# Corroded Surface Prediction of Weathering Steel Plates under Different Corrosive Environments Using Generative Adversarial Network

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In the maintenance of today's steel structures, fast and accurate prediction of corrosion development is of great importance in numerical simulation analysis, saving time and cost. In this research, two kinds of weathering steel plates were subjected to four corrosive environments for different time periods. A system based on GAN data augmentation with UNet as the generator and MobileNetV2 as the discriminator was built. The system can simulate three stages (28 days, 84 days, 168 days) of corrosion based on the dataset collected from experiments. It can also predict the corroded surface of steel plates in the next stage. The discriminator of the system can be used to classify the type of weathering steel and days of corrosion. Based on comparative experiments, our system exhibits outstanding performance and outperforms the baseline model.

## 1. Introduction

Corrosion is a major cause of deterioration and damage to steel structures. Corrosion is a long-term process. It takes a lot of time to determine the degree of corrosion based on observations. Therefore, the simulation and prediction of the corrosive process play an important role in the modeling of corrosion damage and the determination of corrosion status promptly. In previous studies, the fractal and spatial correlation have been used to evaluate the surface characteristics of the corroded surface of steel plates. And the corrosion rate probability distribution is related to the characteristics of the corrosion surface which can be used to build simulation and prediction models (Caleyo, F., et al[1)]). However, these methods have limitations on their target materials and corrosive environments. The relationship between corrosion damage and aging is still unclear. A widely applicable method is in need to effectively predict the corrosion behavior over time.

In this research, SMA400AW and SMA490AW were subjected to four corrosive environments for different time periods. A corroded surface prediction system based on GAN data augmentation with UNet as the generator and MobileNetV2 as the discriminator was built.

## 2. Experiments

Two weathering steels, SMA400AW and SMA490AW, with a total of 48 specimens were tested in four different corrosive environments. 1). ISO 16539: Artificial seawater with a concentration of 3.5% was applied to the surface using a spraying device, and a salt deposition of 28.0 ± 2.8 g/m$^2$ was obtained. The repeated drying and wetting process consisted of three hours of dryness (60 °C, 35% RH) and three hours of wetness (40 °C, 95% RH), and the transition time from dry to wet and from wet to dry was one hour, which is 8 hours per cycle. This is done alternately in 8 cycles (3 days) and 11 cycles (4 days). 2). Combined cycle corrosion test: One complete cycle takes 24 hours. It consists of one hour of wetness (30 °C, 95% RH), two hours of surface spraying with saltwater (30 °C, 5% NaClaq), six repetitions of one and half hour wetness (50 °C, 95% RH), one and half hours of dryness (50 °C, 20% RH), and another one and half hours of dryness (30 °C, 20% RH). 3). Atmospheric exposure I: The experiment runs for 365 days under the real atmospheric exposure situation in Choshi, Japan. 4). Atmospheric exposure II: The experiment runs for 180 days under the real atmospheric exposure situation in Miyakojima, Japan. The tests of 1) and 2) are accelerated corrosion types. In these two experiments, the development of corrosion was observed in three stages. The first stage is 28 days. The second stage is 84 days. The third stage is 168 days. 3) and 4) are corrosion in real corrosion situations. The purpose of the different experimental environments is to compare the corrosion in the artificial environments with the real environments. And to check the applicability of this prediction model in multiple environments. Table 1 shows the distribution of specimens.

Table 1 Number of specimens in different experiments.

| | ISO 16539 | Combined cycle | Choshi | Miyakojima |
|---|---|---|---|---|
| SMA400AW | 9 | 9 | 3 | 3 |
| SMA490AW | 9 | 9 | 3 | 3 |

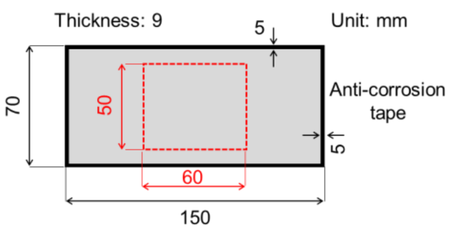



Fig. 1 The size of specimens and corrosion measure area.

