Voltage Sag State Estimation Based On Improved Generative Adversarial Network

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Abstract: ***State estimation is an effective means to solve the observability of the whole network. Traditional voltage sag state estimation usually uses the combination of electrical environmental parameters and mechanism analysis to construct mathematical models. Due to the high permeability, dispersion, and dynamic time-varying nature of distributed power sources and nonlinear loads, power quality operation scenarios are more complicated and model accuracy is reduced. Data-driven state estimation can avoid the limitations of physical models based on mechanism analysis. In this paper, a deep learning method using unsupervised loop generation of confrontation is proposed to realize voltage sag state estimation. This method does not require prior knowledge and calculation of electrical topology relationships, and uses the coupling relationship between multiple nodes for state estimation, effectively solving the influence of the dynamic characteristics of the grid environment on the coupling relationship caused by factors such as line adjustment, grid parameter changes, and new energy uncertainties., Improve the generalization ability of the model. The paper tests the model under the environment with noise, and verifies the validity of the model.***

Keywords: cycle generative countermeasure network, multi-node state estimation, voltage sag, network-wide visibility

1. Introduction

With the rapid development of my country's economic construction and power industry, the large-scale application of equipment such as high-voltage direct current transmission, new energy power generation and variable frequency speed regulation motors, the problems of dynamic reactive power demand and transient voltage instability in large power grids have become more prominent [1], [2] ; the number of sensitive electrical equipment with high-tech content has greatly increased and the compatibility problem has become increasingly complex, and the electricity load has entered the era of voltage sensitivity [3], [4]. Voltage sag accounts for the highest proportion and causes the greatest economic loss, and has become the most serious power quality problem [5], [6].

Source-grid-load power electronics enhance the coupling between disturbance sources and highly sensitive loads, and the power quality influences a wider range. Due to the large-scale access and widespread distribution of pollution sources in the entire network, the superimposed effect generated by them may lead to serious power quality problems in the entire network. Therefore, it is necessary to establish a regional power grid-oriented monitoring system to realize the global collaborative correlation analysis of scattered and superimposed pollution components in the power grid, so as to effectively solve the problem of comprehensive power quality control [7]-[9]. However, in the existing power quality monitoring, in order to reduce costs and data redundancy, monitoring devices are only deployed at PCC points and some sensitive key locations, which affect the observability of the entire network.

State estimation is an effective means to solve the observability of the whole network. Existing research relies on the mechanism model, electrical distance and grid structure parameter model to estimate the state of the remaining nodes other than the monitoring point [10, 11], forming pseudo-measurement data to complement the actual monitoring data, thereby improving the observability. Yao Dongfang et al. [12] proposed a real-time monitoring method at different voltage levels and outgoing end nodes. However, this method has large economic investment, complicated installation, long detection period and too large amount of data, and the application effect is not ideal. Yang Xiaodong et al. [13] proposed a voltage sag random prediction method based on an adaptive trust region algorithm. This method can consider the influence of power node type and load model, but the fixed calculation method is not conducive to the design of general calculation programs. Fu Jin et al. [14] established a voltage sag state estimation model by imitating the electromagnetic algorithm. This method requires that the power grid data is perfect and real to perform mathematical calculations, but there are many influencing factors in the actual power grid data, and the data quality is difficult to guarantee. Tang Lin et al. [15] proposed a pattern matching algorithm, which uses limited measured values and simulation results to perform sag pattern matching, which can evaluate the state and level of grid voltage sags, but the data results are single and lack flexibility in the face of complex grids.

The power quality pollution sources of modern power grids present high density, dispersion and uncertainty, and the state estimation due to mechanism models and high-dimensional parameters is quite different from the actual value, which cannot really improve the whole network observability of the monitoring system. The propagation of voltage sags in the power grid causes coupling effects between nodes. Monitoring data is a true and objective reflection of the system. The change law of index data reflects the coupling relationship between disturbances between nodes. Data is the representative quantity, and the coupling relationship is the essence [17]. All uncertain factors causing complex disturbances are concentrated in the monitoring data reflecting the coupling relationship. Based on the deep neural network model, the use of monitoring data to extract the coupling relationship between nodes provides a new idea for data-driven state estimation.

