial defects. This standardized region was applied to both linear and circular defects to ensure consistency across specimens, thus enhancing the subsequent deep learning model's training efficiency. Within each 20 mm × 58 mm zone, the laser displacement meter systematically recorded corrosion depths at 0.1 mm intervals in both longitudinal and transverse directions. This dense sampling captured fine-scale variations in corrosion morphology, including localized pitting or undercutting corrosion beneath the paint coating. By comparing depth profiles at multiple time points, it became possible to link increases in measured surface depth to visually observable coating damage, confirming that areas with greater depth variation often corresponded to regions of coating failure.

Given the study's scope included 12 specimens, each presenting three types of defects with varying widths or diameters, a systematic numbering from No. 1 to No. 36 was assigned to each defect for clear identification and analysis. The corrosion depth data collection extended over several time points, specifically, 0 (pre-test), 1, 3, 4, and 5 months, resulting in a comprehensive data set comprising 180 corrosion depth measurements. The organization of this data set is detailed in Table 3, which categorizes the 12 specimens, outlines the 36 time-series of corrosion depth data, and compiles a total of 180 individual corrosion depth measurements.

3 Generative adversarial network based model

3.1 Generative adversarial network models

In this study, a series of models based on GAN were

Table 3 Corrosion depth data collected from the experiment

Defect	Coating	Size (mm)	0, 1, 3, 4, 5 months (number)	Total
Linear (width)	A-5	1	3 (Nos. 1–3)	12 specimens, 36 corrosion depth data sets, 180 corrosion depth data
		2	3 (Nos. 4–6)	
		3	3 (Nos. 7–9)	
	C-5	1	3 (Nos. 10–12)	
		2	3 (Nos. 13–15)	
		3	3 (Nos. 16–18)	
	Circular (diameter)	3	3 (Nos. 19–21)	
		6	3 (Nos. 22–24)	
		9	3 (Nos. 25–27)	
	C-5	3	3 (Nos. 28–30)	
		6	3 (Nos. 31–33)	
		9	3 (Nos. 34–36)	

deployed to predict the degradation of coatings on steel surfaces. GAN, as a subset of deep learning architectures, have the capability to analyze a data set and generate new data that share statistical properties with the original set. The GAN architecture is built upon two main components: a Generator and a Discriminator. The Generator aims to replicate the real distributions of corroded surface depth data, starting from a random noise vector to produce data that closely mimics the genuine data set. Depending on the nature of the data and specific requirements, the Generator's architecture may incorporate multi-layer neural networks, including fully connected network, CNN, or recurrent neural network (RNN). Conversely, the Discriminator's role is to discern whether its input data originates from the authentic corrosion depth data set or is the output of the Generator. This component also utilizes a multi-layer neural network to process its input and ultimately determine the likelihood of the data being real.

As shown in Eq. (1). The training methodology for GAN embodies a minimax game, where the Generator strives to minimize a designated objective function, while the Discriminator strives to maximize it [33].

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]. \quad (1)$$

In this study, x is the data from the real corroded surface data distribution p_{data} , z is a noise vector from Gaussian distribution p_z , $G(z)$ is the fake corroded surface data generated by the generator using the noise vector. $D(x)$ is the output of the discriminator for real data x , and $D(G(z))$ is the output of the discriminator for generated data.

Training proceeds in a cyclical manner: first stabilizing the Generator to refine the Discriminator's accuracy in differentiating real from generated data, followed by fixing the Discriminator to enhance the Generator's capacity to produce increasingly realistic data. This iterative process continues until reaching a state of equilibrium, where the Discriminator can no longer reliably distinguish between real and generated data sets.

