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Fault Monitoring Method of Electric Energy Meter Verification Assembly Line Based on Deep Learning

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Abstract:

In order to realize the whole process monitoring and fault warning of the electric energy meter's verification assembly line, the deep learning method is adopted to monitor its faults. First, for complex and multi-source monitoring heterogeneous collected data, VQ-VAE is used to construct a feature extraction model to achieve data dimensionality reduction, while retaining sample information. Subsequently, in order to ensure the mutual correlation and influence between the entities, the Sperman rank correlation coefficient is used to calculate the correlation between the features. CGN is used to construct a fault warning model to realize the fault prediction of the deterioration state of the equipment. Finally, experimental comparative analysis shows the effectiveness of this method. Compared with traditional methods, it improves the real-time and accuracy of monitoring, and provides more accurate information for troubleshooting and prevention of automated assembly line.

Keywords: *assembly line fault monitoring; VQ-VAE; Spearman correlation coefficient; GCN*

I. INTRODUCTION

With the construction of the power grid around China, the usage of compulsory verification measuring instruments such as electric energy meters are very large. The traditional verification processing uses manual method, and the processes such as data storage, circulation, sorting, and disposal are high labor intensity and low efficiency. Therefore, the watt hour meter verification pipelines are used by power grid enterprises [1]. In the future, electric energy will become the core in the energy system. With the further increase of the proportion of electric energy consumption in energy, the number and types of measuring instruments will inevitably increase [2], and the workload and importance of the watt hour meter verification pipeline will also increase. In order to ensure the uninterrupted and efficient operation of the pipeline and meet the requirements of continuous operation condition, it is urgent to adopt effective methods to realize the whole process monitoring and early alarm of the verification pipeline.

At present, there are relatively few studies on automatic pipeline fault alarm system. In paper [3], a pipeline transient performance evaluation model is constructed by using Markov chain. Aiming at minimizing the total system cost, the proposed transient performance evaluation model is used to simulate

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the real-time operation process of the pipeline, generate the data required for neural network training, and use the deep reinforcement learning algorithm to approximately solve the pipeline predictive maintenance strategy. In paper [4] Through the feature extraction of the meter verification data distribution, the abnormal state of the meter is transformed into the abnormality of the data distribution. The local anomaly factor algorithm is used to quantify the anomaly degree of the distribution and mark the meters that produce the abnormal distribution, to realize the on-line anomaly detection of the meters in the automatic verification pipeline. The existing fault diagnosis methods are often based on single equipment fault alarm, which is lack of overall correlation compared with automatic pipeline. With the continuous emergence of new collected data in video, spectrum and other monitoring fields, data collection in all spaces, all time and all frequency domain put forward higher requirements for the real-time and data fusion of monitoring and early alarm. Nowadays deep learning methods can realize feature extraction of high-dimensional data such as images, and sample recognition and classification based on feature data. In paper [5] By combining the variational ayto-coder and attention mechanism, the goal of using deep learning method to detect abnormal network traffic from traffic-based data is realized. In paper [6] Graph neural network has become a hot research field because of its latest performance in many analysis tasks, but its running time and memory consumption of image data processing have become the bottleneck of its application.

Based on the above research, this paper studies the fault alarm method of verification pipeline. The main contributions are as follows:

(1) The feature extraction model is constructed based on the quantized auto-encoder [7], to realize the dimensionality reduction processing of high-dimensional collected data on the premise of retaining the sample fault information. Because the collected image is relatively fixed, most of the position information in the image is repeated and unchanged. After removed them, and the dimension of the image extraction features is further reduced to one-dimensional feature data based on coding table.

(2) The graph convolution neural network [8] is used to build the fault alarm model. On the one hand, it maintains the correlation and interaction between the components of the pipeline. On the other hand, because the graph neural network can also achieve better recognition results based on semi-supervised sorting when there are few fault samples, so it can improve the overall alarm performance of the model [12].

