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Generation of Fault Data from Multiple Types of Bridge Monitoring Sensors Based on Time Series Diffusion Models Fusing Control Conditions and Pseudo Prompt Enhancement

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Abstract: *Bridges are crucial infrastructure components in transportation networks. However, as they age and traffic loads increase, their safety faces significant challenges. Bridge health monitoring systems collect structural data through sensors. However, obtaining sensor failure data is difficult, and traditional data generation methods, such as manually adding standard deviations, often lack data diversity. As a result, they fail to effectively reflect realistic sensor failures, which impairs the generalization ability and accuracy of fault diagnosis models. This paper proposes a bridge sensor fault data generation method based on a time series diffusion model, combining control conditions with pseudo prompt enhancement techniques. The goal is to improve the diversity and quality of the generated data. First, the Variational Autoencoder (VAE) is jointly trained with the inverse denoising process of the diffusion model to generate structured noise and enhance the complex characteristics of the noise. Then, a control condition module is introduced to regulate the quality of noise generation. To address the issue of insufficient data samples or uncertainty in labeling, a Pseudo Prompt Enhancement module is proposed, which utilizes a pre-trained autoencoder or self-supervised learning method to generate pseudo prompts that provide auxiliary information about the sensor device status. Furthermore, a classifier-free guidance mechanism is incorporated into the model training process to further enhance the quality and diversity of the generated data. Experimental results demonstrate that the proposed method yields significant improvements in generating real bridge sensor data. This approach offers a promising solution for generating realistic sensor fault data, advancing bridge health monitoring systems and enhancing their diagnostic accuracy.*

Keywords: *Diffusion model; bridge monitoring sensor failure data; data generation*

1. Introduction

Bridges are critical infrastructures in transportation networks, undertaking a large number of transportation tasks. Over time, many bridges gradually deteriorate, and traffic loads continue to increase. The safety and reliability of bridges have become focal points of societal concern. Damage or collapse of bridges can lead to severe traffic disruptions or even safety accidents, causing substantial losses to both society and the economy. Therefore, reliably monitoring and assessing bridge health is of utmost importance. Bridge health monitoring systems install various types of sensors at key locations of bridges to collect structural health data in real-time, enabling the timely detection of potential issues. However, in practice, sensor failure data from bridge health monitoring systems can compromise the accuracy of monitoring, and obtaining fault data samples is often a significant challenge. Traditional fault data generation methods typically rely on manually adding standard deviations to simulate fault data. However, such methods often result in a lack of diversity in the generated data, making it difficult to adequately reflect the complexity and variety of real-world sensor failures in bridges. This limitation hampers the generalization capability of sensor fault diagnosis models and ultimately affects the overall accuracy of bridge health monitoring systems.

In recent years, deep learning technology has been widely applied in various fields [1][2][3]. Among them, the high scalability, diversity, and modeling advantages of diffusion models have gradually made them a research hotspot in the field of data generation. The framework of generative diffusion models, which is called diffusion models in short, provides a flexible and powerful scheme of generative

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modeling, and it has gained significant attention in recent years due to their impressive performance in various areas in the machine learning community [4].Aiming at the problem of lack of diversity in the traditional manual generation of generated data for bridge health monitoring sensors, it is proposed to combine the generation of control conditions [5] and Pseudo Prompt Enhancement conditions [6] to obtain a method for generating fault data for multiple types of bridge sensors for use in time-series diffusion models, which improves the diversity of the generation of fault data for bridge health monitoring sensors, and thus improves the generalisation ability of the diagnostic model of faults for bridge health monitoring sensors.

