Fault Detection and Diagnosis of Pneumatic Control Valve Based on a Hybrid Deep Learning Model

HAO Hongtao[1,2,*], WANG Kai[1,2]

(1. *School of Mechanical Engineering*, *Ningxia University*, *Yinchuan 750021*, *China*;
2. *Ningxia Key Laboratory of CAE on Intelligent Equipment*, *Yinchuan 750021*, *China.*)

Abstract: As the growing requirements for the stability and safety of process industries, the fault detection and diagnosis of pneumatic control valves have crucial practical significance. Many of the approaches were presented in the literature to diagnose faults through the comparison of residual sequences with thresholds. In this study, a novel hybrid neural network model has been developed to address the issue of pneumatic control valve fault diagnosis. First, the feature extractor automatically extracts in-depth features of the signals through multi-scale convolutional neural networks with different kernel sizes, which not only adequately explores the local distinguishable features, but also takes into account the global features. The extracted features are then fused by the feature fusion layer to reduce redundant features. Finally, the long short-term memory for fault identification and the dense layer for fault classification. Experimental results demonstrate that the average test accuracy is above 94% and 16 out of the 19 conditions can be successfully detected in the simulated actual industrial environment. The effectiveness and practicability of the proposed method have been verified through a comparative analysis with existing intelligent fault diagnosis methods, and the results suggest that the developed model has better robustness.

Keywords: Pneumatic Control Valve, Feature Fusion, Fault Diagnosis, Convolutional Neural Network, Long Short-term Memory

1 Introduction

With the informatization and complexity of modern factories, the condition assessment and fault diagnosis of pneumatic control valves have become particularly important in the production process. As the terminal actuator in process control industrial systems, the pneumatic control valve consists mainly of a positioner, pneumatic servo motor, and valve body. Its primary function is to regulate the flow of liquids and gases in the pipeline according to the control signal [1]. The low price, simple structure, ease of use, and superior explosion-proof performance make pneumatic control valves widely applied in the chemical industry, metallurgy, paper industry, heat and power generation industry, food industry, etc. Over 90% of the actuators and positioners on the market are pneumatic [2]. However, prolonged operation under harsh external conditions often leads to various faults in pneumatic control valves, which not only affects its performance, but also causes control loop failure. According to the collected statistics, control valve faults may lead to 20% to 30% of control loop failures in paper industries and cause about 70% of faults in chemical industries [3]. Unscheduled shut-down due to pneumatic control valve faults may cause economic loss and even human casualties. Therefore, timely fault detection and diagnosis are essential to quickly identify faults and plan for overall plant downtime, thereby reducing maintenance costs.

Many researchers have proposed various approaches for valve fault detection and diagnosis, including mainly model-based and data-driven fault detection methods. The model-based diagnosis method is to develop a comprehensive mathematical model of the pneumatic control valve and then observes the relationship between the model variables and the actual signals to determine whether a fault occurs. Manninen [4] proposed a physical model-based pneumatic control valve fault diagnosis method by dynamics modeling for the control valve. Puig et al [5] built a mathematical model of the pneumatic control valve from multiple perspectives, applying the interval observer to analyze the residual sequence to detect faults. de Almeida et al [6] utilized the Hidden Markov Model to diagnose actuator faults by considering the order of occurrence of faults. Despite the high accuracy of the mechanism model-based fault detection method, it is challenging to establish an accurate mechanism model of a complex nonlinear system such as the pneumatic control valve. In contrast, data-driven approaches based on signal analysis evade the difficulty of establishing the mechanism model and are suitable for the research of complex systems fault diagnosis.

Intelligent classification algorithms based on Data-driven have been widely used for valve fault diagnosis. Bezerra et al [7] developed an unsupervised realtime online self-learning algorithm utilizing the technology of Typicality and Eccentricity Data Analytics for industrial processes fault detection. Nair et al [8] proposed a Minimum Redundancy Maximum Correlation feature extraction method based on Artificial Bee Colony optimization. The extracted features were then provided to a Naive Bayes classifier for valve fault diagnosis. D'Angelo et al [9] transformed raw data into beta distribution data using fuzzy clustering, then utilized the Metropolis-Hastings algorithm to identify change-point probabilities in the transformed time series for fault detection. Chopra et al [10–12] applied Self-Organizing Map to the classification of actuator fault categories, which can effectively classify complex overlapping or similar signals. Ma et al [13] presented a multivariate data-driven fault diagnosis method using canonical variate analysis for calculating hoteling T2 statistics and squared prediction error (SPE) of raw data, and setting appropriate thresholds for fault diagnosis. Kościelny et al [14] discussed the distinguishability of valve fault symptoms under multivalued evaluation conditions. The authors used the three valued residual evaluation to improve the distinguishability of actuator faults. Louro et al [15] adopted a fuzzy neural network, pattern recognition, and a heuristic system, respectively, to diagnose valve faults, none of which produced a false alarm. Calado et al [16] designed a fuzzy qualitative simulation algorithm and a fuzzy neural network to identify the valve faults. Tang et al [17,18] developed a T-S fuzzy model to suit the nonlinear model of valve fault. The model generated various typical fault residuals for fault diagnosis purposes. Rodríguez-Ramos et al [19] proposed a fuzzy clustering-based fault diagnosis approach for online monitoring and automatic learning, which has been validated in the DAMADICS simulator. Przystałka et al [20] utilized the chaos theory and recurrent neural networks to create a neural network model of the system, which showed its effectiveness in the DAMADICS benchmark. Venkata et al [21] analyzed valve outlet vibration signals and classified data into normal and abnormal states using support vector machines (SVM). In addition, many researchers have already employed Artificial Neural Network (ANN) in the study of pneumatic control valve fault diagnosis. Kowsalya et al [22–24] employed principal component analysis (PCA) to perform data dimensionality reduction to abstract essential features, then fed the extracted features into ANN for fault identification. Andrade et al [25] developed an artificial neural network based on the construction of decision tree and residual patterns for pneumatic control valve fault diagnosis. Ortiz Ortiz et al [26] addressed the problem of missing data on the pneumatic control valve. The authors used two imputation methods, the arithmetic mean method and the mode method, to predict missing values, and then applied long short-term memory (LSTM) for fault classification. Although this method has good robustness, too few types of faults can be diagnosed.

The above review of pneumatic control valve fault diagnosis reveals that data-driven fault diagnosis methods perform well for nonlinear systems like pneumatic control valves. However, although existing methods can solve some practical problems, they still have significant limitations.

1. Most current studies are on fault diagnosis by setting thresholds or calculating residuals, and such methods depend more on prior knowledge.

2. Most current data-driven fault diagnosis methods on valves have shallow network structures, which are difficult to mine the in-depth features and take into account both global and local features of complex signals.

3. Most current studies only consider a small subset of fault types, and when the types of fault increase, the effectiveness of these methods decreases dramatically.