This study also examined the application of two GAN variants, Conditional GAN (CGAN) and Information Maximizing GAN (InfoGAN), in predicting paint coating degradation [34,35]. CGAN introduces a conditional variable ' c ' to both the Generator and Discriminator, necessitating that generated data not only appear realistic but also adhere to the constraints imposed by ' c '. In the present study, the condition vector encodes the coating type (A-5 or C-5) and defect shape (linear or circular). The condition vector is concatenated with the noise input for the Generator and is also appended to the Discriminator input through an embedding layer, ensuring that the generated samples adhere to the

specified coating and defect. The learning rate and optimizer configurations match those in the GAN model proposed in this research, and the conditional variables are trained under a cross-entropy objective to preserve alignment between the model output and the imposed condition. InfoGAN extends the original GAN framework by incorporating a mutual information term to encourage the discovery of interpretable latent representations. In the present study, the latent code is designed to capture factors such as coating type and defect shape, along with a continuous variable to account for stochastic corrosion variations. The mutual information term is maximized through an auxiliary network that predicts the latent code from the generated samples. The training procedure, including learning rate and batch size, follows the hyperparameters employed by the GAN model proposed in this research. During each training epoch, the latent variables and the mutual information head are jointly optimized to enhance the interpretability and diversity of the generated corrosion patterns.

Furthermore, this study developed a specialized GAN model tailored for characterizing paint coating degradation, utilizing UNet + ViT for the Generator and MobileNetV2 for the Discriminator. Detailed construction of this model is elaborated in the subsequent section, with its predictive efficiency evaluated through training and comparison against other models.

3.2 Model architecture and data set settings

The architecture of the GAN model developed for predicting paint coating degradation is illustrated in Fig. 4, employing UNet + ViT as the generator and MobileNetV2 as the discriminator. UNet, initially designed for biomedical image segmentation, excels in tasks necessitating precise edge detection, making it apt for analyzing coated surface corrosion [29]. Its symmetric architecture, featuring both contraction and expansion paths, enables the efficient learning of correlations from corroded surface depth data and precise pixel localization. When paired with the Vision Transformer (ViT), which applies the Transformer architecture to image classification by processing image patches with positional encoding, the generator benefits from enhanced detail capture and global context understanding, courtesy of the Transformer's proficiency in recognizing long-range dependencies [30]. This combination allows the generator to generate corroded surfaces that are more accurate in detail and more consistent in their overall distribution. MobileNetV2 serves as a highly efficient discriminator, utilizing an inverted residual structure and depth-separable convolutions for effective feature extraction, object detection, and segmentation. Its lightweight design ensures computational and memory efficiency, with an

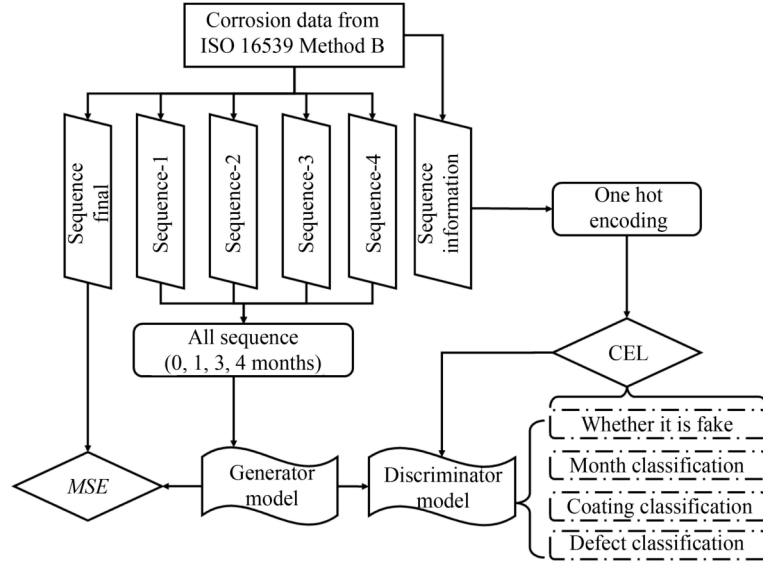


Fig. 4 Model architecture.

additional sigmoid activation function implemented to differentiate between real and fake inputs effectively [31].

This model's innovative combination of UNet + ViT for generation and MobileNetV2 for discrimination facilitates the creation of high-quality, accurate corroded surfaces, optimizing both the quality of image generation and the efficiency of the discrimination process.

For optimization, the Adam optimizer was chosen. The discrepancy between generated and real corroded surface data was quantified using mean squared error (MSE) loss, as depicted in Eq. (2).

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y}_i)^2, \quad (2)$$

where y_i is predicted value, and $\bar{y}_i$ is labeled value.