Reference [17] proposed to use a data-driven deep learning method to extract the coupling relationship between two nodes, and use a base node to estimate the state of the target node. However, in a complex power grid environment, the relationship between two nodes is difficult to summarize all the influencing factors. When the dynamic characteristics of the grid environment caused by factors such as line adjustment, grid parameter changes, and new energy uncertainty affect the physical relationship between nodes [18, 19], the generalization ability of the model is restricted.

In a complex power grid environment, multiple monitoring points generate a coupling relationship with each other. Constructing the multilateral relationship of multiple monitoring points, when one or a few factors change, the multilateral system remains relatively stable, thereby improving the generalization ability of the model. Based on this idea, this paper optimizes the existing Cycle Generative Adversarial Nets (CycleGAN), and studies and proposes a voltage sag state estimation method based on multiple monitoring points.

2. Cycle Generative Adversarial Networks

Generative Adversarial Networks were first proposed by Goodfellow et al. in 2014 [20]. GAN can capture the spatiotemporal distribution characteristics and latent features of data through adversarial game, both generative network and discriminative network. The generative network can generate "realistic" sample data, and the discriminant network can accurately distinguish the true and false data. The two pass the maximum and minimum game, and when the Nash equilibrium is reached, the best fitting model of the sample is obtained.

Different from many improved GAN models, such as conditional generative adversarial networks and deep convolutional generative adversarial networks, CycleGAN does not add certain conditional constraints on the basis of input random noise Z to generate data for a specific single target object [21, 22], instead, two GANs are formed into a ring network, and the two samples X and Y are respectively used as the initial sample input of the two GAN generative models. Through two-way cyclic game and confrontation feedback, the process loss is reduced and the Convergence speed, accurate and efficient extraction of sample features and coupling relationships. The basic structure of CycleGAN network is shown in Figure 1. The networks G and F are generated, and the networks DX and DY are discriminated to form two groups of GANs; sample X and sample Y are the initial input samples for generating networks G and F, respectively. First of all, CycleGAN uses a ring structure, and there are two groups of GANs against each other. Compared with the ordinary GAN model, the adversarial change of its loss function is more obvious, and the model training accuracy is better. Second, cycle consistency ensures that the generative networks G and F do not overfit.

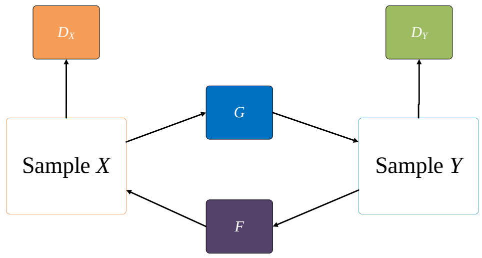

Figure 1: CycleGAN network structure

3. Design of Voltage Sag State Estimation Model Based on CycleGAN

3.1 Overall model structure design

CycleGAN consists of two groups of GANs, including two generative networks and two discriminative networks. The monitoring data of the basic monitoring node and the state estimation target node are used as training samples, and the corresponding two generating networks are respectively input. Through the optimally designed CycleGAN training, the coupling relationship between the basic monitoring node and the state estimation target node is extracted. After the model training is stable, the monitoring device at the state estimation node is removed, and the voltage sag state of the target node can be estimated based on the monitoring data of the basic monitoring node. The basic monitoring node can be a single monitoring point or a group of monitoring points.

The overall logical structure of the model is shown in Figure 2 in:

1) The input data sample X is the data set of the basic monitoring node. The input sample data Y is the state estimation target node data set;
2) The purpose of generating network G is to convert the data of X into real data like Y as much as possible. That is, to find the relationship between the basic monitoring node data and the state estimation target monitoring node data, so as to realize the transformation;
3) The purpose of generating network F is to convert the data of Y into real data like X as much as possible; that is, to find the relationship between the data of the target monitoring node and the data of the basic monitoring node, so as to perform reverse transformation, so that the data from the two The model is trained and optimized by input in each direction;

4) The purpose of discriminating the network DX is to learn the data characteristics of X, and to distinguish whether the data is the real data of the data set X;
5) The purpose of the discriminant network DY is to learn the data characteristics of Y, and to distinguish whether the data is the real data of the data set Y.