In the scientific literature reviewed, no convolutional neural network (CNN) model has been developed yet for fault diagnosis research of valves. Aiming at the challenges mentioned above, this paper designs a novel hybrid fault diagnosis model combining multi-scale convolutional neural network and long short-term memory network (MSCNN-LSTM) of the pneumatic control valve. The model incorporates feature extraction, recognition, and classification methods, which substantially simplifies the diagnosis process. The key contributions of this study are summarized as follows:

1. To the best of our knowledge, it is the first time that a hybrid deep learning model of MSCNN-LSTM is proposed for fault diagnosis of pneumatic control valves. The multi-scale CNN structure with a more abundant field of view effectively extracts the in-depth features of the data, and the use of feature fusion layer greatly reduces the impact of redundant features.

2. The model accurately identifies 16 out of the 19 conditions of the pneumatic control valve in a simulated actual industrial environment. Comparison with the existing methods indicated that the MSCNN-LSTM framework can effectively detect the maximum number of faults.

3. Due to the limited fault data of pneumatic control valves, the model has been developed and verified on a small sample set.

The structure of the paper is organized as follows. Section 2 introduces the relevant theoretical context and explains the structure of the framework in detail. Section 3 describes the dataset, the model training process, and the validation results. Section 4 visualizes the model inference process, classification effect comparison, and robustness experiments, and finally, Section 5 draws the brief conclusion from the result and highlights the planned future work.

2 Materials and Methods

2.1 Convolutional Neural Network

CNN is a biologically inspired feedforward neural network and also one of the typical deep learning algorithms [27]. It is widely used in speech recognition, fault classification, image processing, etc. Generally, the time domain signals or frequency domain signals are used as the input to the one-dimensional CNN. As with other neural networks, it is essential to normalize the input features of CNN, as this can greatly enhance their operational efficiency and learning performance.

The cornerstone of feature extraction lies in the convolution layer, whereby the convolutional kernels have the pivotal role of capturing the corresponding data features. An increase in the number of convolution kernels leads to progressively more abstract feature extraction [28]. The present study proposes a model consisting of multiple convolutional layers. The convolutional layers perform convolution operation on the input features, generating an output that is further nonlinearly processed by the Tanh activation function before being passed to the next convolutional layer. This process enables the network to mine increasingly complex representations of the input data, thereby improving its learning capability. The mathematical formulation is elucidated as follows:

$$Z_i^l(j) = \omega_i^l \times x^l(j) + u_i^l, \quad (1)$$

where $Z_i^l(j)$ is the output feature of the convolution operation at l-th layer, w_i^l is the weights at l-th layer, $x^l(j)$ is the input feature at l-th layer, u_i^l is the bias, and i represents the i-th filter.

Pooling layers are commonly utilized in the CNN architecture and are typically positioned between two convolutional layers. This placement allows for the pooling layer to perform as a down-sampling operation, creating a sparser feature map and efficiently reducing the overall network parameters. The most popular pooling layer is the maximum pooling layer, and its transform function is commonly described as follows:

$$P_j^{l+1}(i) = \max_{(i-1)X+1 \leqslant t \leqslant iX} \{q_j^l(t)\}, \quad (2)$$

where t represents the t-th neuron, l represents the l-th layer, $q_j^l(t)$ represents the value of neuron, X represents the scale of the pooling area, and $P_j^{l+1}(i)$ is the output result of the pooling operation.

The primary purpose of the fully connected layer is to convert the pooled neurons into a unidimensional vector representation. For multiclassification problem, the activation function applied to the last fully connected layer is commonly the softmax function, to obtain the probability distribution of samples belonging to each category. The fully connected layer can be represented as:

$$Z^{l+1}(i) = f\Big(\sum_{j=1}^{m}\sum_{t=1}^{n} X_{itj}^l a_j^l(t) + u_i^l\Big), \quad (3)$$

where X_{itj}^l represents the weights at layer l, $Z^{l+1}(i)$ is the output value of the fully connect operation at layer l+1, u_i^l indicates the bias, $a_j^l(t)$ is the output result at layer l; $f(\cdot)$ is the softmax activation function.

Activation functions are essential for the ANN model to understand complex nonlinear signals. The commonly used activation functions mainly include ReLU, Tanh, and Sigmoid. Whose mathematical formulations are:

$$Sigmoid(v) = \frac{1}{1+e^{-v}} \quad (4)$$

$$\mathrm{Tanh}(v) = \frac{e^v - e^{-v}}{e^v + e^{-v}} \quad (5)$$

$$\mathrm{Re}LU(v) = \max(0,\ v) \quad (6)$$

2.2 Long Short-term Memory

Due to the gradient disappearance and gradient explosion problems, the learning ability is limited to traditional recurrent neural networks. LSTM is an improved recurrent neural network whose advantages in relatively long-term memory make it widely used in time series prediction [29–32]. LSTM uses special hidden units to retain long-term memory, for a time domain signal x_t, its internal hidden cell and output can be expressed as follows:

$$f_t = \sigma\big(H_f \cdot [k_{t-1},\ x_t] + u_f\big) \quad (7)$$

$$i_t = \sigma\big(H_i \cdot [k_{t-1},\ x_t] + u_i\big) \quad (8)$$

$$o_t = \sigma\big(H_o \cdot [k_{t-1},\ x_t] + u_o\big) \quad (9)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot tanh\big(H_c \cdot [k_{t-1},\ x_t] + u_c\big) \quad (10)$$

$$k_t = o_t \odot tanh\big(c_t\big) \quad (11)$$

Where u represents the bias; and H represents the weights. i indicates the input gate, f indicates the forget gate, O indicates the output gate, σ is the sigmoid activation function, k_t is the corresponding output, and c is the cell state.

2.3 Proposed Hybrid Model of MSCNN-LSTM

Generally, time series signals exhibit both local and global features. To thoroughly extract both features, this paper proposed a MSCNN-LSTM hybrid deep learning model for pneumatic control valve fault detection and diagnosis. The MSCNN-LSTM hybrid model consists of a feature extractor and a feature identifier, its detailed structure is shown in Fig.1. The small fields of view are sufficient to extract the local key features of the signal deeply, and the large fields of view are sufficient to capture the positional relationships between the long-term features of the signal. Despite multi scale CNN with strong feature extraction capability, its ability to classify features is

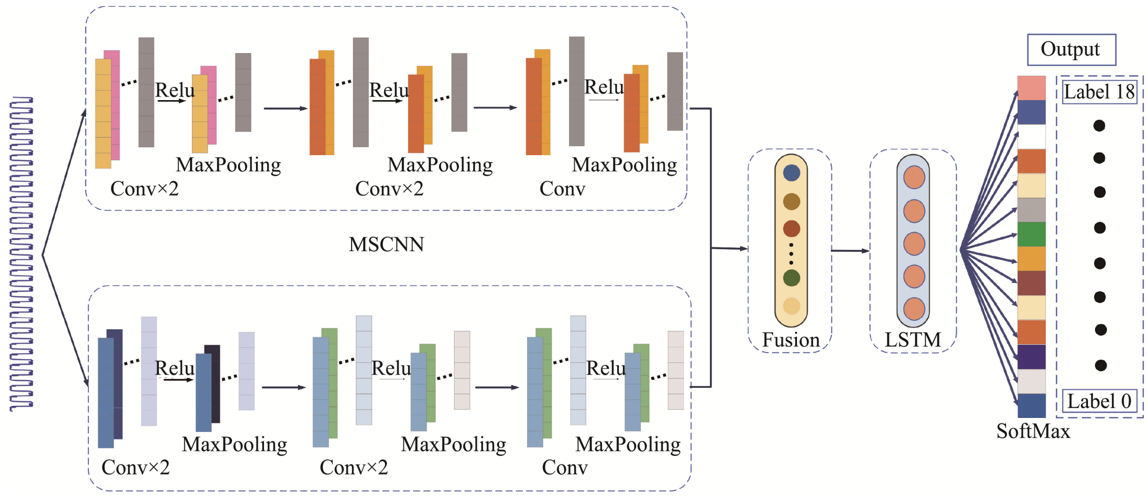


Fig.1 Proposed Hybrid Model of MSCNN-LSTM

limited. LSTM can learn the long-term dependency between two entities to handle global features, which has some advantages in feature identification. Therefore, the hybrid neural network model MSCNN-LSTM can effectively handle such fault signals. Moreover, the distinctive gate structure of LSTM has a filtering effect on noise and hence enhances the anti-noisy capability of the model, making the MSCNN-LSTM hybrid model more robust than other models.

