An Intermittent Fault Data Generation Method Based on LSTM and GAN

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Junyou Shi, Yufei Ding *, Zhenyang Lv
School of Reliability and Systems Engineering
Beihang University
Beijing, China
dyfynbs@163.com

Abstract—**Intermittent fault has the characteristic of degradation, and may eventually evolve into permanent failure. In some areas, the data of intermittent fault collected through actual operation cannot meet the large requirement for fault diagnosis and degradation assessment. This paper proposes a novel GAN model based on LSTM. Combined with GAN's adversarial idea and LSTM's ability to process time series. The generative model is able to automatically generate intermittent failure data under the condition of very few samples, so as to achieve the enrichment and supplement of intermittent failure data.**

Keywords-intermittent failure, long short-term memory, generative adversarial network

I. INTRODUCTION

An intermittent fault can be defined as a fault that restores its function within a limited time or under appropriate conditions without being repaired [1]. Intermittent fault has its own unique behavioral patterns, such as short duration, randomness, intermittency and repeatability [2]. As the system degenerates, intermittent faults may eventually evolve into permanent faults. Connectors and welding wires will experience intermittent faults due to vibration, thermal expansion coefficient mismatch, stress relaxation [3].

RNN (Recurrent Neural Network) shows good adaptability when analyzing time series. But gradient disappearance makes RNN difficult to train, LSTM (Long Short-Term Memory) is therefore proposed [4]. LSTM adds cell state and gate structure to selectively filter information, making this network capable of learning long-term dependencies.

In 2014, Goodfellow proposed GAN (Generative Adversarial Network) [5]. GAN is composed of two deep neural networks, a generator and a discriminator. The generator is used to learn the characteristics of real samples and generate similar data. The discriminator is used to judge whether the input data is real or fake. These two optimize their networks simultaneously in adversarial learning, and finally reach the Nash equilibrium.

Training LSTM model to map the relationship between samples and labels requires a large number of data samples as the training set and the test set [6]. In actual engineering, intermittent fault data has the problem of small sample size and high experiment cost. The discriminator of the GAN network can repeatedly receive the same set of data as real data to train the generator. Therefore, the LSTM-based GAN model not only solves the problem of insufficient samples of data, but also generates diverse experimental data to enrich the intermittent fault data.

the main contributions of this paper are as follows:

- We select and analyze intermittent fault data under different degradation states in a power change circuit. The data of intermittent fault are decomposed into single intermittent fault waveforms to form real data sets.
- We carry out the design of synthetic intermittent fault GAN model based on LSTM model and implement Python code.
- We select a single intermittent fault data in different degradation state as input to the LSTM-based GAN model to obtain the optimal generation model. And we use the generative model to generate several intermittent fault data to testify the data's validity.

Section II is the model structure and training mechanism of LSTM and GAN. Section III selects and analyzes intermittent fault data. Section IV designs and implements GAN model based on LSTM. Section V analyzes the results of intermittent fault data generation. Section VI concludes the paper.

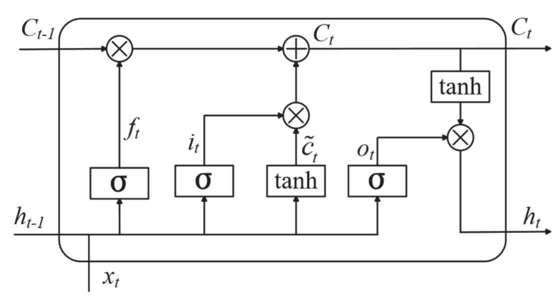


Figure 1. The structure of LSTM

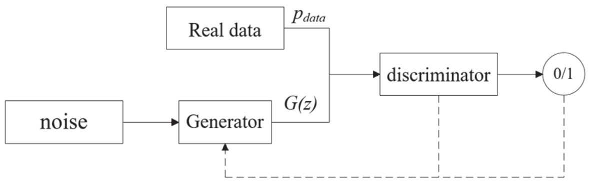


Figure 2. The structure of GAN

II. PRELIMINARIES

A. Long Short-Term Memory (LSTM) Networks

The structure of the traditional RNN includes an input layer, a hidden layer and an output layer. The output of the hidden layer at the current moment depends not only on the input but also on the output of the previous hidden layer. However, RNN is more sensitive to short-term information. If the sequence is long enough, it is difficult to associate current information with earlier information.