As shown in Figure 2, the state estimation method based on CycleGAN, the overall network structure of the model is essentially a ring network, mainly composed of two generating networks and two discriminative networks. The model wants to be able to transform data sample X into data sample Y. In order to realize this process, two generation networks G and F are required to convert the data of sample X and sample Y to each other respectively. The data of sample X is generated by generator G to generate data of sample Y, and then reconstructed back to the original data input by sample X by generator F; the data of sample Y is generated by generating network F to generate data of sample X, and then reconstructed by generating network G Return the original data input by sample Y. The discriminative networks DX and DY play a discriminative role.

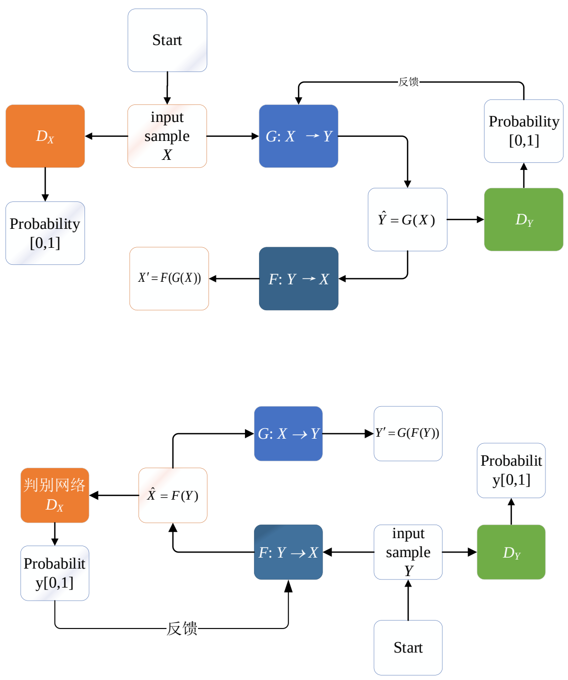

Figure 2: CycleGAN-based voltage sag state estimation model

3.2 Model loss function of CycleGAN

There are two groups of GANs in the model, the first group is composed of the generative network G and the discriminant network DY; the second group is composed of the generative network F and the discriminant network DX. The model consists of two generative network models G: X → Y and F: Y → X. In addition, this paper introduces two adversarial discriminative networks DX and DY, where the purpose of DX is to distinguish between the real data X and the results of the generative network F $\hat{X} = F(Y)$; similarly, the purpose of DY is to distinguish the real data Y and the results of the generative network G $\hat{Y} = G(X)$, the structure is as follows Figure 1.

Based on this structure, the model contains two types of losses: adversarial loss, which makes the distribution of the generated data closer to the real data; and cycle consistency loss, which prevents the learned mappings G and F from contradicting each other. Both generative networks are set with adversarial losses. The loss function for the generating network G and its discriminative network DY is shown in formula (1).

$$L_{GAN}(G, D_Y, X, Y) = E_{Y \sim Pdata(Y)}[\log D_Y(Y)] + E_{X \sim Pdata(X)}[\log(1 - D_Y(G(X)))] \quad (1)$$

When the generative network G tries to generate the data G(X) similar to the sample Y, the discriminant network DY is also trying to distinguish the generated data G(X) from the real data sample Y. The probability that the generative network G wishes to decrease by optimization is opposed to the probability that the generative network F wishes to be optimized to increase.