The fault diagnosis based on the MSCNN-LSTM hybrid model consists of two steps. First, the training set will be fed into the hybrid model for model training, and then, the trained model will be utilized to diagnose faults in the testing dataset. The processing of the model can be outlined as follows:

1. Apply PCA to the raw data for reduction in dimensionality;

2. Perform data augmentation using the sliding window method and then label the dataset;

3. Divide the dataset into training, validation, and test sets;

4. Set the initial parameters of the model, then input the training set into the network for parameter optimization until the diagnostic accuracy on the validation dataset can meet the practical requirements, and skip to step 6;

5. Utilize the test dataset for model validation and evaluate the diagnostic capability of the model.

3 Experiments and Results

3.1 DAMADICS Benchmark

The DAMADICS selected three industrial actuators from the sugar production process at the Lublin sugar factory in Poland as the experimental objects, according to the working principles of the actuators, the comprehensive consideration of the detailed physical and electrical structure characteristics of the industrial actuators and their typical engineering requirements for working in harsh environments, along with the large amount of real data generated during operation, were utilized to complete the development and validation of the platform [33]. The actuator consists of a control valve, pneumatic servo motor, and positioner shown in Fig.2. The sub-elements of the actuator correspond to the industrial devices: servomotor type 37, positioner A785, and equal percentage control valve [34]. The actuator controls the valve opening through the control external signal CV and regulates the system state by setting the basic parameters liquid temperature T1, Valve inlet pressure P1 and outlet pressure P2, and the resulting feedback signals stem displacement X and the fluid flow F will be used for fault diagnosis. During the operation of a pneumatic control valve, several components such as the control valve, positioner, servo motor, and pneumatic actuator could break down. The benchmark can simulate 19 specific fault types, as shown in Table 1.

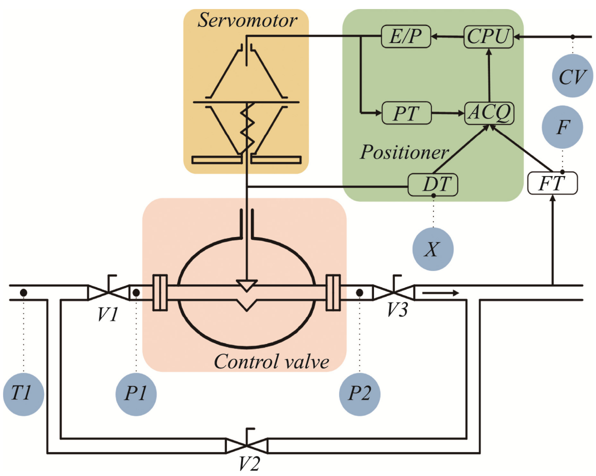


Fig.2 Structure of the DAMADICS

3.2 Dataset Description and Preprocessing

Principal Component Analysis (PCA) is a methodology for projecting high-dimensional information into a low-dimensional subspace and maximizing the retention of the raw information. Moreover, PCA can eliminate the effect of redundant data. Since the original signals are two-dimensional data, irrelevant and redundant parameter features are bound to exist in the data set. PCA technique is introduced to reduce the data dimensionality and enhance the computational efficiency. Meanwhile, to satisfy the model training requirements, this study uses the sliding window sampling for data augmentation [35]. The sampling method is shown in Fig.3. Supposing that the selected sample length is L and the step size is S, if the data set has N data points, we can obtain ((N-L)/S)+1 training samples.

Totally 4066 samples were produced for the normal and abnormal operating conditions of the pneumatic control valves, with 214 samples for each state, and each sample is 1024 in length. The samples are divided into two sets randomly, of which 80% are used for model training and 20% for model validation. The labels are labeled using the One-hot encoding technology.

Table 1 Details of the Generated Dataset

Fault	Description	Label	Fault	Description	Label
F0	No fault	0	F10	Diaphragm perforation of servo motor	10
F1	Valve clogging	1	F11	Spring fault of servo motor	11
F2	Valve plug sedimentation	2	F12	Fault of Electro-pneumatic transducer	12
F3	Valve plug erosion	3	F13	Rod displacement sensor fault	13
F4	Bushing friction	4	F14	Caused by electronics	—
F5	External leakage	5	F15	Positioner feedback fault	14
F6	Internal leakage	6	F16	Positioner supply pressure drop	15
F7	Medium evaporation	7	F17	Unexpected pressure changes	16
F8	Piston rod twist of servo motor	8	F18	Fully or partly opened bypass valves	17
F9	Tightness of the servo motor's housing	9	F19	fault of flow rate sensor	18

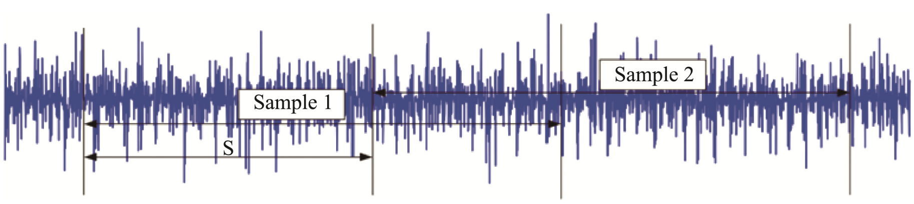


Fig.3 Overlapping Sampling Method

3.3 Experiment Setup

The selection of model hyperparameters is also crucial for the model to attain high accuracy and better robustness. There is no defined guideline for setting model parameters, and we have obtained an optimal set of model hyperparameters by experimenting with the network architecture composed of various parameters. These parameters include mainly the number of kernels, the size of the kernels, the activation function, the size of the features, and the number of neurons in the LSTM. The model takes the cross entropy as the loss function. Table 2 shows the model hyperparameters. The model is developed based on Tensorflow2.9.1, and all results are obtained from 100 training iterations on the Windows 10 64 bit operating system, Intel(R) Core (TM) i7-7700HQ CPU @ 2.80GHz, and 8 GB RAM.