Given the multi-classification nature of this task, cross entropy loss (CEL) was employed to evaluate the difference between the model's predicted probability distribution and the actual label distribution, as depicted in Eq. (3).

$$CEL = - \sum_{i=1}^n (y \log(\bar{y}) + (1 - y) \log(1 - \bar{y})), \quad (3)$$

where n is the number of categories, y is labeled value, and $\bar{y}$ is predicted value.

The data set was divided into training and test sets as delineated in Table 4. The time-series corroded surface depth was measured of each specimen at 0, 1, 3, 4, and 5 months. Training sets included specimens numbered 1, 2, 4, 5, 7, 8, 10, 11, 13, 14, 16, 17, 19, 20, 22, 23, 25, 26, 28, 29, 31, 32, 34, and 35, while the test set comprised specimens numbered 3, 6, 9, 12, 15, 18, 21, 24, 27, 30, 33, and 36. This study's coating deterioration prediction model used data from the initial four time periods to

Table 4 Training set and testing set settings

Defect	Coating	Size (mm)	No.	
			Training set	Testing set
Linear (width)	A-5	1	1, 2	3
		2	4, 5	6
		3	7, 8	9
	C-5	1	10, 11	12
		2	13, 14	15
		3	16, 17	18
	A-5	3	19, 20	21
		6	22, 23	24
		9	25, 26	27
Circular (diameter)	C-5	3	28, 29	30
		6	31, 32	33
		9	34, 35	36

predict the coating deterioration at the final period. The prediction results were compared with the actual experimental data to obtain the accuracy of the model.

3.3 Model training

The training of the prediction model for coating degradation prediction involved a series of methodical steps. Initially, the raw corrosion depth data from each specimen, with an original size of 201×581 , was rescaled to 256×1024 pixels to fit the input specifications. The generator and discriminator were both assigned a batch size of four during the training process. The variance squared (σ^2) was employed as the activation function in the model, referred to as sigma (σ) activation, with a leakage rate set at 0.2 to manage the flow of information during the learning process. The Adam

optimization algorithm was configured with beta values of [0.5,0.99], enhancing the convergence stability during the training. All experiments were conducted in Python 3.9 on Google Colab with a single A100 GPU, and each complete training run took approximately 50 min.

Gaussian noise was introduced to the coating surface degradation data from the preceding four time periods, serving as input to the UNet + ViT generator, while the target for the model was defined as the coating surface degradation data from the subsequent time period. The aim was to enhance the model's predictive capacity by incorporating the inherent randomness and variability in corrosion progression through the input noise. MobileNetV2, as the discriminator, played a pivotal role in discerning whether the incoming images were synthetic, produced by the UNet + ViT generator, or authentic corrosion images. Training ensued following the standard adversarial framework, where the GAN model underwent alternate steps of discriminator optimization and generator updates.

At the conclusion of each training epoch, a fine-tuning phase was implemented where only the UNet + ViT generator was trained. This step was crucial in refining the generated data's resemblance to the real corrosion depth data, thereby minimizing the *MSE* loss and aligning the generated output closely with the actual corrosion patterns. Furthermore, the training incorporated *CEL*, a pivotal factor in classifying the state of the inputs in terms of their authenticity, the month of corrosion progression, the type of coating defect, and the type of coating, as outlined by the one-hot encoding scheme for sequence information. This loss function facilitated the model's classification capabilities.

Figure 5 illustrates the mean absolute error (*MAE*) curves recorded over 20 epochs for A-5 specimens, highlighting how the model steadily converges as the epochs progress. These curves reflect a consistent downward trend in the *MAE* values, indicating that the model effectively learns representative features of corrosion behavior. By the final epochs, the losses stabilize at relatively low levels, suggesting that the

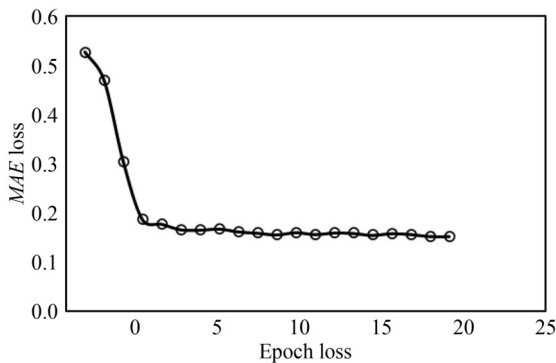


Fig. 5 Training *MAE* loss curve.

trained model is well-positioned to predict corrosion depth for subsequent time periods with high accuracy.