Formula (1) is actually exactly the same as the original GAN loss function, but it cannot be trained by simply using this loss. The reason is that the generative network G can completely map all samples X to the same set of data in the Y space, invalidating the loss. So design another generation network F, which can convert the sample data Y in the Y space to the data F(Y) in X. A discriminator DX is also introduced for F, so that the loss of a GAN can also be defined. The loss function for the generation network F and its discriminator DX is shown in formula (2).

$$L_{GAN}(F, D_X, X, Y) = E_{X \sim Pdata(X)}[\log D_X(X)] + E_{Y \sim Pdata(Y)}[\log(1 - D_X(F(Y)))] \quad (2)$$

The cycle consistency loss is that the generation network G can completely map the data of all samples X to the same set of data in the Y space, making the loss invalid. As shown in Figure 3.

In theory, adversarial training can learn to generate networks G and F, and generate outputs with a distribution similar to the target datasets Y and X. Strictly speaking; this requires that the generation networks G and F should be a random function. However, when a dataset has a large enough capacity, any randomly permuted input dataset can be mapped to an output distribution that matches the target dataset. Therefore, there is no guarantee that a generative network learned by adversarial loss alone can convert each individual input x to the desired y.

However, in the data set of voltage sag, due to the relationship of time, each set of data is paired, because the voltage transient disturbance data that occurs at the basic monitoring node in a certain period of time should also be the target node of state estimation. dataset at the same time. Therefore, in order to make each group of data correspond to each other, a circular consistency requirement is introduced, so that each group of data x in sample X corresponds to each group of data y in sample Y in turn. The correspondence of the data is guaranteed.

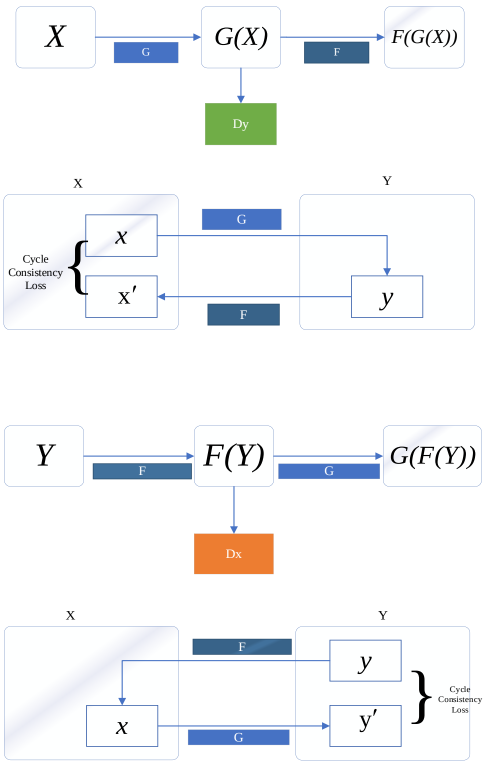

Figure 3: Schematic diagram of cyclic consistent loss

To further reduce possible losses, the function should be cycle-consistent. As shown in formula (3), each group of data x in the data domain X should be able to return x to the origin of the translation in the cyclic translation, and vice versa, that is, the forward and backward cycles are consistent, as shown in Figure 3. Show:

$$\begin{aligned} &x \to G(x) \to F(G(x)) \approx x \\ &y \to F(y) \to G(F(y)) \approx y \end{aligned} \tag{3}$$

Using the cycle consistency loss as an incentive, there is a cycle consistency loss function such as formula (4):

$$\begin{aligned} L_{cyc}(G,F) = {} & E_{x \sim Pdata(x)}[\| F(G(x)) - x \|_1] \\ & + E_{y \sim Pdata(y)}[\| G(F(y)) - y \|_1] \end{aligned} \tag{4}$$

Therefore, the overall loss function has three parts, two parts are generated adversarial loss function and one cycle consistency loss function, the total loss function formula is as formula (5).

$$\begin{aligned} L(G,F,D_X,D_Y) = {} & L_{GAN}(G,D_Y,X,Y) \\ & + L_{GAN}(F,D_X,X,Y) \\ & + \lambda L_{cyc}(G,F) \end{aligned} \tag{5}$$

where, λ controls the relative importance of the two models (G, F).

3.3 Model training process

Since CycleGAN runs the input data in both directions. So the training process is divided into two parts.