Firstly, to improve the quality of the generated samples and enhance the structural properties of the noise in the diffusion model, the noise generated by the VAE model is jointly trained with the reverse denoising process of the diffusion model. This hybrid noise generation method enables the creation of noise with more complex features. Secondly, to effectively control the quality of the noise generated by the VAE model, a control condition module is introduced. The control conditions of this module include factors such as timestamp and fault type. Additionally, during the network training phase, to address the issue of insufficient bridge sensor fault data samples and to handle cases of missed labeling or uncertainty regarding whether labeling is necessary, a Pseudo Prompt Enhancement module is introduced. This module utilizes a pre-trained autoencoder or self-supervised learning method to extract latent representations from the sensor data. The latent representations, combined with auxiliary information related to the sensor data, are used to generate pseudo prompts through a generative model, which can roughly reflect the state of the sensor device. Finally, to further enhance the quality and diversity of the generated data, a classifier-free guidance mechanism is incorporated to optimize the model. In the experimental section, we collected a large amount of sensor data from real bridge monitoring systems and constructed a simulated dataset. To evaluate the effectiveness of the proposed method, comprehensive experiments were conducted, and several mainstream diffusion models were selected for comparison. The main contributions of this paper are summarized as follows:

(1) A time series diffusion model based on the fusion of control conditions and Pseudo Prompt Enhancement is proposed. The control conditions and pseudo prompt conditions are combined to form the final condition inputs, which are then fed into the denoising network of the diffusion model. Through the inverse diffusion process, time series data of sensor faults that conform to the specified conditions are generated.

(2) A hybrid noise generation method is proposed to generate bridge sensor fault data using the noise generated by the VAE model and the inverse denoising process of the diffusion model for joint training to improve the structure of the noise in the diffusion model.

(3) It is proposed to introduce a control condition module for noise generation control to effectively control the quality of noise generated by the VAE model.

(4) The introduction of a Pseudo Prompt Enhancement module is proposed to reflect the state of the sensor device and address the issue of insufficient bridge sensor fault data samples. This module also resolves the challenges of labeling omissions or uncertainties during the network training phase.

2. Methodology

In practical applications, obtaining fault data samples from bridge health monitoring sensors is a significant challenge. Traditional fault data generation methods typically involve manually adding standard deviations to generate fault data. However, this approach often results in a lack of diversity in the generated data, making it difficult to effectively capture the complexity and diversity of real-world bridge sensor faults, thus limiting the generalization ability of the sensor fault diagnosis model. Drawing on the successful use of diffusion models in audio generation, we employ a diffusion model to generate time series data of bridge health monitoring sensor faults. Simultaneously, we integrate control conditions to enhance generation control and the concept of Pseudo Prompt Enhancement to construct an efficient and controllable generative model. This model is designed to generate various types of bridge health monitoring sensor fault data. Firstly, to improve the quality of the generated samples and enhance the structural characteristics of the noise in the diffusion model, the noise generated by the VAE model is jointly trained with the reverse denoising process of the diffusion model. This hybrid noise generation method is capable of producing noise with more complex features. Secondly, to effectively control the quality of the noise generated by the VAE model, a control condition module is introduced to regulate the noise generation. At the same time, during the network training phase, to address the issue of insufficient bridge sensor fault data samples, as well as the problem of omitted or uncertain labeling, a

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Pseudo Prompt Enhancement module is introduced. In the specific training process, the control conditions and pseudo prompt conditions are combined to form the final condition input, which is then fed into the denoising network of the diffusion model. Through the inverse diffusion process, sensor fault time series data that meet the specified conditions are generated. Finally, to further improve the quality and diversity of the generated data, a classifier-free guidance mechanism is introduced to optimize the model. During the training phase, the model is allowed, with a certain probability, to operate independently of the conditional information, thereby training an unconditional denoising model. The main architecture of the fusion control condition and Pseudo Prompt Enhancement-based diffusion model is shown in Fig. 1.