3.4 Experimental Results

Following the training, the developed model is tested with the test set to evaluate its performance. Table 3 depicts that the average test accuracy for the model is above 94%, and Fig.4 presents the confusion matrix for the test outcomes, which indicates some misclassifications. Specifically, the model misclass the label 0 to labels 8 and 15, label 4 to label 12, label 8 to label 0, and label 15 to labels 0 and 8. The major factors for such phenomenon are that some of the samples are so similar or even overlapping with each other or the signals used for fault diagnosis are weakly impacted by these faults. And the high similarity of samples is attributed to the similar occurrence mechanism of these faults. Nevertheless, the model can successfully detect 17 faults, and 15 faults achieve 100% detection accuracy. However, to provide a comprehensive and scientific evaluation, this paper also presents additional indices for assessment, including precision, recall, and F1-score. Whose function expressions are:

Table 2 Model Hyperparameters

Name	Filters	Kernel size/stride	Units	Input size	Output size	Activation function
conv1d_1	50	64/2		1024×1	481×50	tanh
conv1d_2	50	64/2		481×50	241×50	tanh
maxpooling_1		2/2		241×50	120×50	
conv1d_3	30	32/2		120×50	60×30	tanh
conv1d_4	30	32/2		60×30	30×30	tanh
maxpooling_2		2/2		30×30	15×30	
conv1d_5	16	4/2		15×30	8×16	tanh
maxpooling_3		2/2		8×16	4×16	
conv1d_6	50	4/2		1024×1	511×50	tanh
conv1d_7	50	4/2		511×50	256×50	tanh
maxpooling_4		2/2		256×50	128×50	
conv1d_8	40	3/2		128×50	64×40	tanh
conv1d_9	40	2/2		64×40	32×40	tanh
maxpooling_5		2/2		32×40	16×40	
conv1d_10	16	2/2		16×40	8×16	tanh
maxpooling_6		2/2		8×16	4×16	
LSTM			8	4×16	4×8	tanh
batch normalization				4×8	4×8	
flatten			64	4×8	1×32	
dense			19	1×32	1×19	Softmax

$$\text{Accuracy}=(TP+TN)/(TP+FP+FN+TN) \quad (12)$$

$$Precision=TP/(TP+FP) \quad (13)$$

$$Recall=TP/(TP+FN) \quad (14)$$

$$F1 = 2\times Precision\times Recall / (Precision + Recall) \quad (15)$$

where TP denotes the quantity of true positive outcomes, TN denotes the quantity of true negative outcomes, FP denotes the quantity of false positive results, and FN denotes the quantity of false negative results.

Table 3 presents the precision, recall, and F1-score achieved by the proposed model in fault diagnosis. Except for labels 0, 8, and 15, the model exceeds 90% for each index of 16 faults. Note that the whole fault diagnosis outcomes illustrate that the MSCNN-LSTM hybrid framework can effectively detect 17 faults.

4 Discussion

4.1 Network Visualization and Classification Performance Visualization

ANN model is an end-to-end learning approach. Despite its superior performance in feature extraction and fault classification, its processing is still a black box model. To explore its underlying inference process and rationality of construction, this section visualizes the internal structure of the model. Feed the test set into the trained model to visualize the activation state of each hidden layer unit, as shown in Fig.5 which visualizes the hidden layer of fault F3. The yellow hue presents that a region is activated, and the green hue presents that the region is not activated. It can be seen that the first hidden layer has few activation points, and it is difficult to distinguish the faults from each other. However, as the network goes deeper, the feature map

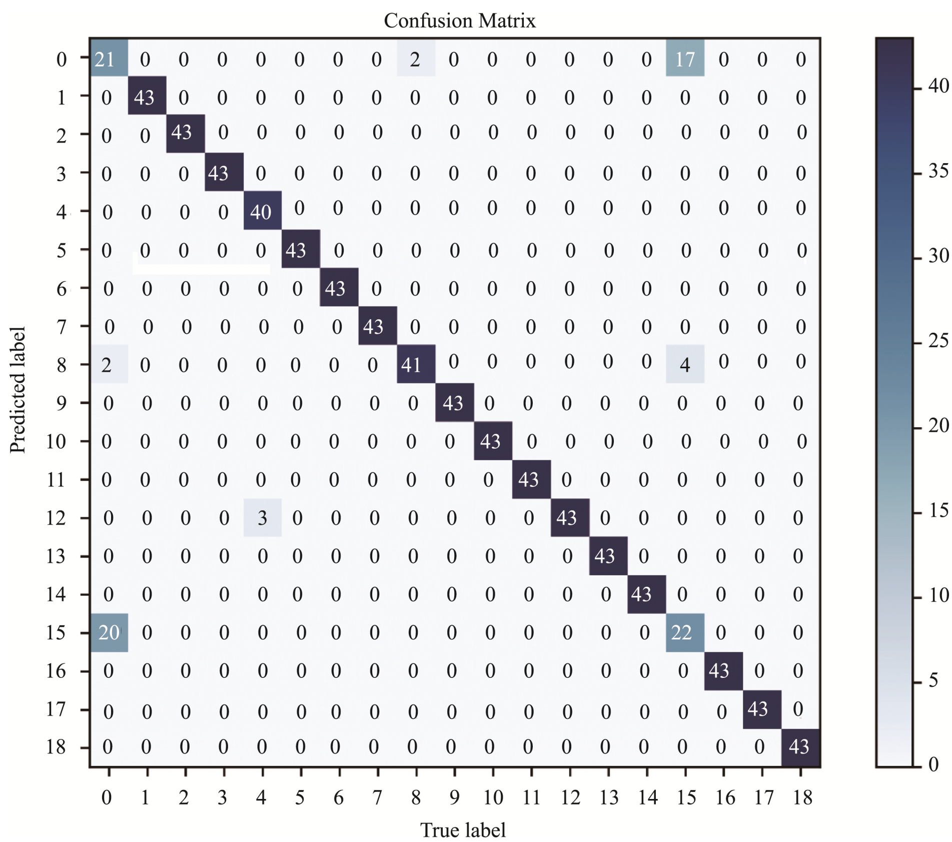


Fig.4 Confusion Matrix of the Model Classification Results

Table 3 Pneumatic Actuator Fault Diagnosis Results Using MSCNN-LSTM

Label	Precision (%)	Recall (%)	F1-score (%)
0	53	49	51
1	100	100	100
2	100	100	100
3	100	100	100
4	100	93	96
5	100	100	100
6	96	100	98
7	100	100	100
8	87	95	91
9	100	100	100
10	100	100	100
11	100	100	100
12	93	100	97
13	100	100	100
14	100	100	100
15	52	51	52
16	100	100	100
17	100	100	100
18	100	100	100
	Accuracy	94.1	

becomes more evident and the activations of the two channels are different. Comparing the activation of the both channels, it can be found that the first channel has superior activation for shallow features, while the second channel has excellent activation for in-depth features, and then the two features are feature-complemented in the fusion layer to provide more comprehensive features for subsequent feature identification.