1. Basic monitoring point sample data input

Step 1: Input the data of the basic monitoring point data set sample X into the generation network G and the discriminant network DX respectively, so that 1 the generation network G generates samples according to the data of the sample X; 2 the discriminant network DX learns the data features of the real sample X to use Authentication data.

Step 2: Input the data generated by the generation network G into the discrimination network DY for discrimination, and feed it back to the generation network G. At the same time, the input is generated to the network F, and the generation network F tries to reversely generate X´=F(G(X)), so that it is as close to the original dataset X as possible.

2. State estimation target node sample data input

Step 1: Input the data of the target node dataset sample Y into the generation network F and the discriminant network DY respectively, so that (1) the generation network F generates samples according to the data of the sample Y; (2) the discriminant network DY learns the data characteristics of the real sample Y to use future identification data.

Step 2: Input the data generated by the generating network F into the discriminating network DX, make a judgment, and feed it back to the generating network F, so that it can generate more realistic data. At the same time, the input generation network G is generated, so that the generation network G tries to generate Y´=G(F(Y)) in reverse, so that the closer Y´=G(F(Y)) is to the original dataset Y, the better.

4. Experimental Design and Results Analysis

4.1 data acquisition

In this paper, an IEEE 14-node standard power distribution network is built on the PSCAD platform for experimental data simulation acquisition. The network topology is shown in Figure 4.

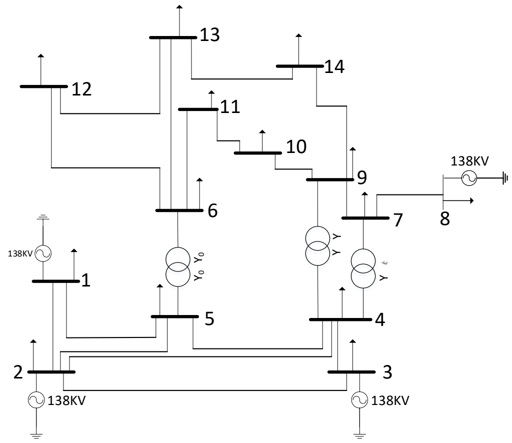

Figure 4: Network structure topology diagram

The power supply reference voltage is 138.0 kV and the frequency is 50.0 Hz. Set the target node M of state estimation as node 6, take M as the center, select nodes A, B, C as a group of basic monitoring points according to the principle of electrical distance proximity, which are node 5, node 11 and node 12 respectively. A voltage sag event is added between node 4 and node 5, which is in line with the actual situation of the power grid. Because there is a voltage sag event between nodes 4 and 5, the voltage sag state can be captured at nodes A, B, C and M, captured by the power quality monitoring device and entered into the database. The voltage sag state of node M is estimated by monitoring data of nodes A, B, and C, and power quality monitoring devices are installed at nodes A, B, C and M to collect voltage sag data. The specific measurement conditions should meet the following two points: ①Nodes A, B, C and M are relatively close in geographical and electrical topology diagrams and have a relatively close coupling relationship; ②Simultaneous measurement of nodes A, B, C and M For data acquisition, at least 10 complete cycles of voltage sag data of these 4 nodes are acquired for each measurement, and a model training data set is established in groups;

The simulation time is 2 s and the sampling frequency is 5 kHz, considering that the voltage sag amplitude and the number of voltage terms in the actual power grid are different. Adjust the voltage amplitude, duration, and number of voltage terms of the sag event, respectively. A total of 100 groups of experiments were carried out and collected in the form of group data, and a total of 1000 groups of data samples were obtained.

4.2 Data preprocessing

The voltage sag data needs to be preprocessed. First, normalize the data and map the resulting data values to [0, 1]; then, convert the voltages of each phase of the sag sample nodes A, B, C and M into 32*32* 1 matrix, and use a grayscale image to display single-phase voltage sag, and converting 1-dimensional raw data into two-dimensional data is conducive to data processing using GAN; The phase grayscale image corresponds to the three channels of RED, GREEN, and BLUE of the color image, and the three grayscale images can be synthesized into a color image (32*32*3), as shown in Figure 5(a). The data of node M is converted into a two-dimensional grayscale image, as shown in Figure 5(b).