Compared with RNN, the cell structure of LSTM in Fig. 1 includes input gate, forget gate, output gate and cell state [7]. The cell state runs through the entire LSTM network and continuously transmits information. The input gate determines the proportion of the input data saved to the cell state. The forget gate is used to determine the proportion of the cell state from the previous moment to be saved. The output gate controls the proportion of the current cell state output.

B. Generative Adversarial Networks (GAN)

The structure of GAN is shown in Fig. 2. The generator and the discriminator are essentially differentiable functions. The purpose of the generator is to produce data conforming to the distribution of real data. When training different networks, the discriminator takes real data or fake data as input. The output of the discriminator is the probability of the input being real. In an ideal situation, the generator captures the characteristics of the real data, the discriminator can no longer judge the authenticity of the input data, and the experimental discriminator judges the output probability of 0.5 each time.

The training mechanism of GAN can be divided into two steps. The first step is to optimize the discriminator without changing the parameters of the generator, so that the model D has the greatest accuracy in discriminating the authenticity of the input data. The second step is to optimize the generator while the parameters of the discriminator is being fixed, so that the model D has the smallest accuracy. If and only if $p_{data} = G(x)$, the global optimal solution is reached, that is when $D(x)=0.5$.

III. MATERIALS

A. Intermittent Fault Waveform Acquisition

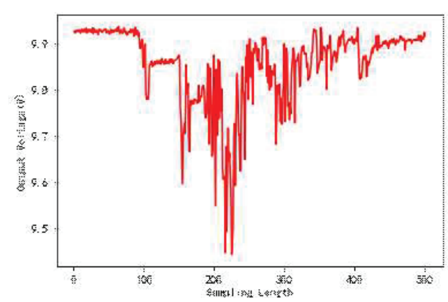
Based on the data set of intermittent fault test of typical power supply change circuit with the signal sampling frequency of 15625Hz. The experiment selects two typical test data under different degradation states, which are respectively marked as degradation state A and degradation state B. In the normal operation of the circuit, the output voltage is 10 V. Intermittent faults show different characteristics at different degradation levels. The degradation degree of intermittent faults in the degradation state A is relatively low, and the circuit output value is between 9V and 10V. The degradation degree in the degradation state B is rather high, and the difference between the maximum value and the minimum value exceeds 10V. Intermittent fault data in degradation state A belong to small intermittent faults that occur in the initial stage, and the degree of degradation of intermittent fault data in degradation state B is significantly higher.

The multiple intermittent fault data under each degradation state is decomposed into multiple single intermittent fault waveforms. In order not to increase the computational complexity of the neural network, and under the condition of ensuring that the waveform is not distorted, one waveform data is saved every fixed sampling point to obtain compressed single intermittent fault data to form a real data set. Finally, a waveform is extracted from each degradation states as experimental data, see Fig. 3 and Fig. 4.

B. Data Analysis

We construct the average value, root mean square, and difference value as the basis for distinguishing intermittent faults in different states and analyzing numerical characteristics. The numerical characteristics of data under different degradation states have obvious differences. The average value can reflect the impact of intermittent faults on the voltage output.

Figure 3. Intermittent fault waveform in degradation state A



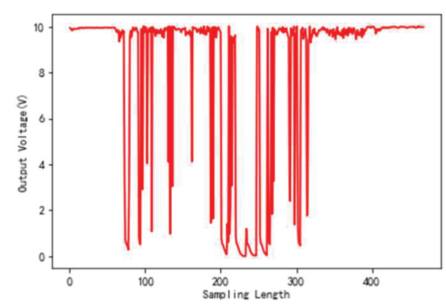


Figure 4. Intermittent fault waveform in degradation state B

TABLE I. NUMERICAL CHARACTERISTICS OF INTERMITTENT FAULT DATA

Degradation State	Average Value	Root Mean Square	Difference Value
A	9.8554	0.0843	0.49594
B	8.2193	3.5550	10.0421

Average value:

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

Root mean square:

$$X_{rms} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{2}$$

Difference value:

$$X_D = \max\{x_i\}_{i=1}^{n} - \min\{x_i\}_{i=1}^{n} \tag{3}$$

TABLE I. is the numerical characteristics of intermittent fault data in degradation state A and degradation state B.