Evaluating the performance of a model solely on the basis of its output is both illogical and unconvincing. To provide further substantiation for the effectiveness of the model, this study employs the t-distributed stochastic neighbor embedding (T-SNE) technology to visualize the classification effect. The outputs of the last layer for both channels, the fusion layer, the LSTM layer, and the dense layer of the model were visualized, as illustrated in Fig.6. The T-SNE results indicate that distinguishing the 19 different state signals from raw data inputs is not feasible. However, when the features of original data are extracted by the feature extractor, the signals have a certain degree of discrimination and the classification effect of the two channels are different, which corresponds to the visualization of the inference process in Fig.5. After fusing the features of two channels by the fusion layer, the distances among the fault samples become farther. Then, LSTM effectively classifies all signals except labels 0, 8 and 15 and the classification result becomes more apparent after the dense layer. Fig.4 shows that the model misclassifies some labels 0, 8 and 15 for each other and a few labels 4 as label 12, which are reflected in the last layer output visualization in Fig.6(f). The visualization of the classification effect confirms the reliability of the model classification results and the reasonability of the structure.

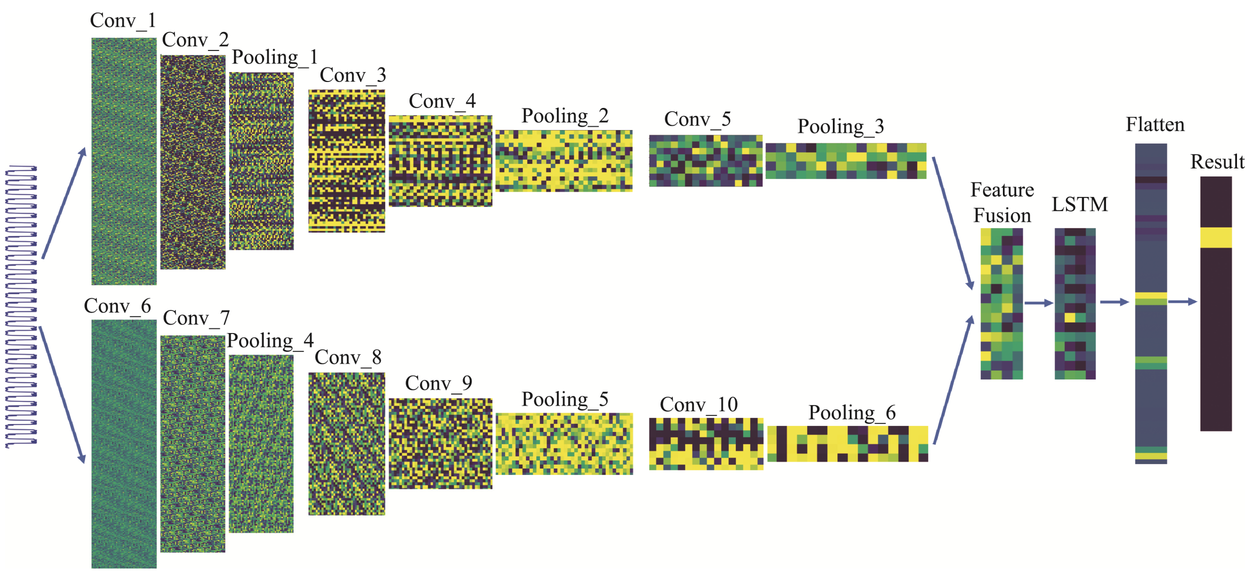
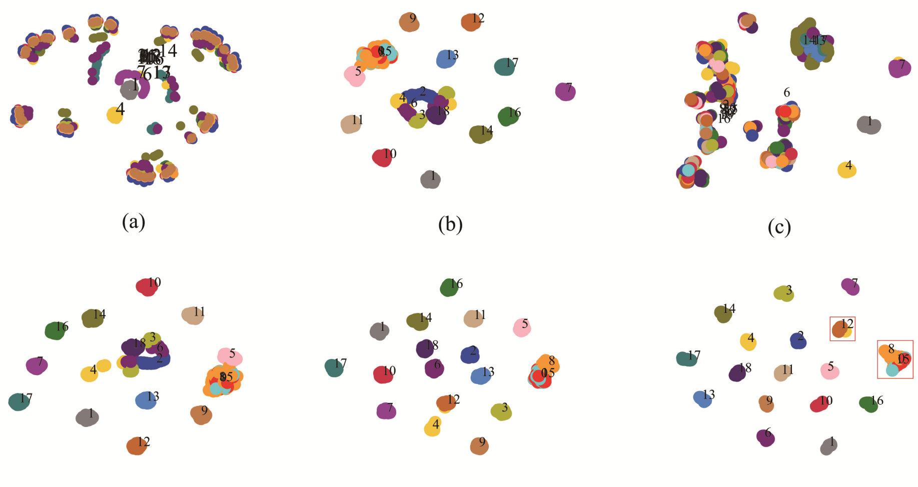


Fig.5 Hidden Layer Unit Activation State Visualization of Fault F3



(a) (b) (c)

(d) (e) (f)

Fig.6 The Output Features Visualization of Different Layers

(a) Raw Signal; (b) The Output Features of the Last Layer of the First Channel; (c) The Output Features of the Last Layer of the Second Channel; (d) The Output Features of the Fusion Layer; (e) The Output Features of the LSTM; (f) The Output Features of the Dense Layer

4.2 Comparison between Other Methods and Our Proposed Model

The above comprehensive analysis and verify the effectiveness of the method for pneumatic control valve fault diagnosis. In order to demonstrate the superiority of the proposed method, the CNN, Recurrent neural network (RNN), LSTM, K-nearest neighbor (KNN), and SVM are tested separately on the same dataset. As shown in Fig.7(d), CNN and LSTM have higher accuracy, 87% and 74%, respectively. However, the hybrid model achieves the highest detection accuracy of 94.1%, and outperforms other data-driven methods. This section also compares the precision, recall, and F1 score of the proposed method with other data-driven methods in Fig.7(a)(b)(c). The comparison reveals that these models can detect fewer types of faults and have poor classification performance, which is incompetent for the fault classification of pneumatic control valves. This may be attributed to the high similarities between the fault signals, and the shallow features extracted by these networks that are insufficient to distinguish the discrepancy between the signals.

The proposed framework is also compared with existing methods presented in the current scientific literature according to the test accuracy in Table 4. Rodríguez-Ramos et al [19] realized the online detection of 8 faults. Ortiz Ortiz et al [26] reported only results for abrupt faults. Subbaraj et al [24] detected only valve faults. D'Angelo et al [9,16] detected fewer types of faults although it has achieved 100% correct accuracy. Bezerra et al [7] detected all 19 types of faults, but the detection accuracy for F4 and F13 was extremely low, and only 8 faults were detected with an accuracy of more than 90%. Ma et al [13] used the Hotelling T2 statistic and the Squared Prediction Error (SPE), respectively, to assess whether a fault occurred. The results of the two methods with higher detection accuracy are listed in the table, which showed that about 10 faults could be detected. Han et al [3] detected 14 of the 19 faults successfully and more than 99% diagnostic accuracy for 12 faults. Przystałka et al [20] had a high detection accuracy of more than 95% for 13 faults. The proposed MSCNN-LSTM model achieved an average diagnostic accuracy of 94.1%, and the diagnostic accuracy of more than 90% for 17 faults, 15 of which reached 100%. The comparative results have indicated the superiority of the method over other methods proposed in the literature.