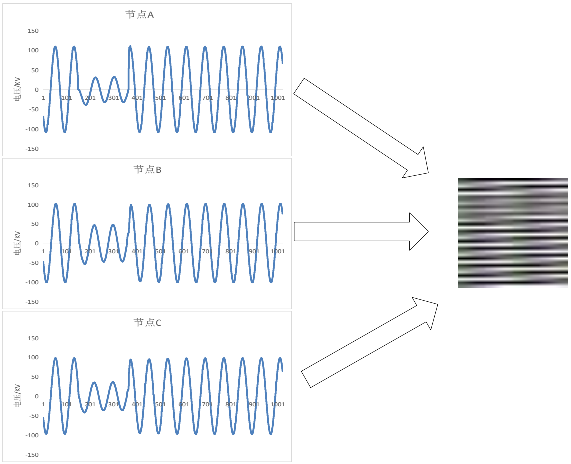

Figure 5: Voltage sag data preprocessing

4.3 Training process

The training model is implemented by programming on the TensorFlow platform. The environment settings are as follows: the processor model is AMD Ryzen5 3600X, the main frequency of the processor is 3.80 GHz, and the memory capacity is 16 GB. When training the model, the method of alternating training is adopted, the optimization frequency of the discriminator is set higher than that of the generator, and the ratio of the update times of the generation network model to the discriminant network model is 1:2. The learning rate is set to 0.0002, and Adam stochastic gradient descent is used in the training process. First, a small learning rate is used to learn 100 epochs, and then 100 epochs of learning are performed to gradually decay the learning rate. Update the model when done. The cycle consistency loss weight is set to 1, and the adversarial loss is set to 0.1. The network for the discriminant model uses cross entropy loss function.

For the data samples collected by the simulation example in this paper, 50 sets of data will be reserved as the test set before training, and the remaining data will be used as the training set. According to the result of adjusting the number of groups in the experimental training set, when the experimental training set increases again, the model will appear overfitting.

The node A, B, C sample training set X is used as the input of the generation network, and the node M sample training set Y is used as the input of the discriminant network. In the process of training the generator network, the weight of the generator network is constrained according to the deviation of the voltage sag data of the generator network generation nodes A, B, C and the real data of the node M, and the discrimination result of the discriminant network. In the process of training the discrimination network, it is necessary to input the real samples and the voltage sag data of the generation network generation nodes A, B, C into the discrimination network, and the discrimination network determines the probability that the input data is the real data of the node M, and updates itself according to the discrimination probability. parameter.

Input the color map data set into the generation model of the model, input the gray image M into the discriminant network of the model, and train the generation network and discriminant network of CycleGAN alternately. Whether the degree map comes from the real training sample grayscale map M set, or from the sample generated by the generation model G, at this time, the probability of discrimination is 0.5, which means the training is completed. The training parameters are set as shown in Table 1.

Table 1: Training parameter table

Parameter	Settings
Training Data	1000
Batch Size	50
Batch Round	200
Cycle Consistency Loss Weight	1
Adversarial Loss Weights	0.1
Learning Rate	0.0002
Gradient Momentum	0.5

After the training is completed, the generated model G is the coupling relationship between the grid nodes A, B, C and node M. The monitoring device at node M can be removed at this point. Take out the successfully trained generative network model G. The power quality monitoring devices deployed at nodes A, B, and C are used to continuously collect new measurement data, and when the data of nodes A, B, and C are input to the generation network G, the data of node M can be generated through the generation model, so as to realize state estimation.

In the training process, a picture class is designed to cache the objects of the picture queue. Use this queue for training. By using the pictures output by the generator cached in the queue to train the discriminator, the stability of the discriminator can be maintained and cached. The capacity of the queue is 50, that is, the discriminator is trained using the images from the first 50 iterations.