II. OVERALL PROCESS DESCRIPTION

In order to realize fault alarm through continuous monitoring of watt hour meter verification pipeline, this paper adopts the fault warning method of watt hour meter verification pipeline based on deep learning to realize the integration of fault early warning and diagnosis of verification pipeline, and provide more accurate information for fault troubleshooting and prevention of automatic pipeline. The overall process is shown in figure 1:

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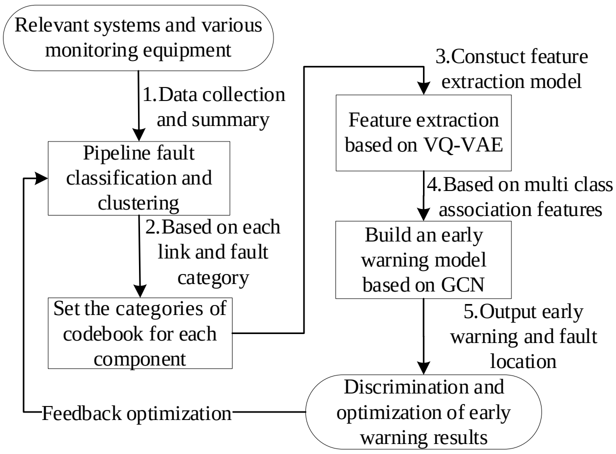

Fig.1 Overall flow of assembly line fault monitoring

Firstly, all kinds of collected data are obtained and preprocessed based on relevant systems and monitoring equipment[13]; Then, based on the data collected from each component of the pipeline, various fault samples are analyzed, and the monitoring data are classified based on the analysis results, to determine the amount of monitoring data for different fault classes[14]; The number of codebook classes of Vector Quantized - Variational Auto Encoder (VQ-VAE) is determined based on the number of categories of various monitoring data; Then, the feature extraction model is constructed based on VQ-VAE, to realize the dimensionality reduction processing of high-dimensional collected data on the premise of retaining the sample fault information. See details in Section 2; At last, taking various data of each component of the pipeline as the model input[10], a fault alarm model based on graph convolutional network (GCN) is constructed to output fault alarm information. See details in Section 3; Carry out manual on-site verification based on fault alarm information, and continuously improve the accuracy and effectiveness of the model through the verification results feedback and optimization.

III. FEATURE EXTRACTION MODEL BASED ON VQ-VAE

In order to improve the data collecting multi-dimensional fast perception ability of the pipeline monitoring, color high-resolution fixed monitoring is used to collect the real-time picture of the key positions and components on (such as central control room, laboratory entrance and exit, robot position, conveyor line, palletizer, buffer line, etc.), so the collected data includes a large number of high-dimensional image and video data. In order to improve the usability of collected data and avoid the impact of large amount of data processed online, real-time, or offline on the performance of pipeline fault alarm and monitoring, VQ-VAE is used to extract the features of image collected data.

In VQ-VAE, The picture data of n × n ×3 is passed into the encoder to obtain a continuous coding vector z:

$$z=encoder(x) \tag{1}$$

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In the above equation, z is m × m vectors of size d.

The number of initialization definition coding classes of the coding table monitoring data categories is k, which is recorded as

$$E=[e_1,e_2,\ldots,e_k] \quad (2)$$

In the above formula, ei is m × m vectors of size d, $i \in (1,2,\cdots,k)$. Map Z to one of the above K vectors through the nearest search:

$$z \to e_k, k = \arg\min_j \|z - e_j\|_2 \quad (3)$$

The coding table vector obtained corresponding to z is recorded as zq, which means the feature data extracted from the collected image belongs to this category within a certain threshold range, to avoid the prediction disturbance caused by different extracted feature data to the identification results. Input zq into decoder to reconstruct the original image $\hat{x} = decoder(z_q)$.

The overall process is as follows:

$$x \xrightarrow{encoder} z \xrightarrow{\text{nearest}} z_q \xrightarrow{decorder} \hat{x} \quad (4)$$

In the above process, z is m × m × d. The position structure information of the image is still retained, and then each vector is mapped into one of the coding tables to obtain zq, which is then used for reconstruction of $\hat{x}$.

After model training, input image acquisition data and output zq to realize dimension reduction discrete coding. The training process is to make the original image x as close as possible to the restored image $\hat{x}$, so the following objective loss function is adopted:

$$loss = \left\|x - decoder\left(z + sg\left[z_q - z\right]\right)\right\|_2^2 + \beta\left\|sg[z] - z_q\right\|_2^2 + \gamma\left\|z - sg\left[z_q\right]\right\|_2^2 \quad (5)$$

In the above formula, sg (stop gradient) is the gradient value within [], so in the forward propagation calculation, the loss function loss is decoder(z+zq−z)=decoder(zq), and then when calculating the gradient by back propagation, it is decoder(z) because zq−z does not provide gradient; In order to maintain the coding table, according to the nearest search process of the output coding z of VQ-VAE, it is expected that zq of the coding table is the cluster center of the output coding z of each class[11],Since the output feature coding z needs to ensure the image reconstruction result, the coding table zq should be as close to the cluster center of z as possible. Therefore, in the gradient calculation process of forward propagation, formula $\|sg[z] - z_q\|_2^2$ is used which is equivalent to fixing z and making zq as close as to z. In the process of back propagation gradient, we use $\|z - sg[z_q]\|_2^2$, which is equivalent to fixing zq and making z as close as to zq, where β and γ are proportional adjustment factors. In order to ensure that zq is as close to the cluster

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center of z as possible, $\gamma < \beta$ is set.