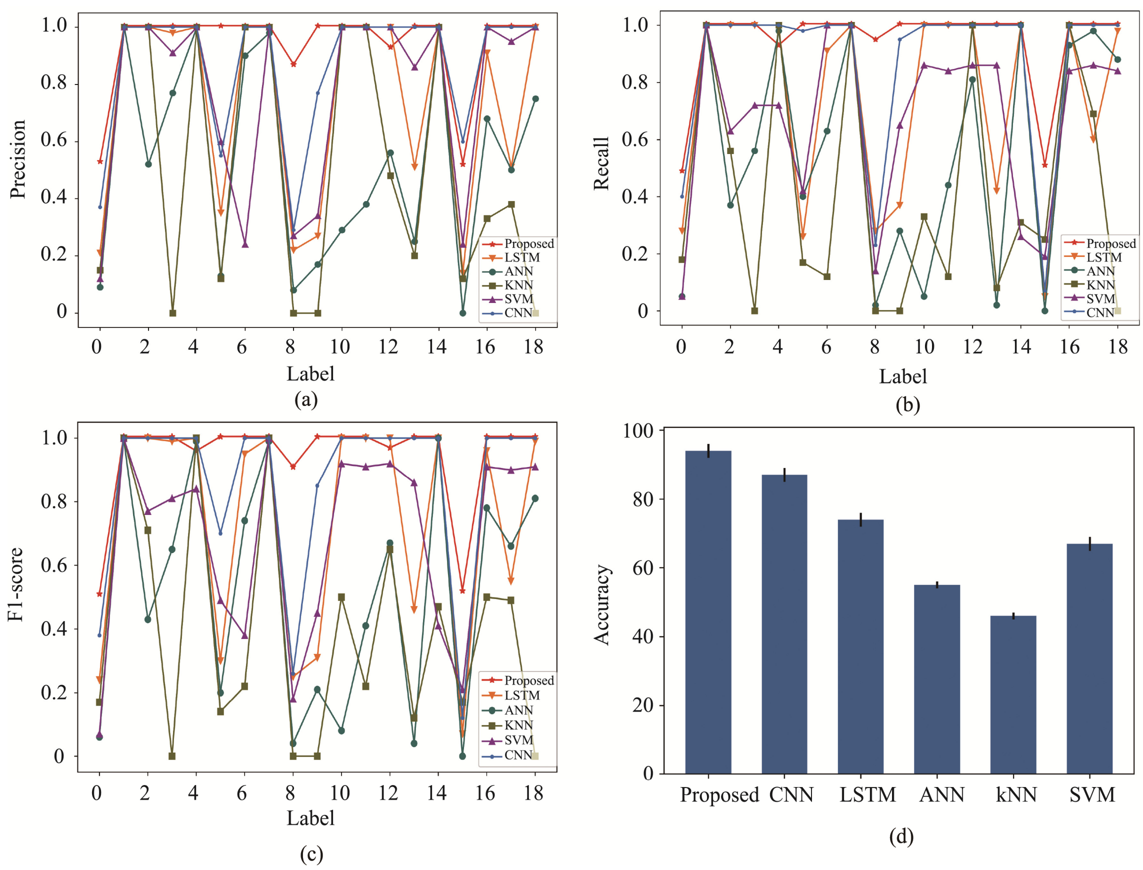


Fig.7 Comparison Results of Different Algorithms

(a) Precision of All Labels under Different Fault Diagnosis Methods; (b) Recall of All Labels under Different Fault Diagnosis Methods; (c) F1-score of All Labels under Different Fault Diagnosis Methods; (d) Average Accuracy of Different Fault Diagnosis Methods

Table 4 Comparison of Methods Used to Detect Faults in Pneumatic Actuators

Fault	[26]	[7]	[24]	[13]	[19]	[20]	[3]	[16]	[9]	Proposed
	Ortiz Ortiz et al	Bezerra et al	Subbaraj et al	Ma et al	Rodríguez-Ramos et al	Przystałka et al	Han et al	Calado et al	D'Angelo et al	Hao et al
Normal	98.5	—	—	—	100	—	—	—	—	49
F1	97.5	92.01	100	77.06	—	100	100	—	—	100
F2	—	83.33	97.6	100	—	100	100	100	—	100
F3	—	36.63	100	2.41	—	93	—	—	—	100
F4	—	0	99.4	1.27	—	55	86.21	—	—	93
F5	—	72.28	99.1	2.28	—	60	—	—	—	100
F6	—	73.27	99.3	2.34	—	96	31.96	—	100	100
F7	99.5	100	99	100	99.17	99	100	100	—	100
F8	—	93.33	—	2.41	—	—	—	—	—	95
F9	—	91.3	—	2.34	—	19	—	—	100	100
F10	—	91.67	—	59.44	—	100	100	100	—	100
F11	—	89.74	—	6.97	—	99	100	100	100	100
F12	99.5	93.02	—	1.71	99.58	95	99.63	—	—	100
F13	—	0.09	—	77.06	—	100	100	100	100	100
F14	—	80.76	—	2.41	—	—	—	—	—	—
F15	97	68.63	—	98.80	97.17	99	100	—	—	100
F16	—	83.52	—	53.74	97.25	99	100	—	—	51
F17	—	83.93	—	100	92.33	99	99.71	100	100	100
F18	—	93.65	—	76.68	100	100	100	100	100	100
F19	99	97.16	—	75.29	96.83	100	100	100	—	100

4.3 Performance of Different Models in the Simulated Actual Industrial Environment

To validate the generalization performance of the model in the actual industrial environment, by superimposing white Gaussian noise and 50Hz sine to the original signals to simulate the noise interference and the sensor errors reasonably, and set the artificial noise amplitude to 2.5% of the nominal range of the signal [33]. Fig.8 shows the added noise signal.

Fig.9 depicts the average detection accuracy of different algorithms in the simulated actual industrial environment. The average detection accuracy of all models decreased compared to the noise-free environment, but the accuracy of the MSCNN-LSTM hybrid model still achieves the highest accuracy of 87%. The average detection accuracy decreases mainly because the model has misdetection cases for some faults. From Fig.10, it can be seen that the model misidentifies label 0 as labels 8 and 15, label 4 as label 7, label 8 as labels 0 and15 and label 15 as labels 3, 8 and 11. Due to the similarity between the faulty samples, adding noise to the signals leads to some fault data overlapping each other and being difficult to distinguish. However, the model could still identify 16 faults accurately. Notably, the proposed MSCNN-LSTM hybrid model exhibits better robustness in the simulated real industrial environment.