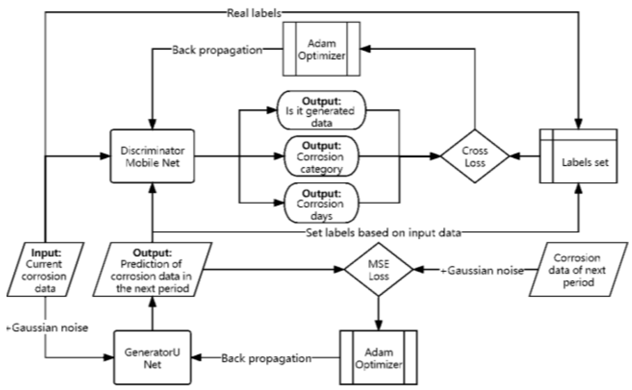



Fig. 2 System architecture.

The length, width, and thickness of each specimen are 150 mm, 70 mm, and 9 mm. Each plate is wrapped with a 5 mm anti-corrosion tape along all its edges. Fig. 1 explains the size of each steel plate and the corrosion measurement area. The corrosion depth data in a 50 mm times 60 mm area in the middle of the steel plate is used for modeling.

## 3. Method

In this research, we use Gaussian noise and GAN to enrich the dataset. UNet is the generator and MobileNetV2 is the discriminator for GAN. The generator is mainly used to simulate the regression of the next phase of the input data; the role of the discriminator is to determine whether the input data is the data generated by the generator. In addition, the discriminator used in this paper can also be used to predict the type of corrosion and the stage of the corrosion. We use Adam optimizer as the optimizer in our system. Fig. 2 illustrates the system architecture and its procedure.

Generative adversarial network (GAN) is a class of machine learning frameworks, it learns from a dataset and generates new data with the same statistics. GAN is commonly used for data augmentation, especially when the dataset is limited. In this research, we can only obtain limited data as the original dataset. We choose GAN to enrich the dataset and generate new training samples based on the corrosion samples we collect from experiments. If not the same, the distribution of the newly generated data samples is rather similar to the original dataset. In this research, we choose GAN and its one variant: Information Maximizing GAN (InfoGAN).

The UNet was designed for Bio-medical Image Segmentation developed by Olaf Ronneberger et al[2]. There are two paths in architecture. One is the contraction path (or the encoder), a traditional stack of convolutional and max-pooling layers, which captures the context in the image. The other path is the symmetric expanding path (or decoder) which enables precise localization using transposed convolutions. It can handle images of any size and it is a fully convolutional network (FCN).

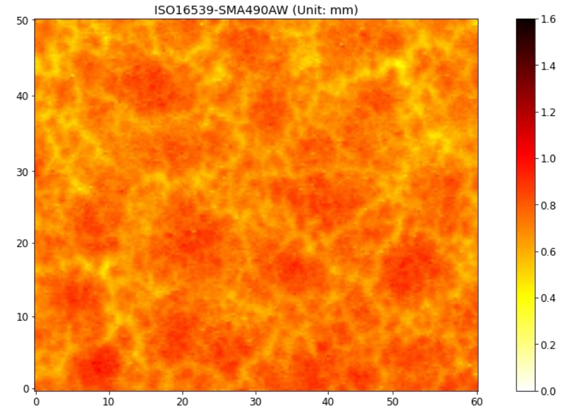
MobileNetV2 is an effective model for feature extraction, object detection, and segmentation. It is a mobile architecture based on an inverted residual structure, using depthwise separable convolution as efficient building blocks. The model allows decoupling of the input / output domains from the expressiveness of the transformation, which provides a convenient framework for further analysis. To be more suitable for the discriminator, an additional Sigmoid activation function is added to the end of MobileNetV2, 0 is Fake, and 1 is Real.