When the template loss function is less than a certain threshold, the feature extraction model based on VQ-VAE is completed, and the output coding zq is used as the extracted feature of the image. As shown in the experiment, the feature extracted from the original 128 × 128 ×3 graph is 32 × 32, which image position information and detection information can be easily retained. Then, because the collected image is relatively fixed, most of the position information in the image is repeated and unchanged. Therefore, it is only necessary to extract features based on different coding features, to remove the fixed unchanged features. Based on the changed features, the image collected data is divided into n categories. At this time, n is assigned to k to update the number of categories in the coding table, Further, the dimension of image acquisition features is reduced to one-dimensional feature data, and the n+1 category is set as the unknown category to verify the new fault.

IV. PIPELINE FAULT ALARM MODEL BASED ON GCN

In this paper, the fault early warning model of watt hour meter verification pipeline is constructed based on GCN. The process is shown in figure 2:

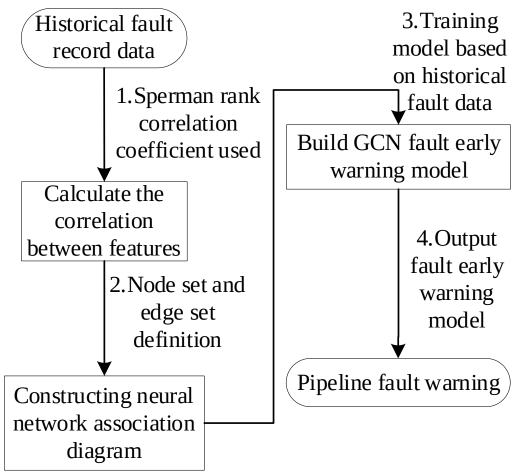

Fig.2 Assembly line fault monitoring model

Based on the monitoring data of various pipeline operation conditions obtained by relevant systems and monitoring equipment, the characteristics of different monitoring types are normalized, and the correlation degree between different features is calculated by Spearman correlation coefficient (Sperman rank correlation coefficient) [9] as the relationship between feature nodes of graph neural network. The specific process examples are as follows:

Define feature X and feature Y, $X=\{x_1,x_2,x_3,\cdots,x_m\}$, $Y=\{y_1,y_2,y_3,\cdots,y_m\}$ where x and y represent the

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feature data values of the feature in different monitoring data samples, and m represents the number of samples, and represents the sampling time;

The Spearman's rank correlation coefficient is used to calculate the linear relationship between feature X and feature Y. Firstly, rank the values of X and Y in the order from small to large. R_{xi} represents the rank of x_i and R_{yi} represents the rank of y_i. If the two rank values are the same, they are both rank intermediate values. If the values of rank 3 and rank 4 are the same, they are both rank 3.5. The rank interpolation is:

$$d_i = R_{xi} - R_{yi}$$

Then the correlation calculation process is as follows:

$$\rho(X,Y) = 1 - \frac{6\sum_{i=1}^{m} d_i^2}{m(m^2-1)} \tag{6}$$

Where, $\rho(X,Y)$ represents the Spearman's rank correlation coefficient of X and Y, $i \in (1,2,\cdots,m)$, and represents the same time of feature X and feature Y. Therefore, when the data distribution does not obey the normal distribution, the correlation between features can still be measured.

Define the fault category of the history record as $C_1 = \{c_1, c_2, \text{L}\ , c_N\}$, and take all kinds of collected feature data as the entity nodes of the neural network layer. The single-layer neural network association diagram is represented as $G=(V,E)$, where V and E represent the node set and edge set of the diagram respectively. There are V nodes in total, and each node has time-series collected characteristic values. Due to the operation of various equipment in the pipeline, as time goes by, it will gradually deteriorate from the healthy state to the fault state. Therefore, in order to realize the monitoring based on the deterioration characteristics of various equipment in the pipeline at any time, realize the fault alarm, and retain the D-dimensional time series collection data of each node, the eigenvalues of all nodes in the neural network association diagram are grouped into a V × D-dimensional matrix X, and then the relationship between each node will also form a V×V-dimensional matrix A, and the value of matrix A is calculated and obtained according to the correlation $\rho(X,Y)$ between features. X and A are the inputs of the model, and the propagation function between the neural network input layer and the first layer is:

$$H_1 = \mathrm{Re}LU\left(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{1/2}XW_0\right) \tag{7}$$