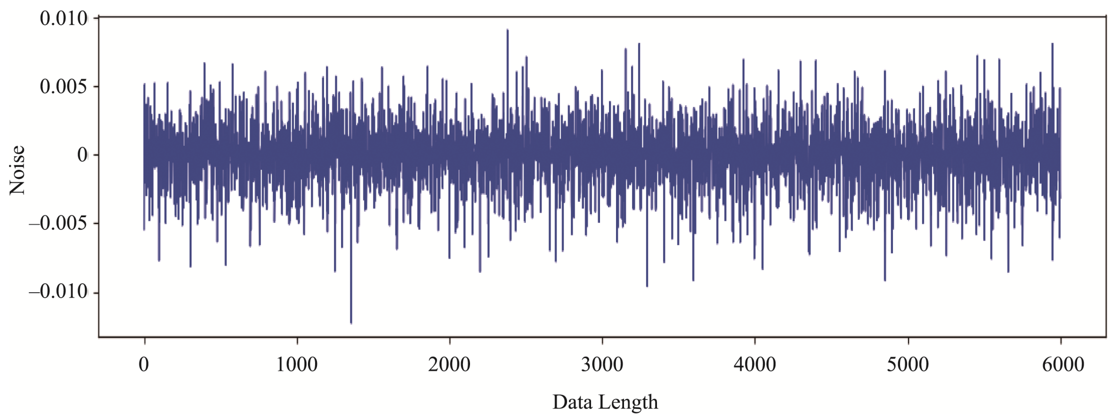


Fig.8 Noise Signal (2.5% noise)

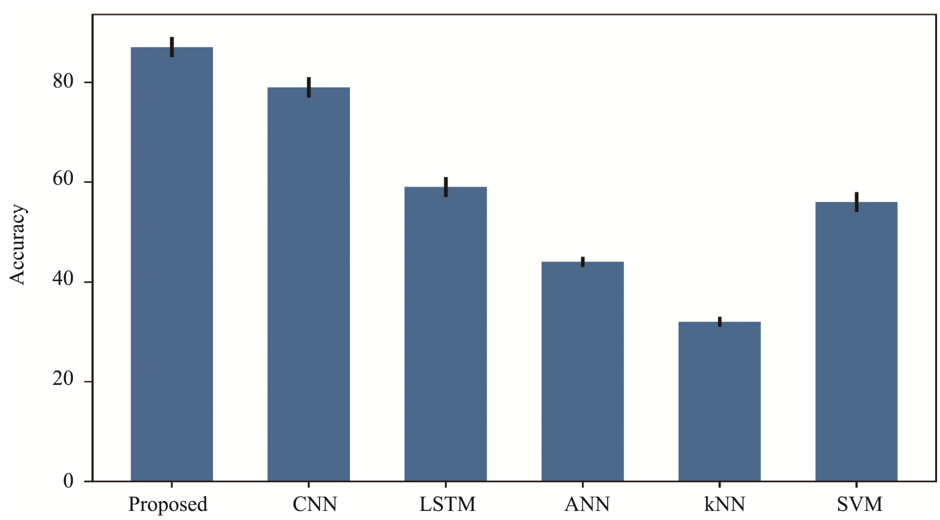


Fig.9 Average Detection Accuracy of Different Models in the Simulated Actual Industrial Environment

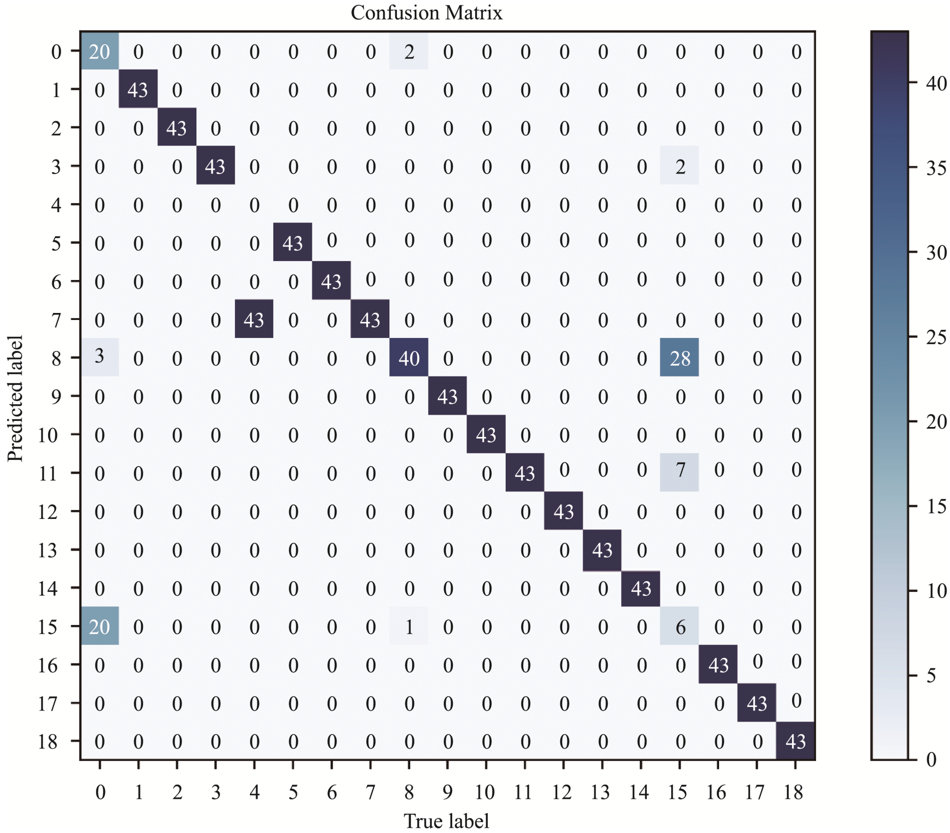


Fig.10 Confusion Matrix of the Classification for the Model in the Simulated Actual Industrial Environment

5 Conclusion

To achieve accurate pneumatic control valve fault diagnosis with insufficient actual fault condition data, an intelligent diagnosis approach for pneumatic control valves based on a MSCNN-LSTM hybrid model was presented in this paper. The multi scale CNN simultaneously extracts the local key features and long-term features with rich fields of view to maximize provide distinguishable in-depth features for subsequent feature recognition operations. All fault data are collected from the DAMADICS simulator. The experimental results indicate that the average test accuracy is above 94%, and successfully detects 16 out of the 19 conditions in the simulated actual industrial environment. Comparative analyses of various artificial neural network algorithms and corresponding scientific literature further demonstrate the superiority of the proposed model. The hybrid model not only does not require prior knowledge, but also has remarkable advantages and better robustness for handling complex nonlinear timeseries fault signals such as the pneumatic control valve.

The limitations of the proposed model are that all data used for model training are derived from the simulator, and only two kinds of sensor signals are considered. Our future work will focus on multi sensor fusion for pneumatic control valve fault diagnosis.

Funding: This research was funded by the “Ningxia Key Research and Development Project”, grant number “2022BEE02002”.

References

[1] Jha S K, Kaistha N. Valve positioning control for process through put maximization[J]. Chemical Engineering Research and Design, 2007, 85(11): 1465-1475.

[2] Hägglund T. A friction compensator for pneumatic control valves[J]. Journal of process control, 2002, 12(8):

897-904.

[3] Han X, Jiang J, Xu A, et al. Fault detection of pneumatic control valves based on canonical variate analysis[J]. IEEE Sensors Journal, 2021, 21(12): 13603-13615.

[4] Manninen T. Fault simulator and detection for a process control valve[J]. 2012.

[5] Puig V, Stancu A, Escobet T, et al. Passive robust fault detection using interval observers: Application to the DAMADICS benchmark problem[J]. Control engineering practice, 2006, 14(6): 621-633.

[6] de Almeida G M, Park S W. Fault detection and diagnosis in the DAMADICS benchmark actuator system–A hidden Markov model approach[J]. IFAC Proceedings Volumes, 2008, 41(2): 12419-12424.