4.4 Experimental results and analysis

Based on the characteristics of the experimental data, the mean absolute error and the root mean square error are used as the evaluation indicators of the model. RMSE is more intuitive in magnitude. For example, if RMSE=10, it can be considered that the regression effect is 10 different from the real value on average. The formula is as follows:

$$L_{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{6}$$

$$L_{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \tag{7}$$

The evaluation index results are in the range [0, +∞), and it is equal to 0 when the predicted value is completely consistent with the actual value, that is, a perfect model; the larger the error, the larger the value. A degree of fit calculation is then performed on the data for the true value and the generated estimate. The calculated results are then averaged, and the result is LMAE=0.0423; LRMSE=0.0562.

In Figure 6, the blue is the real value of the state estimation target node M, and the red is the generated estimated value. If the two are completely coincident, it means that the error is zero. With the increase of training rounds, the method in this paper can effectively estimate the voltage sag amplitude of node M through the voltage sag data of nodes A, B, and C, and obtain an accurate change curve.

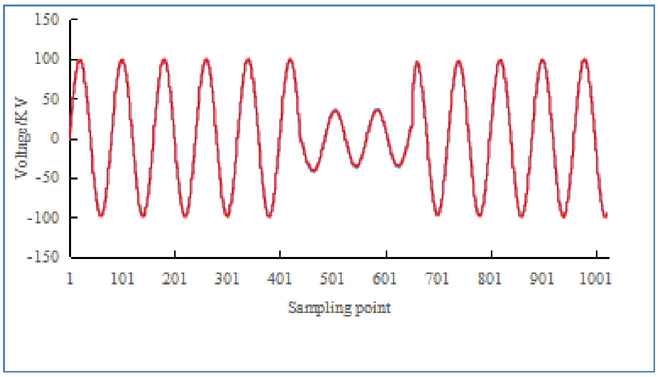

Figure 6: Data fitting effect chart

4.5 Experimental results and analysis

4.5.1Estimate the optimal number of nodes

The basic monitoring nodes A, B, C, D, and E are selected according to the principle of short electrical distance, corresponding to nodes 5, 11, 12, 13 and 10 in Fig. 4, respectively. The target node M corresponds to the node 6 . The state estimation of the target node is performed based on the basic monitoring node as follows.

Use node A to estimate node M, and convert the data input to node A into a two-dimensional grayscale image.

Use nodes A and B to estimate node M, replace the data of nodes A and B with the RED, GREEN and BLUE channels respectively, and use the full 255 matrix instead, and then input the model for training.

Use the four points A, B, C, D to estimate node M, convert the data of the four nodes A, B, C, D into a 32*32*4 matrix, and modify the input layer of the model so that it reads directly Matrix data for training.

Similarly, if five points A, B, C, D, and E are used to estimate node M, the data of five nodes A, B, C, D, and E are converted into a 32*32*5 matrix.

The training results are shown in Figure 7. When the number of input nodes increases to 3-4, the RMSE value of the model tends to be stable. The evaluation indicators corresponding to different number of nodes in multi-node estimation are shown in Table 2. Considering the topology structure of the power grid and the above analysis, when three-node estimation is performed, the data can show the intuitive characteristics of the data through pictures, and the training effect is excellent, which is the most "cost-effective" number of nodes.

Table 2: Find the best node experiment

Estimated number of nodes	L_{MAE} (kV)	L_{RMSE} (kV)
Single Node Estimation	0.1712	0.2034
Two-node estimation	0.1124	0.1537
Three-node estimate	0.0423	0.0562
Four-node estimate	0.0371	0.0447
Five-node estimate	0.0334	0.0405

4.5.1Test Experiments and Comparative Experiments

The previous part of the experiment realized the state estimation of node M by nodes A, B, C, but at the same time caused two problems to think about. The actual power grid circuit relationship has changed, resulting in a change in the coupling relationship between nodes, so that the trained model can no longer maintain a high-accuracy state estimation. The second question: Since the simulation data is used in the training of this experiment, compared with the simulation data, the measured data contains some interference from irregular factors such as harmonics, noise, disturbance and oscillation, which increases the difficulty of model training. Therefore, in order to measure the training effect of the model, as well as the noise resistance, generalization and robustness of the model, the following test experiments and comparison experiments are carried out in this paper.