4 Results

The efficacy of various models in predicting the progression of paint coating surface degradation was meticulously evaluated in this section. The root mean square error (*RMSE*), as delineated in Eq. (4), served as the metric for model performance, with a lower *RMSE* indicating higher predictive accuracy.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Y_i - f(x_i))^2}, \quad (4)$$

where Y_i is the experimental value, and $f(x_i)$ is the predicted value.

The *RMSE* results, as detailed in Table 5, compare each model's performance regarding linear defects, while Table 6 showcases the *RMSE* for circular defects. Across all scenarios, the UNet + ViT model introduced in this study demonstrated superior performance over its counterparts, demonstrating outstanding predictive accuracy.

Table 5 *RMSE* results of the models with linear defects

No.	GAN	CGAN	InfoGAN	UNet + ViT
3	15.232	1.236	2.133	0.417
6	8.099	1.688	3.523	0.895
9	14.652	1.104	2.098	0.538
12	6.448	1.712	1.872	0.244
15	12.719	2.331	1.900	0.885
18	5.606	1.016	1.113	0.498

Table 6 *RMSE* results of the models with circular defects

No.	GAN	CGAN	InfoGAN	UNet + ViT
3	18.104	0.956	2.010	0.080
6	7.851	1.343	2.291	0.162
9	9.633	1.120	1.985	0.222
12	8.405	1.355	1.343	0.085
15	12.093	1.908	1.192	0.152
18	10.885	0.566	1.235	0.255

Regarding the predictive performance of three GAN-based models applied in this study: CGAN, InfoGAN, and the proposed GAN model incorporating UNet + ViT for the Generator and MobileNetV2 for the Discriminator. While CGAN utilizes an explicit conditional vector (coating type and defect shape) to guide the generation process, it relies on relatively simpler generator and discriminator architectures. This design constrains CGAN's capacity to capture fine-

grained spatial features in paint coating deterioration. InfoGAN, on the other hand, introduces a mutual information component to encourage interpretable latent representations, yet it employs a basic convolutional structure that may struggle with the highly localized corrosion patterns observed in certain specimens. In contrast, the GAN model proposed in this research integrates UNet + ViT in the Generator to effectively preserve spatial details and capture long-range dependencies, while MobileNetV2 in the Discriminator ensures efficient feature extraction and robust adversarial training. The synergy between UNet's encoder-decoder architecture and ViT's global attention mechanism contributes to more accurate predictions of corrosion depth, as evidenced by lower *RMSE* and *MAE* values in Tables 5 and 6. Moreover, the lean yet powerful MobileNetV2 Discriminator maintains computational efficiency without sacrificing discrimination quality. These architectural advantages allow the proposed model to adapt better to complex corrosion morphology, thereby outperforming both CGAN and InfoGAN in terms of predictive accuracy.

Furthermore, a comparative analysis of the prediction accuracy for linear versus circular defects revealed a notable trend: the models exhibited enhanced accuracy

for circular defects. This observation is attributed to the more uniform corrosion patterns exhibited by circular defect samples as compared to linear ones, likely due to the relatively smaller circumference of the corrosion area in circular defects, resulting in simpler corrosion patterns and thus, more predictable coating degradation progression.

Figure 6 provides a visual representation of the predictive capability of the model for linear defects. Here, corroded surface data from specimen No. 3 at 0, 1, 3, and 4 months were utilized to predict the 5-month corroded surface. Figure 6(a) displays the predicted coating surface degradation, Fig. 6(b) shows the actual degradation, and Fig. 6(c) presents a photograph of the real paint coated surface after degradation. Similarly, Fig. 7 depicts the application of the model for circular defects. Here, corroded surface data from specimen No. 21 at 0, 1, 3, and 4 months were utilized to predict the 5-month corroded surface. Figure 7(a) displays the predicted coating surface degradation, Fig. 7(b) shows the actual degradation, and Fig. 7(c) presents a photograph of the real paint coated surface after degradation. Figure 8 shows the comparison between the actual and predicted corroded surfaces at the 5-month mark for all specimens in the test set.