## 4. Results

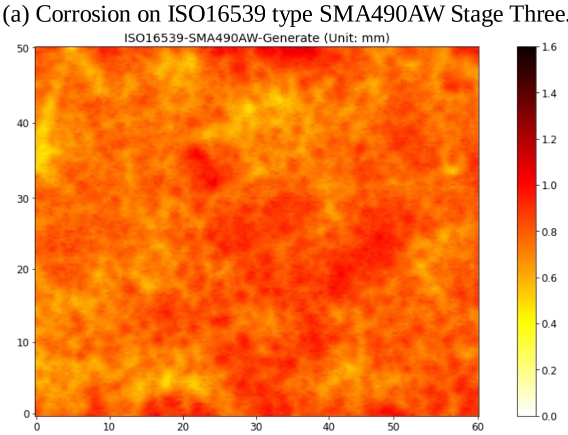
There are six scenarios of dataset usage in our experiment design, which are six configurations of the training set and testing set. “d1”, “d2”, “d3”, and “d4” are corresponding to the specimens from the four experiments: ISO16539, Combined cyclic corrosion test, Atmospheric exposure I (Choshi), and Atmospheric exposure II (Miyakojima). For example, in Scenario 1, we use “d1”, sample data from ISO16539, as a training set, and “d3”, sample data from Atmospheric exposure I, as a testing set. We conduct comparative experiments on three different models. The baseline model XceptionNet and using GAN-based augmentation models: GAN and InfoGAN. In this research, we use Root Mean Square Error (RMSE) as the main evaluation metric. Table 2 lists the results of our comparative experiments. Based on the results, the two models using GAN-based augmentation show better performance than the baseline model XceptionNet. Since InfoGAN require a huge amount of data for training, it doesn’t demonstrate advantages over GAN in this problem. Using GAN for augmentation outperforms all other models in four scenarios. Fig. 3 uses SMA490AW as an example to show the comparison of the corrosion on steel plates in stage three from the ISO16539 experiment and corresponding simulated corrosion generated by this prediction system. They show a similar pattern of corrosion distribution, which means our system can simulate the future corrosion situation in the measured area.

Table 2 Comparative Results.

| | Train: d1<br>Test: d3 | Train: d1<br>Test: d4 | Train: d2<br>Test: d3 |
|---|---|---|---|
| GAN | 0.423 | 0.397 | 0.337 |
| InfoGAN | 0.423 | 0.368 | 0.363 |
| Xception | 1.492 | 0.952 | 0.587 |
| | Train: d2<br>Test: d4 | Train: d1+d2<br>Test: d3 | Train: d1+d2<br>Test: d4 |
| GAN | 0.462 | 0.244 | 0.198 |
| InfoGAN | 0.433 | 0.347 | 0.233 |
| Xception | 0.882 | 0.884 | 0.902 |




(a) Corrosion on ISO16539 type SMA490AW Stage Three.




(b) Corrosion on predicted type SMA490AW Stage Three.

Fig. 3 Corrosion on ISO16539 type SMA490AW steel plate Stage Three and corresponding predicted corrosion.

## 5. Conclusions

In this research, a GAN-based machine learning model was proposed to augment the dataset and simulate and predict the corrosion of two kinds of weathering steel in four environments. The GAN structure composed of UNet and MobileNetV2 provided outstanding performance to address the research problems in this paper. Through comparative experiments, our model achieved high prediction accuracy and was verified to be reliable and generally applicable.

## References

1) Caleyo, F., et al.: Probability distribution of pitting corrosion depth and rate in underground pipelines: A Monte Carlo study, Corrosion Science, 51.9, 1925-1934, 2009.

2) Ronneberger O., Philipp F., and Thomas B.: U-Net: Convolutional Networks for Biomedical Image Segmentation, arXiv:1505.04597, 2015.