Journal of Zhejiang University-SCIENCE A (Applied Physics & Engineering) 2022 23(4):303-313
www.jzus.zju.edu.cn; www.springer.com/journal/11582
E-mail: jzus_a@zju.edu.cn

Research Article
https://doi.org/10.1631/jzus.A2100598

Data-driven fault diagnosis of control valve with missing data based on modeling and deep residual shrinkage network

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Abstract: A control valve is one of the most widely used machines in hydraulic systems. However, it often works in harsh environments and failure occurs from time to time. An intelligent and robust control valve fault diagnosis is therefore important for operation of the system. In this study, a fault diagnosis based on the mathematical model (MM) imputation and the modified deep residual shrinkage network (MDRSN) is proposed to solve the problem that data-driven models for control valves are susceptible to changing operating conditions and missing data. The multiple fault time-series samples of the control valve at different openings are collected for fault diagnosis to verify the effectiveness of the proposed method. The effects of the proposed method in missing data imputation and fault diagnosis are analyzed. Compared with random and k-nearest neighbor (KNN) imputation, the accuracies of MM-based imputation are improved by 17.87% and 21.18%, in the circumstances of a 20.00% data missing rate at valve opening from 10% to 28%. Furthermore, the results show that the proposed MDRSN can maintain high fault diagnosis accuracy with missing data.

Key words: Control valve; Missing data; Fault diagnosis; Mathematical model (MM); Deep residual shrinkage network (DRSN)

1 Introduction

The increasing complexity of engineering systems such as industrial processes, manufacturing systems, and electrical and electronic equipment, increases the risk of the system experiencing various failure modes which affect its reliability and safety. In modern industrial processes, timely detection and diagnosis of abnormalities are essential for monitoring process operations (He et al., 2014; Yang et al., 2020). Therefore, there is an urgent need to develop diagnostic and prediction methods to achieve stable operation of complex systems. Diagnosing industrial systems help prevent accidents and improve safety (Jardine et al., 2006; Soleimani et al., 2021).

Artificial intelligence technology has become an essential trend in industrial production (Lei et al., 2020). It has been shown to be suitable for diagnosing and predicting problems in complex industrial scenarios (Yuan et al., 2020). As an essential component of the process industry (Kim et al., 2016), the operation and maintenance of control valves is moving towards intelligent monitoring. The primary goal is to extend the service life of the control valve, reduce unnecessary shutdown tests, and ensure the safe operation of the valve. By monitoring the status of the control valve, analyzing the process data, and performing an online diagnosis of the operational status of the control valve, the intelligent maintenance of valve is realized. However, although there is a large amount of data in the process industry concerning control valves, it is difficult to collect enough labeled failure data due to differences in maintenance and life cycles. Therefore, machine learning, signal processing, pattern recognition, and other predictive maintenance methods are receiving much attention in control valve management (Lv et al., 2021). Based on the diversity of data, data-driven methods have become commonplace in fault diagnosis (Xie et al., 2021). Many data-driven tools are available to increase the speed and simplicity of implementation. By collecting enough data, we can identify relationships that have not been considered before. In addition, data-driven methods deal with

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Received Dec. 4, 2021; Revision accepted Dec. 27, 2021; Crosschecked Mar. 1, 2022; Online first Apr. 20, 2022

objective data to consider all relationships objectively. However, data-driven methods require large amounts of data, including all possible failure modes of the same or similar systems. In addition, if there is insufficient or incomplete data, the health assessment process can be unreliable or only partially applicable.

Most existing fault diagnosis methods assume that the class distribution is roughly balanced (Yang et al., 2020). However, absence of data is widespread in industrial production (Liu et al., 2020), and that absence seriously affects the accuracy and availability of diagnosis (Guo et al., 2020). Moreover, the accuracy of the deep learning fault diagnosis model and the effectiveness of the diagnosis method cannot be guaranteed. It should also be noted that many fault classifiers require complete feature data and cannot handle incomplete data. Therefore, using incomplete data to achieve an accurate and fast online diagnosis of faults has always been a focus of attention in academia and industry (Llanes-Santiago et al., 2018). At present, the main task of fault diagnosis based on incomplete data is to clean up insufficient data (Du et al., 2020) and delete incomplete data with statistical interpolation or interpolation based on deep learning (Guo et al., 2020). However, not all technologies consistently produce satisfactory results. Firstly, simply ignoring incomplete data may cause loss of information and change the distribution of data. Secondly, most statistical interpolation techniques are based on a linear prototype and have limited estimation capabilities. Thirdly, interpolation based on deep learning has advantages in nonlinear parameters but changing the data set and calculation time may limit its application in certain situations. On the other hand, fault diagnosis becomes more complicated with missing data (Razavi-Far et al., 2020). Therefore, it is worth further study to improve the accuracy of fault diagnosis while improving the imputation algorithm.

To solve the problem of fault diagnosis with data imbalance and incompleteness in the control valve system, combined with the working conditions of the control valve, this paper designs a hybrid method combining the control valve mathematical model (MM) and the data-driven model. Moreover, it is applied to fault diagnosis of the control valve with missing data. The contribution of this research is to accurately realize the fault diagnosis of the control valve from the unbalanced and incomplete data by constructing a balanced sample set. The paper is structured as follows: Section 2 introduces the method of data missing filling based on the MM of the control valve and the modified deep residual shrinkage network (MDRSN) for control valve fault diagnosis. Case studies on the missing data with different models and fault types are described in Section 3, the online fault diagnosis of the control valve is presented in Section 4, and the work is concluded and summarized in Section 5.