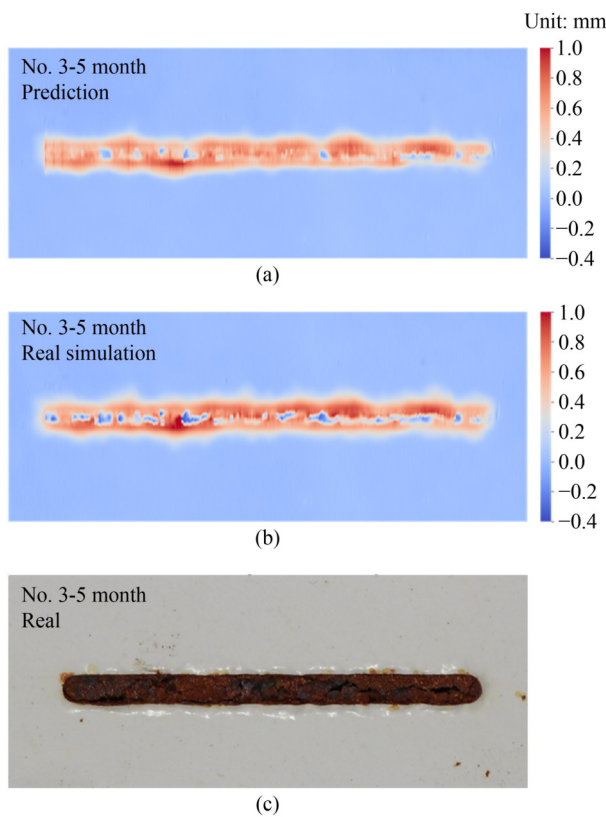


Fig. 6 Predicted result for specimen No.3 with linear defects: (a) predicted coating surface degradation; (b) real coating surface degradation; (c) photograph of real coating surface degradation.

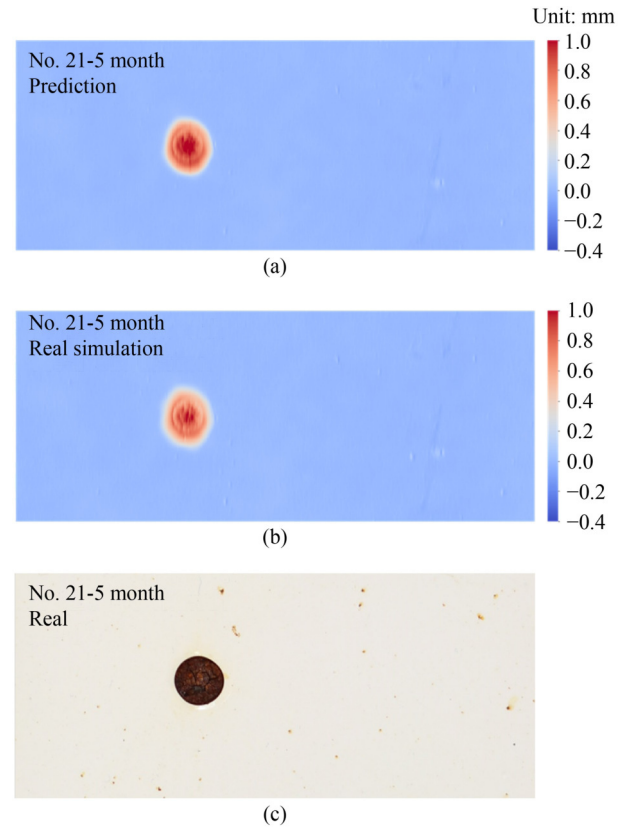


Fig. 7 Predicted result for specimen No.21 with circular defects: (a) predicted coating surface degradation; (b) real coating surface degradation; (c) photograph of real coating surface degradation.