IV. Methods

A. Construction of LSTM-based GAN

This experiment uses a many-to-one LSTM model to construct the discriminator. The data is composed of two sequences, which are the sampling length as the abscissa and the circuit output voltage as the ordinate. The discriminator output is a probability value of 0 to 1.

The generator uses a many-to-many LSTM model. The input of the model is the matrix generated in the latent space. Most of them are composed of multiple random sequences conforming to a certain distribution.

The specific structure and parameters of the complete model are shown in Fig. 5. The random matrix generated from the latent space conforms to the normal distribution. There are 10 random vectors in the matrix. The experiment constructs a generator with a single-layer LSTM model containing 8 neurons, and outputs two sequences of circuit output voltage and sampling length. The discriminator is built with stacked LSTM and consists of 3 LSTM layers. Each layer has 20, 10, and 5 neurons respectively.

Since the discriminator is a dichotomizer, its loss function adopts a binary cross-entropy loss function. The calculation formula is:

$$l = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(p(y_i)) + (1-y_i)\log(1-p(y_i))\right] \tag{4}$$

where y_i is the label of the point, that is, the result of judgment, and i is the predicted probability that the point is 1.

While training the generator, the parameters of the discriminator should remain unchanged, so the discriminator is set to untrainable. We choose the mean square error (MSE) as the loss function of the generator network:

$$l = \frac{1}{n}\sum_{i=1}^{n}\left\| y_i - \hat{y}(x_i)\right\|_2^2 \tag{5}$$

The optimization method of the discriminator and generator is to use the adaptive moment estimation Adam (Adaptive Moment Estimation). Adam not only retains the idea of the gradient descent algorithm, but also can adaptively select the better learning step size. The iterative range of each learning rate can be clarified and the weight parameters can be changed steadily.

B. Generative Model Aquisistion

In the process of training the LSTM-based GAN model, when the generated data meets set requirements, the network stops training and saves the generator's network structure and weights. In addition, we design a network that calls weights, and use the random vector input to the generator, which can repeatedly generate intermittent fault data to achieve the purpose of this research.

There are two generative models obtained in the experiment, one takes a single intermittent fault data in degradation A as input, and the other takes a single intermittent fault data in degradation B as input. The experiment will compare the waveform and numerical characteristics of generated data and real data to draw conclusions.

V. Experiment And Result

We uniformly set the average value of the degradation state A is limited to the range of 9.8 to 9.9, and the average value of the degradation state B is in the range of 8.0 to 8.3. When the generated data meets the above criteria, the neural network will save the current generator. The saved generator is the intermittent fault data generation model, and countless sets of intermittent fault data can be obtained by the generator network.