In the first test experiment, add 40db Gaussian white noise to the data of input node C, and then input the training set of nodes A and B and the data of node C with Gaussian ratio noise added into the model to test the model by adding noise to the data. noise immunity. The data fitting evaluation indicators are shown in Table 3.

In the second test experiment, the network topology is fine-tuned by modifying the load parameters to test the robustness of the model when the structure is changed and the coupling relationship between nodes changes slightly. Input it into the previously trained generative model, and compare the data fitting evaluation indicators as shown in Table 3.

It can be seen from the results of the test experiment that after adding 40db of Gaussian white noise, the error of the data fitting effect increases by about 0.1. In the case of fine-tuning the network topology, the voltage estimation error does not exceed 0.17, which proves that the model has good anti-noise ability.

Table 3: Test experiment

Test experimental conditions	L_{MAE} (kV)	L_{RMSE} (kV)
The method of this paper	0.0423	0.0562
Single node plus noise (40db)	0.1228	0.1742
Fine-tune the network topology	0.1607	0.2192

Reference [17] designed a two-node harmonic state estimation network model based on pix2pix. Using the network structure characteristics of pix2pix, a data-driven harmonic state estimation method is designed and implemented. Use the simulation data in this paper to train the pix2pix-based network model, then test the training effect and add 40db noise to the single node of the model and fine-tune the network topology. The comparative experimental results are shown in Table 4.

Table 4: Index table compared with pix2pix single node estimation method

Models used & experimental conditions tested	L_{MAE} (kV)	L_{RMSE} (kV)
CycleGAN & three-node estimation (method in this paper)	0.0423	0.0562
pix2pix & single node estimation + no noise	0.4049	0.5202
pix2pix & single node estimation + single node plus noise	0.6896	0.7509
pix2pix & single node estimation + fine-tuning network structure	0.7016	0.8398

The above experiments show that the method in this paper can accurately estimate the voltage state of the target node, and can also accurately estimate the state for the occurrence of sag events. It also has certain anti-noise and robustness to noise and fine-tuning topology. Through the selection of the optimal number of nodes for multi-node estimation, it can be seen that three nodes have better anti-noise performance for one node estimation method. Compared with the single-point state estimation model based on pix2pix proposed in [17], the model in this paper has better noise resistance and stronger model generalization.

5. Conclusion

In this paper, GAN in deep learning algorithm is applied to voltage sag state estimation, and a multi-node voltage sag state estimation network model based on CycleGAN is designed. Through the network generation confrontation iterative training, the trained generation network can fully fit the coupling relationship between multiple nodes, and achieve accurate estimation of the voltage state of the target node, and realize the data-driven voltage sag state estimation method. The specific conclusions are as follows:

1) The multi-node voltage sag state estimation network model based on CycleGAN, through two-dimensional grayscale image reconstruction and color image reconstruction of one-dimensional measurement data, the cycle consistency of the model, the CycleGAN used in this model has two Group GAN, the loop is characterized by a bidirectional transition that will run the input data in two ways. It can effectively improve the model learning and training effect. Training one set of generative networks while testing another set of GANs improves the efficiency of learning relationships between data. The two groups of GANs confront each other with feedback, which can improve the accuracy of the model.

2) In the verification of the numerical example in this paper, considering factors such as electrical topology distance between multiple nodes, noise interference and changes in topology structure, the noise immunity and robustness of Comparative Experiment 1 are obviously inferior to single node estimation. Three nodes are used for state estimation, and the estimation errors of different models are compared in comparative experiment 2. According to the values of MAE and RMSE, it is proved that the model designed in this paper has good noise resistance and generalization ability.

However, when the power grid topology changes greatly and the coupling relationship between nodes changes greatly, it is recommended to retrain the model.

3) The voltage sag state estimation network model based on CycleGAN in this paper is mainly aimed at the coupling relationship between monitoring nodes and target nodes with close electrical distances. The recent historical data is used for model training to achieve state estimation between nodes. Realize the visibility of the entire network, spread into a network, and use limited node monitoring devices to estimate the status of nodes in the entire network.

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