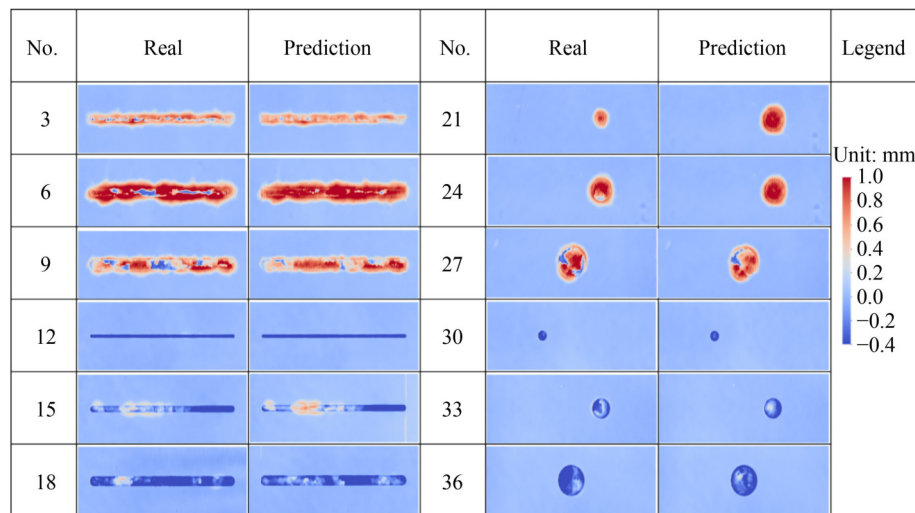


Fig. 8 Comparative results of all specimens in the test set.

In these figures, the congruence between predicted outcomes and experimental data underscores the model's validity. The close resemblance attests to the predictive prowess of the developed model, confirming its applicability for accurate simulation of the progression of paint coating surface degradation.

5 Conclusions

Paint coated steel plays a pivotal role in structural engineering, and the development of a reliable method for predicting corrosion on paint coated steel is critical for the maintenance of infrastructure. This study explored the deterioration progression on paint coated steel with linear and circular defects, representing the common forms of coating damage encountered in real-world scenarios. Accelerated corrosion tests in accordance with ISO 16539 Method B were performed on two types of paint coated steels. The gathered corrosion depth data at different time periods formed the foundation of a data set for model training. Utilizing this data set, various GAN-based models were applied and their predictive outcomes were compared. The comparative analysis revealed that the accuracy of the proposed model surpasses that of other models. This approach is capable of predicting subsequent stages of coating degradation from preceding data, as well as classifying the coating types, defect types, defect sizes, and the current condition of the steel plate.

The approach introduced by this study offers a straightforward and practical method for predicting future degradation from earlier states. It contributes to simplifying the assessment of deterioration in paint coated steel structures and reduces the time and costs associated with maintenance. The proposed method could be integrated into predictive maintenance frameworks. This holds substantial value for the precision-oriented maintenance of steel structures.

The findings of this study underscore the potential of the proposed GAN-based model for accurately predicting paint coating degradation in steel structures. In real-world structural engineering contexts, such predictive insights could facilitate proactive maintenance scheduling, minimizing costly downtime and reducing the risk of catastrophic failures. By providing reliable forecasts of coating deterioration, engineers and asset managers can optimize inspection intervals, focus remediation efforts on vulnerable locations, and extend the service life of steel infrastructure.

In the future, the intention is to broaden the scope of the research by incorporating a wider array of corrosion scenarios. This expansion will involve refining the differentiation between the shapes and sizes of coating defects and extending the model to predict corrosion progression underneath the coating, thereby enhancing its capacity to capture both surface and substrate steel corrosion. Furthermore, additional corrosion environments, such as high salinity or industrial pollutant conditions, will be considered to reflect real-world variability. A multi-scale modeling approach may be employed to integrate macro-level atmospheric data with micro-level surface topography, thereby improving predictive resolution. Finally, techniques such as transfer learning or advanced data augmentation (e.g., using generative models) could help mitigate data scarcity, allowing the model to adapt more effectively to novel corrosion environments and coatings. By refining the scope of corrosion scenarios and incorporating these methodological improvements, future iterations of the model are expected to achieve greater robustness and accuracy, further bridging the gap between laboratory-scale experiments and full-scale engineering applications.

Funding note Open Access funding provided by The University of Osaka.

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Competing interests The authors declare that they have no competing interests.

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