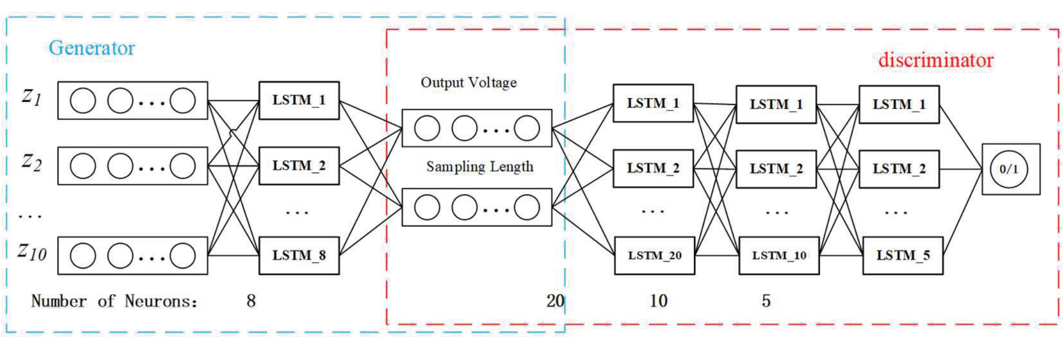
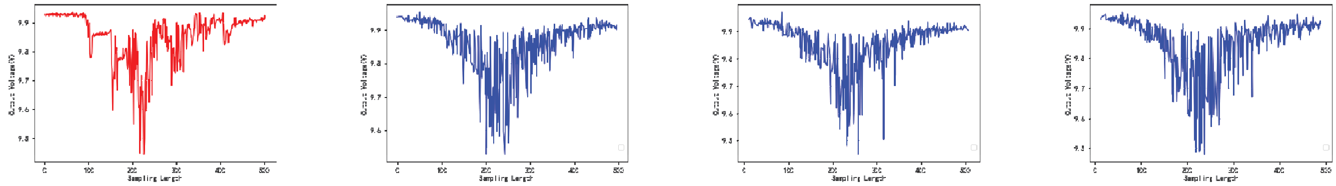
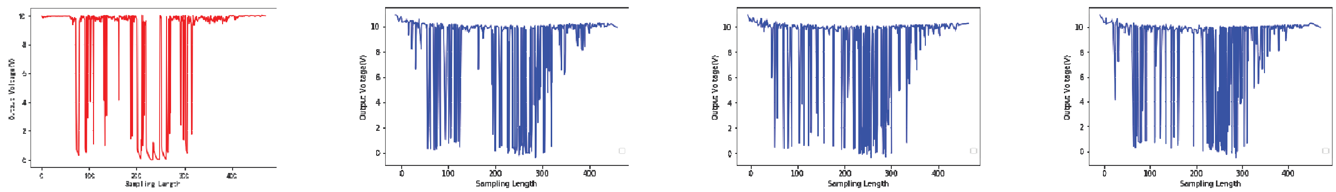


Figure 5. The structure of LSTM-based GAN



(a) (b) (c) (d)

Figure 6. Intermittent fault data in degradation state A, (a) real data, (b), (c) and (d) are three generated data



(a) (b) (c) (d)

Figure 7. Intermittent fault data in degradation state B, (a) real data, (b), (c) and (d) are three generated data

TABLE II. NUMERICAL CHARACTERISTICS OF REAL AND GENERATED DATA IN DEGRADATION STATE A

data	Average Value	Root Mean Square	Difference Value
(a)	9.854	0.0843	0.49594
(b)	9.8594	0.0871	0.4365
(c)	9.8566	0.0897	0.4905
(d)	9.8626	0.0832	0.4852

TABLE III. NUMERICAL CHARACTERISTICS OF REAL AND GENERATED DATA IN DEGRADATION STATE B

data	Average Value	Root Mean Square	Difference Value
(a)	8.2193	3.5550	10.0421
(b)	8.2620	2.9080	10.3653
(c)	8.2590	3.2078	10.3779
(d)	8.2018	3.3127	10.3273

Here, we use these two generative models to each output 3 sets of intermittent fault data, the waveforms of the data are shown in Fig. 6 and Fig. 7. It can be seen that these generated data waveforms resemble the real data waveform. We further calculated the numerical characteristics of the generated data and the real data, shown in TABLE II. and TABLE III. . The difference between these two sets of data in the average, root mean square, and difference value is not obvious. the generated data is very close to the real data in terms of the waveform and the numerical characteristics.

VI. CONCLUSION

Combining the training process and the data obtained from the above generative models, the following points are summarized:

- The data generated in the two degradation states are basically consistent with the real data in average, root mean square and difference value, which can prove the validity of the data.
- The generative model saved in accordance with the standard has high stability and strong repeatability. From the perspective of training efficiency, it takes less than one and a half hour to obtain an effective model.

This paper adopts the neural network method to build a LSTM-based GAN model to automatically generate intermittent fault data, which solves the problems of limited intermittent fault data and expensive triggering experiments. This method can realize the supplement and improvement of intermittent fault data, and provide a basis for fault diagnosis and degradation assessment.

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