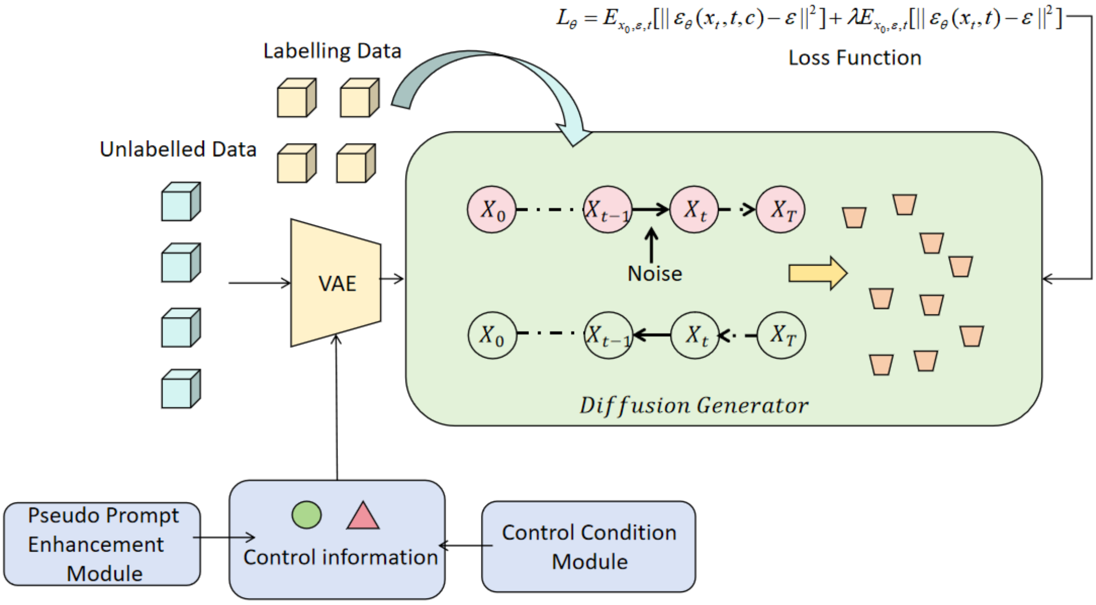

Figure 1: Fusion of control conditions and Pseudo Prompt Enhancement to generate the main architecture of the diffusion model.

2.1. Traditional Bridge Health Monitoring Sensor Failure Data Generation Methods

The fault types of bridge health monitoring sensors mainly include Deviation Fault, Drift Fault, Gain Fault, Precision Degradation Fault, Complete Failure Fault, and Outlier Fault. In practice, obtaining sensor fault data samples for bridge health monitoring is challenging. The commonly used method for generating bridge health monitoring sensor fault data is manual generation, typically by using formulas or adding standard deviations to generate various types of sensor fault data. Table 1 presents a summary of commonly used methods for generating bridge health monitoring sensor fault data. Figure 2 illustrates the manually generated fault data for the Deviation Fault of a bridge health monitoring sensor using a 2 times standard deviation approach. Figure 3 shows the manually generated fault data for Precision Degradation Fault of a bridge monitoring sensor using a 1.5 times standard deviation approach..

Table 1: Table of commonly used bridge health monitoring sensor fault generation methods.

Fault Type	Standard Deviation
Deviation Fault	2σ
Drift Fault	5σ
Gain Fault	G=2
Precision Degradation Fault	1.5σ
Complete Failure Fault	A=0

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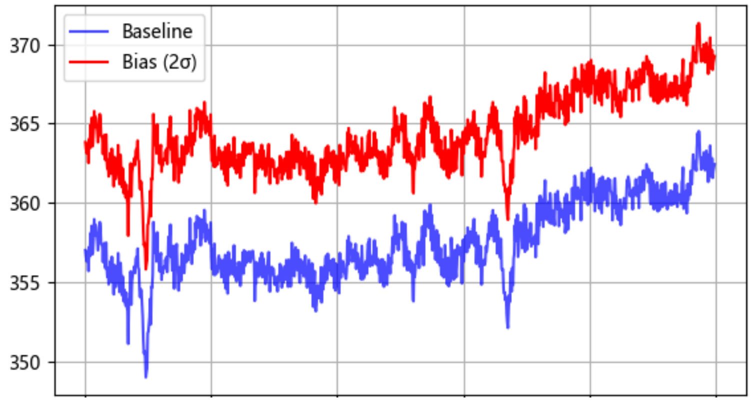

Figure 2: Manual Generation Approach to Generate Bridge Health Monitoring Sensor Deviation Fault Data.