In $\tilde{A}$=A+I, I is the identity matrix, and $\tilde{D}$ is the degree matrix of $\tilde{A}$. The formula is $\tilde{D}_{ii} = \sum j\tilde{A}_{ij}$, where W is the parameter matrix, and H is the characteristic matrix of each layer of neural network, in which the subscript represents the level, and the initial input is X, and ReLU is the activation function.

The propagation function between the first layer and the second layer of the neural network is:

$$H_2 = \mathrm{Re}LU\left(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{1/2}H_1W_1\right) \tag{8}$$

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Then input the eigenvalues in the obtained hidden layer characteristic matrix into the softmax function to obtain the fault alarm category:

$$\hat{c} = \arg\max\left(soft\max\left(WH_2 + b\right)\right) \tag{9}$$

Where, $\hat{c}$ is the fault alarm category determined according to the maximum probability value, represents the prediction label, that is, the output result, and the actual fault type is c.

Then, the cross-entropy loss function is calculated according to all labeled nodes:

$$loss = -\sum_{G}\sum_{j=1}^{j=N}\delta\left(c_j, \hat{c}_j\right)\log\left(p\left(c_j \mid H_2\right)\right) \tag{10}$$

Where, N is the total number of pipeline fault types, δ is the Kronecker function, if $c_j = \hat{c}_j$, then $\delta\left(c_j, \hat{c}_j\right) = 1$, otherwise it equals 0.

During the operation of the watt hour meter verification pipeline, all equipment cooperate and influence each other, that is, there are fault types of single equipment and fault problems caused by the influence of the whole pipeline equipment. To consider and analyze, the fault causes and phenomena are too complex, resulting in difficulty in fault early warning and positioning. In this paper, the continuous data collected in a certain time is used as the data input of fault alarm, so that the fault prediction can be realized based on the deterioration state of the equipment; The Sperman's rank correlation coefficient is used to extract the network correlation degree between equipment, and then the neural network correlation layer of GCN is constructed. The fault alarm model is constructed based on GCN. On one hand, the correlation and interaction between various entity objects in the pipeline are maintained. On the other hand, because the graph neural network has few fault sample labels, it can also achieve better classification and recognition effect based on semi supervised classification, to improve the overall alarm performance of the model.

V. ALGORITHM AND ANALYSIS

Based on the energy meter verification pipeline of a power company of the State Grid as the data monitoring source, the data acquisition processes include patrol information, fault alarm information, operation and maintenance, patrol tool operation and other information, as well as hardware equipment information, operation data, software information and operation status information obtained from relevant systems. The running environment of the program is a personal computer with windows 10, 2.60GHz CPU and Intel Core i7 processor.

4.1 Data collection and summary

From January 2020 to June 2021, more than 140 fault samples of watt hour meter were collected from verification pipeline. Among them, there are 11 kinds of pipeline monitoring equipment, involving 7

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categories of collected data. Based on the information recorded in the daily maintenance, overhaul of the equipment, the experimental process is designed to obtain 10 types of pipeline fault. The monitoring equipment included, collected data and fault types are shown in the table I:

TABLE I. Collected data table

Name	Equipment involved
Pipeline Monitoring Equipment	Verification machine, infrared thermometer, HD video camera, inspection robot, infrared thermal imager, air quality meter, radiation detector, scanner, RF door, photoelectric sensor, fixed monitoring camera, etc.
Collected Data	Key function special machine, loading and unloading, key nodes of conveyor line, abnormal discharge channel and other important nodes of pipeline image acquisition data; Temperature data acquisition of current probe, cabinet, power distribution system, UPS, and other equipment; Smoke, PM10 and other abnormal gas monitoring data; Site temperature and humidity data; Video monitoring data of key positions and links on site (central control room, laboratory entrance and exit, robot position, conveyor line, palletizer, buffer line, etc.); Relevant hardware equipment information and operation data, software information and operation status information; Measurement, production, operation, and maintenance related standards, etc.
Fault Types	The equipment does not act, the line is blocked, The box is stuck, the meter is stuck, the card tray is stuck, worn circuit, verification unit current pin overheating, the motor performance is degraded, the shape of the verification line is changed, electromagnetic interference, etc.