[7] Bezerra C G, Costa B S J, Guedes L A, et al. An evolving approach to unsupervised and real-time fault detection in industrial processes[J]. Expert systems with applications, 2016, 63: 134-144.

[8] Nair B B, Preetam V M T, Panicker V R, et al. A Novel Feature Selection method for Fault Detection and Diagnosis of Control Valves[J]. International Journal of Computer Science Issues (IJCSI), 2011, 8(3): 415.

[9] D'Angelo M F S V, Palhares R M, Takahashi R H C, et al. Fuzzy/Bayesian change point detection approach to incipient fault detection[J]. IET control theory & applications, 2011, 5(4): 539-551.

[10] Chopra T, Vajpai J. Classification of faults in damadics benchmark process control system using self organizing maps[J]. Int. J. Soft Comput. Eng, 2011, 1(3): 85-90.

[11] Katunin A, Amarowicz M, Chrzanowski P. Faults diagnosis using self-organizing maps: a case study on the DAMADICS benchmark problem[C]//2015 Federated Conference on Computer Science and Information Systems (FedCSIS). IEEE, 2015: 1673-1681.

[12] Prabakaran K, Kaushik S, Mouleeshuwarapprabu R, et al. Self-organizing map based fault detection and isolation scheme for pneumatic actuator[J]. International Journal of Innovation and Applied Studies, 2014, 8(3): 1361.

[13] Ma L, Li X, Lei C, et al. Process monitoring of the pneumatic control valve using canonical variate analysis[C]//2017 Chinese Automation Congress (CAC). IEEE, 2017: 2784-2788.

[14] Kościelny J M, Bartyś M, Rzepiejewski P, et al. Actuator fault distinguishability study for the DAMADICS benchmark problem[J]. Control engineering practice, 2006, 14(6): 645-652.

[15] Louro R. Fault diagnosis of an industrial actuator valve[D]. MSc Dissertation, Technical University of Lisbon, Portugal, 2003.

[16] Calado J M F, da Costa J M G S, Bartys M, et al. FDI approach to the DAMADICS benchmark problem based on qualitative reasoning coupled with fuzzy neural networks[J]. Control Engineering Practice, 2006, 14(6): 685-698.

[17] Tang M, Li X. Fault detection and diagnosis of pneumatic control valve based on fuzzy method[C]//2021 China Automation Congress (CAC). IEEE, 2021: 1386-1391.

[18] Mendonça L F, Sousa J M C, da Costa J M G S. An architecture for fault detection and isolation based on fuzzy methods[J]. Expert systems with applications, 2009, 36(2): 1092-1104.

[19] Rodríguez-Ramos A, da Silva Neto A J, Llanes-Santiago O. An approach to fault diagnosis with online detection of novel faults using fuzzy clustering tools[J]. Expert Systems with Applications, 2018, 113: 200-212.

[20] Przystałka P, Moczulski W. Methodology of neural modelling in fault detection with the use of chaos engineering[J]. Engineering Applications of Artificial Intelligence, 2015, 41: 25-40.

[21] Venkata S K, Rao S. Fault detection of a flow control valve using vibration analysis and support vector machine[J]. Electronics, 2019, 8(10): 1062.

[22] Kowsalya A, Kannapiran B. Principal component analysis based approach for fault diagnosis in pneumatic valve using DAMADICS benchmark simulator[J]. special issue-07, IJRET: International Journal of Research in Engineering and Technology, (May 2014), 2014: 702-707.

[23] Sundarmahesh R, Kannapiran B. Fault diagnosis of pneumatic valve with DAMADICS simulator using ANN based classifier approach[J]. Int. J. Comput. Appl, 2013: 11-17.

[24] Subbaraj P, Kannapiran B. Fault Diagnosis of Pneumatic

Valve using PCA and ANN techniques[C]//Trends in Computer Science, Engineering and Information Technology: First International Conference on Computer Science, Engineering and Information Technology, CCSEIT 2011, Tirunelveli, Tamil Nadu, India, September 23-25, 2011. Proceedings. Springer Berlin Heidelberg, 2011: 404-413.

[25] Andrade A, Lopes K, Lima B, et al. Development of a methodology using artificial neural network in the detection and diagnosis of faults for pneumatic control valves[J]. Sensors, 2021, 21(3): 853.

[26] Ortiz Ortiz F J, Rodríguez-Ramos A, Llanes-Santiago O. A Robust Fault Diagnosis Method in Presence of Noise and Missing Information for Industrial Plants[C]//Pattern Recognition: 14th Mexican Conference, MCPR 2022, Ciudad Juárez, Mexico, June 22-25, 2022, Proceedings. Cham: Springer International Publishing, 2022: 35-45.

[27] Gu J, Wang Z, Kuen J, et al. Recent advances in convolutional neural networks[J]. Pattern recognition, 2018, 77: 354-377.

[28] He Z, Shao H, Zhong X, et al. Ensemble transfer CNNs driven by multi-channel signals for fault diagnosis of rotating machinery cross working conditions[J]. Knowledge-Based Systems, 2020, 207: 106396.

[29] Zhou F, Jin L, Dong J. Premature ventricular contraction detection combining deep neural networks and rules inference[J]. Artificial intelligence in medicine, 2017, 79: 42-51.

[30] Supriya S, Siuly S, Wang H, et al. EEG sleep stages analysis and classification based on weighed complex network features[J]. IEEE Transactions on Emerging Topics in Computational Intelligence, 2018, 5(2): 236-246.

[31] Ran X, Shan Z, Fang Y, et al. An LSTM-based method with attention mechanism for travel time prediction[J]. Sensors, 2019, 19(4): 861.

[32] Wang K, Ma C, Qiao Y, et al. A hybrid deep learning model with 1DCNN-LSTM-Attention networks for short-term traffic flow prediction[J]. Physica A: Statistical Mechanics and its Applications, 2021, 583: 126293.

[33] Bartyś M, Patton R, Syfert M, et al. Introduction to the DAMADICS actuator FDI benchmark study[J]. Control engineering practice, 2006, 14(6): 577-596.

[34] Bartyś M, Syfert M. Using damadics actuator benchmark library (dablib)[J]. Final, ver, 2001, 1: 01-20.

[35] Xu Y, Yang L. Based on improved CNN bearing fault detection[C]//Journal of Physics: Conference Series. IOP Publishing, 2022, 2171(1): 012073.

Author Biographies

HAO Hongtao received the M.E. degree in vehicle engineering and the Ph.D. degree in mechanical engineering from Shanghai Jiao Tong University, Shanghai, China, in 2006 and 2015, respectively. He is currently an Associate Professor with the College of Mechanical Engineering, Ningxia University. He has authored or coauthored more than 20 journal articles. His main research interests include deep learning, fault diagnosis, vehicle advanced transmission, etc.

E-mail: haoht_03@126.com

WANG Kai received the B.E. degree in mechanical engineering from the Hefei University of Technology, Hefei, China, in 2021. He is currently a M.Sc. candidate with Ningxia University, Yinchuan, China. His main research interests include deep learning and fault diagnosis.

E-mail: kaik_01@126.com