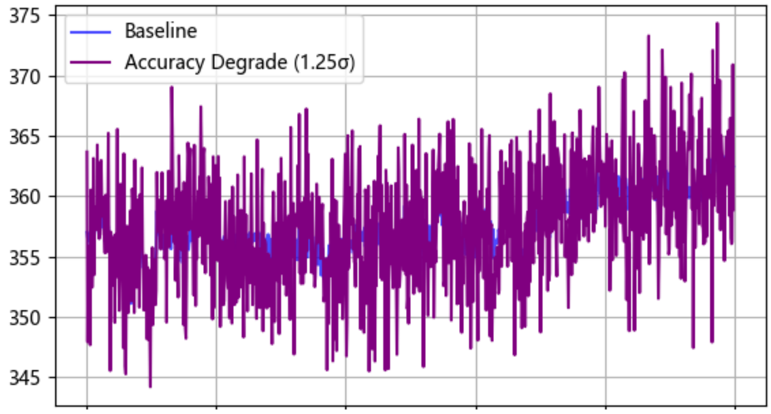

Figure 3: Manual Generation Approach to Generate Bridge Health Monitoring Sensor Precision Degradation Fault Data.

2.2. Diffusion Models

Diffusion models are a class of probabilistic-based generative models that have made significant progress in recent years in areas such as image generation, audio generation, and text generation. The core idea of the diffusion model is to generate data by gradually adding noise to data, such as images or time series, until the data becomes completely noisy. The model then learns how to remove this noise to regenerate the data. Diffusion models are primarily divided into the forward diffusion process and the reverse diffusion process. In the forward diffusion process, given a real data sample X_0, the model gradually adds noise to it, so that after multiple iterations, the original data becomes almost entirely noise. This process is typically carried out using additive Gaussian noise, as shown in Equation 1.

$$q(x_t|x_{t-1}) = N(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t I) \tag{1}$$

Among these, β_t controls the intensity of the added noise at each step, and x_t represents the sample at step t. In the reverse diffusion process, the model attempts to recover the original data from the noisy data. This process is achieved by learning a conditional probability distribution, where the network predicts the next step of recovered data x_{t-1} based on the current noisy data x_t, gradually denoising it step by step, and ultimately recovering a clear image or data sample. The key to the reverse process lies in how to train the model to accurately predict the denoising process at each step. Typically, maximum likelihood estimation or variational inference methods are used to train the network. For sensor fault data, this process is described in Equation 2.

$$x_t = \sqrt{a_t}x_0 + \sqrt{1-\alpha_t}\varepsilon \tag{2}$$

Among thses, X_0 is the original sensor failure time series data and $\varepsilon \sim N(0,I)$ is the standard Gaussian noise, and α_t is a predefined noise scheduling parameter that decreases with increasing time steps. The goal of the model is to learn a denoising function $\varepsilon_\theta(x_t,t,c)$, where C denotes the conditional information, and train the model by minimising the Eq. 3 loss function.

ISSN 2616-5775 Vol. 8, Issue 3: 1-9, DOI: 10.25236/AJCIS.2025.080301

$$L_\theta = E_{x0,\varepsilon,t}[||\varepsilon_\theta(x_t, t, C) - \varepsilon||^2] \tag{3}$$

2.3. Control Condition Module

The control condition module is introduced into the control VAE model to improve the quality of the generated noise when using the diffusion model to generate the bridge monitoring sensor fault data.The control conditions in the control condition module include timestamps, fault types, and so on. These control conditions are processed by the control condition encoder to generate the corresponding embedding vectors $C_{control}$. assuming that there are D different fault types, each of which corresponds to a label yd, and the time step information in the time series t_i. The control conditions are shown in Equation 4.

$$\mathrm{Ccontrol} = \mathrm{MLP}(yd) \oplus \mathrm{PosEmb}(ti) \tag{4}$$

MLP is a network consisting of multiple fully connected layers for mapping the fault type label yd to a high dimensional embedding space. yd is a uniquely hot coded vector with dimension D, and the embedding vector ed obtained after passing through has dimension H as shown in Equation 5.