4.2 Comparative analysis of results

Since the collected data includes image and video data, in order to improve the availability of collected data and avoid the impact of large amount of data processed online, real-time or offline on the performance of pipeline fault alarm and monitoring, VQ-VAE is used to extract the features of image collected data, and further reduce the dimension of image collected features to one-dimension feature data according to the number of classes in the coding table, The fault alarm model is a two-layer neural network diagram, with 58 nodes and 186 edges in each layer. The comparison scheme is as follows:

Solution 1: CNN convolution neural network is used to extract the features of the collected image data, and then it is used as data input with other collected data;

Solution 2: after image feature extraction with VAE, it is used as data input with other collected data;

Solution 3: after extracting image features by this paper's method, it is used as data input with other collected data.

The comparison of operation monitoring performance is as follows:

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TABLE II. Operation monitoring performance comparison

Solution Name	Average time of single monitoring /ms
Solution 1	519
Solution 2	128
Solution 3	82

As shown in Table II, in Solution 1, the feature extraction obtained by CNN convolutional neural network is used as the model input. Compared with schemes 2 and 3, the real-time performance of system operation monitoring is poor; Although VAE is also used to extract image features in Solution 2, in order to ensure that the extracted data can effectively restore the original image, to retain too much location information and content information, the extracted features still have a certain dimension, and other types of collected data improve the dimension of collected data in response to the availability of unified data form. Therefore, the real-time monitoring performance of Solution 2 is lower than that of Solution 3.

Then, based on the obtained 10 pipeline fault types, a total of 120 fault samples were marked for 30, 60, 90 and 120 fault alarm tests, and the average value was calculated from the accumulated 5 experimental data, as shown in the figure below:

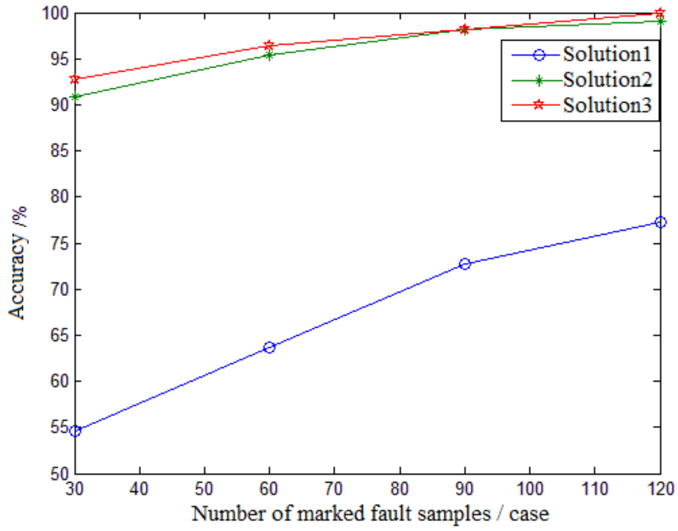

Fig.3 Comparison chart of experimental results

As shown in Fig. 3, the experimental results of Solutions 1, 2 and 3 are compared. It can be seen from the figure that Solution 1 adopts CNN convolution neural network algorithm, which is difficult to effectively capture fault features, especially when there are few labeled sample data, the classification performance is not ideal; Based on the semi supervised attribute of VAE, Solution 2 and Solution 3 can achieve better fault feature extraction even when there are few labeled sample data. Compared with Solution 2, Solution 3 adopts quantized features to further weaken the impact of noise data on prediction results. Based on the efficient recognition performance of graph neural network, in the drawing stage of network layer, The calculated value of feature correlation degree with empirical attribute is added, so the performance of fault alarm classification is further improved.

VI. CONCLUSIONS

In order to strengthen the real-time monitoring and fault alarm level of the whole process of electric energy meter verification, this paper carries out the fault alarm research of electric energy meter verification pipeline based on deep learning. Firstly, the required real-time and historical data of on-site operation are extracted from the on-site operation database, the basic information such as equipment status is obtained from the equipment life cycle management module, the pipeline fault classification is realized, and the feature extraction of the original pipeline data is realized through VQ-VAE; Then, a GCN based fault alarm model is built to continuously monitor the operation status of various equipment in the pipeline, alarm possible faults, output fault alarm information, conduct manual on-site verification based on the fault alarm information, and feedback and optimize the verification results, to continuously improve the accuracy and effectiveness of the model, Realize the integration of fault alarm and diagnosis of verification pipeline.

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