$$ed = \mathrm{MLP}(yd) = \sigma(W2 * \sigma(W1 * yd + b1) + b2) \tag{5}$$

W1 and W2 are the weight matrices of the MLP, b1 and b2 are the bias vectors, σ is the activation function, and PosEmb(ti) is the position embedding, which is used to represent the position information of the time step ti. The position embedding is encoded using a fixed position encoding method, such as sine and cosine function encoding, or through trainable position embedding vectors as shown in Equation 6.

$$\mathrm{PosEmb}(ti) = \mathrm{PE}(ti) \tag{6}$$

The dimension of the position encoding PE(ti) is also H, $\oplus$ denoting the vector splicing operation. In this way, the control condition Ccontrol is integrated into the denoising process of the diffusion model, allowing the generated time series data to better match the predefined control condition.

2.4. Pseudo Prompt Enhancement module

Inspired by the diffusion model of Make an audio [6], during the network training phase, to address the issue of limited fault data samples from bridge health monitoring sensors in practice, and the occurrence of omitted or uncertain labeling of fault data in the network training process, the Pseudo Prompt Enhancement module is introduced. This module extracts latent representations from the sensor data using a pre-trained autoencoder or self-supervised learning method. These latent representations are then combined with auxiliary information related to the sensor data through a generative model to form a pseudo prompt, which can roughly reflect the state of the sensor device. Specifically, the following steps are performed: first, the latent representation Z is extracted from the sensor data using a pre-trained autoencoder or a self-supervised learning method, and this latent representation is capable of capturing the main features of the data, as shown in Equation 7.

$$Z = \mathrm{Encoder}(X0) \tag{7}$$

Next, a mechanism is designed to generate pseudo prompts that represent meta-information related to the sensor data, such as the device status and whether the bridge monitoring sensor is malfunctioning. This pseudo prompt is combined with the latent representation through a generative model to form the enhanced conditional information $_{Cpseudo}$, as shown in Equation 8.

$$\mathrm{Cpseudo} = \mathrm{GeneratePrompt}(z, \mathrm{Metadata}) \tag{8}$$

Metadata contains auxiliary information related to the sensor data, and GeneratePrompt is a generative function used to generate pseudo prompts based on the latent representations and metadata. These pseudo prompts are used as additional conditional information to further guide the diffusion model in generating time series data that better aligns with the needs of the actual application.

2.5. Model Training

In the specific training process, the control conditions and pseudo prompt conditions are combined to form the final conditional input C, as shown in Equation 9.

ISSN 2616-5775 Vol. 8, Issue 3: 1-9, DOI: 10.25236/AJCIS.2025.080301

$$C = [Ccontrol, Cpseudo] \tag{9}$$

This combination of conditions is then fed into the denoising network of the diffusion model as shown in Equation 10.

$$\varepsilon_{\theta}(x_t, t, c) = \varepsilon_{\theta}(x_t, t, [Ccontrol, Cpseudo]) \tag{10}$$

The model is trained by minimising the joint loss function of Equation 11.

$$L_\theta = E_{x0,\varepsilon,t}[||\varepsilon_\theta(x_t, t, [Ccontrol, Cpseudo]) - \varepsilon||^2] \tag{11}$$

In the generation phase, given specific control conditions and pseudo prompt conditions, the eligible sensor failure time-series data are gradually generated through an inverse diffusion process. Specifically, the initialisation samples the noise XT~N(0,1) from a standard Gaussian distribution, and then the data are generated through the iterative process of Eq. 12.

$$X_{t-1} = \frac{1}{\sqrt{\alpha_t}}(x_t - \frac{1-\alpha_t}{\sqrt{1-\alpha'_t}}\varepsilon_\theta(x_t, t, [Ccontrol, Cpseudo])) + \sigma_t\varepsilon \tag{12}$$

Among them,$\alpha'_t = \prod_{s-1}^{t}\alpha_s$, $\sigma_t$is the noise scheduling parameter, which controls the amount of noise at each step. In this way, the generated time series data can not only retain the statistical characteristics of the original data, but also strictly follow the preset control conditions to achieve fine control of the generation process.

In the process of model optimisation, in order to further improve the quality and diversity of the generated data, a classifier free bootstrapping mechanism can be introduced. Specifically, in the training stage, an unconditional denoising model is trained by making the model independent of the conditional information with a certain probability. The training loss function is adjusted as shown in Equation 13.

$$L_\theta = E_{x0,\varepsilon,t}[||\varepsilon_\theta(x_t, t, [Ccontrol, Cpseudo]) - \varepsilon||^2] \tag{13}$$

In the generation phase, the impact of the condition information on the generation results is balanced by adjusting the guidance scale, as shown in Equation 14.

$$\varepsilon_\theta^{guided}(x_t, t, C) = \varepsilon_\theta(x_t, t, C) + W(\varepsilon_\theta(x_t, t, C) - \varepsilon_\theta(x_t, t,)) \tag{14}$$

This method can effectively control the characteristics of the generated data during the generation process while maintaining the diversity and quality of the generated samples. In the data preprocessing stage, the sensor failure time series data are normalised to ensure the consistency of the data distribution and the stability of the model training, and the time series data of each sensor are normalised as shown in Equation 15.

$$x'_0 = \frac{x_0 - \mu}{\sigma} \tag{15}$$

μ and σ are the mean and standard deviation of the data, respectively, so that the processed data is more suitable for use in the training and generation process of the diffusion model.

3. Experiments

3.1. Experimental Setup

We conducted comparison and ablation experiments using a personal server. an I7-14700KF was used for the GPU, an NVIDA RTX 4090D was used for the GPU, and the server memory size was 64 GB. the main setup parameters are shown in Table 2.

Table 2. Experimental Results.

Item	Setting
Operating System	Ubuntu22.04
CPU	I7-14700KF
GPU	NVIDA RTX 4090D
RAM	64G
CUDA	12.1
Pytorch	2.0
Python	3.11

ISSN 2616-5775 Vol. 8, Issue 3: 1-9, DOI: 10.25236/AJCIS.2025.080301

Initial Learning Rate	1e-4
Batchsize	64
Embedding Dimension (D)	256
Position Encoding Dimension(Dp)	128
Noise Intensity	0.1
Guidance Scale(S)	1.5
Unconditional Training Probability	10%

The dataset in the experiment consists of sequences collected from 18 sensors, with approximately 5000 samples collected from each sensor. Five fault types：Deviation Fault, Drift Fault, Gain Fault, Precision Degradation Fault, and Outlier Fault—are generated using the method proposed in the paper, and compared with the manually generated fault data. Comparative experiments and ablation studies are conducted, with evaluation metrics including MSE, MAE, RMSE, MAPE, and R^2.

3.2. Experimental results display

Figure 4 shows a comparison of manually generated versus using a diffusion model to generate bridge health monitoring sensor deviation fault data. Figure 5 shows a comparison of using manual generation versus using a diffusion model to generate bridge monitoring sensor accuracy degradation faults.

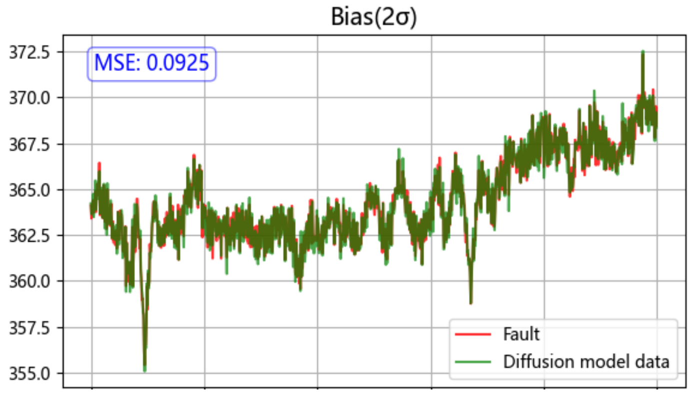

Figure 4: Comparison of manually generated versus using a diffusion model to generate sensor bias failure data for bridge health monitoring.

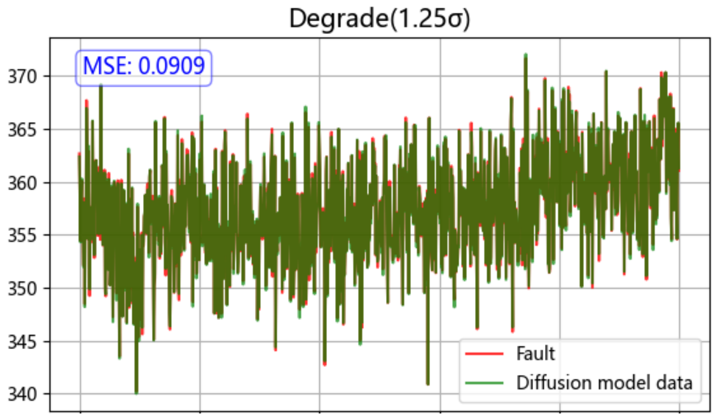

Figure 5: Comparison of manually generated versus using a diffusion model to generate sensor degrade failure data for bridge health monitoring.

3.3. Results Analysis

Table 3 lists the results of the comparison experiments. Comparing our proposed diffusion model with the deep learning model, our proposed model performs best in MSE, MAE, RMSE, MAPE, and R2 evaluation metrics, outperforming the other comparative models. Specifically, the MSE of our proposed model is 0.078, MAE is 0.192, REMS is 0.279, MAPE is 0.098, and R2 is 0.961. It is higher than the models of Stable Diffusion[7], MPS-GAN[8], FedCSCD-GAN[9], WGAN[10], CGAN[11], and VAE[12], which indicates that our proposed model combines the advantages of control condition and pseudo-cue

ISSN 2616-5775 Vol. 8, Issue 3: 1-9, DOI: 10.25236/AJCIS.2025.080301

generation fusion to generate real bridge health monitoring sensor failure data more comprehensively and efficiently, showing excellent robustness, while other models have limitations.

Table 3. Experimental Results.

Backbone	MSE	MAE	RMSE	MAPE	R^2
VAE	0.135	0.275	0.368	0.185	0.892
TCN	0.124	0.263	0.352	0.169	0.903
GAN	0.118	0.252	0.344	0.174	0.911
CGAN	0.109	0.239	0.330	0.158	0.921
WGAN	0.096	0.223	0.310	0.135	0.937
FedCSCD-GAN	0.091	0.215	0.302	0.128	0.943
MPS-GAN	0.085	0.204	0.291	0.115	0.950
Stable Diffusion	0.081	0.198	0.284	0.106	0.956
Ours	0.078	0.192	0.279	0.098	0.961

The ablation results in Table 4 discuss the impact of each component on the performance of the proposed model. The complete model performs best across all metrics. Model performance decreases significantly when any of the three modules are removed. Removing the Pseudo Prompt Enhancement module, the control condition module, or the classifier-free guidance mechanism all lead to a reduction in model performance, with the most notable decrease occurring when the control condition module is removed. The results of the ablation experiments demonstrate that each component plays a critical role in improving model performance.

Table 4. Ablation Study.

Ablation Setup	MSE	MAE	RMSE	MAPE	R^2
Full Model	0.078	0.192	0.279	0.098	0.961
Remove Pseudo Prompt Enhancement Module	0.093	0.214	0.305	0.123	0.944
Remove Control Conditions Module	0.104	0.228	0.322	0.145	0.932
Remove Classifier Free Bootstrapping	0.098	0.221	0.313	0.113	0.939

4. Conclusion

To address the challenge of the scarcity of bridge health monitoring sensor fault data samples, this paper proposes a diffusion model based on the fusion of control conditions and Pseudo Prompt Enhancement for generating bridge sensor fault data. Experimental results demonstrate that our proposed model outperforms other adversarial generation models and diffusion models in the generation of bridge sensor fault data. However, using the diffusion model to generate bridge health monitoring sensor fault data requires significant computational resources. Future research could focus on reducing the computational resources required for this process.

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