2 Proposed method

The problematic controller accounts for about two-thirds of industrial controllers classified as poor or fair (Desborough and Miller, 2001). Thus, establishing an accurate MM is the key to a model-based automatic control or fault diagnosis system. Furthermore, incomplete data is a common phenomenon in a working environment (Zhu et al., 2018). Fault diagnosis generally involves two problems: incomplete data processing and fault diagnosis or classification. Thus, we first reconstruct the missing information into a complete data set in this section. Then we use the completed data set to determine the fault diagnosis. The most common method for dealing with missing data is imputation, replacing each missing element with an estimated value.

2.1 Incomplete feature data

It is essential for data processing to process the missing control valve data, which plays a vital role in fault diagnosis. Missing data refers to the observed variable in the database with incomplete data which causes the database to have unreliable samples. However, unreliable samples account for only a small part of the entire data set. Most data sets can be considered reliable, which is reasonable. Fig. 1 shows the principle of data interpolation based on the MM of the control valve proposed in this study with missing data. After imputation, the initial incomplete data set becomes a complete data set.

2.2 Imputation based on a mathematical model of the control valve

The core of the MM is to combine the model with data and use a simplified model that can reflect the physical relationship to describe the state of the

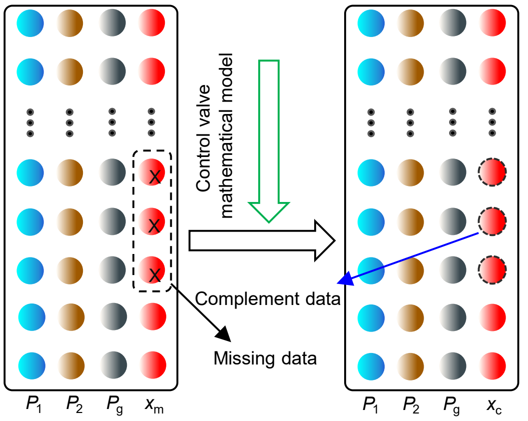

Fig. 1 Schematic diagram of complement feature based on a control valve mathematical model (P_1, P_2, and P_g are the pressures before and after the control valve and the gas pressure in the valve, respectively. x_m is the valve opening with missing data, and x_c is the completed valve opening after imputation)

control valve. According to the data model of the control valve and other complete data, the missing data of the control valve can be interpolated. According to the mechanism of the flow-open pneumatic membrane control valve proposed in this paper, the MM of the control valve actuator is established (Fig. 2b). When the valve stem is moving, the main external effects applied during the movement are the pressure of the membrane air chamber, F_g, the elastic force of the spring, F_{sp}, the frictional resistance of the valve stem movement, F_f, and the valve stem displacement, x.

Based on Newton's second law, the motion equations of the valve stem are:

$$\dot{x} = v, \tag{1}$$
$$m\dot{v} = F_g + F_{sp} + F_f + F_p + F_i, \tag{2}$$

where m is the mass of valve stem, and v stands for its velocity.

$$F_g = P_g A_e, \tag{3}$$
$$F_{sp} = -k_s x, \tag{4}$$
$$F_f = -F_s \text{sign}(v) - vF_v, \tag{5}$$

where A_e is the diaphragm area, and k_s is the spring stiffness coefficient. F_s is the Stribeck friction forces, and vF_v is the Coulomb friction. Both the force F_p due to the fluid pressure drop and the extra force F_i required to compel the valve stem plug into the seat are assumed to be zero due to their negligible contributions (Kayihan and Doyle III, 2000; Fang et al., 2016).

$$P_g A_e - k_s x - vF_v - F_s - ma = 0. \tag{6}$$

When the displacements of the valve stem are x_1 and x_2, the valve stem is guaranteed to be in a stable state. a is the acceleration of the valve stem. According to Eq. (6),

$$P_{g1} A_e - k_s x_1 - vF_v - F_s - ma = 0, \tag{7}$$
$$P_{g2} A_e - k_s x_2 - vF_v - F_s - ma = 0, \tag{8}$$

where P_{g1} and P_{g2} are the pressures of the valve air chamber when the stem displacements are x_1 and x_2,

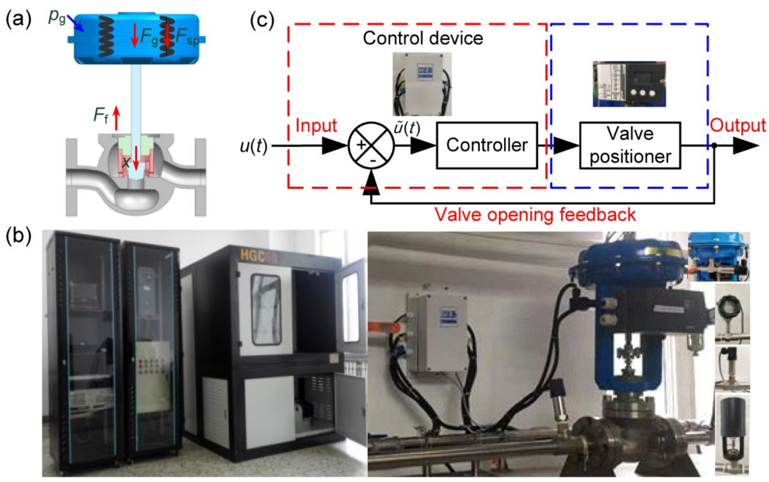

Fig. 2 Mathematical model of pneumatic control valve (a); physical map of the test system: water hydraulic system, test control valve, and sensors (b); control loop diagram of control valve (c). $u(t)$ is the electric control signal and $\tilde{u}(t)$ is the intermediate signal

respectively. When the valve stem of the control valve is stable at a certain position, the speed is about zero. Then

$$\frac{k_\mathrm{s}}{A_\mathrm{e}}=\frac{P_\mathrm{g1}-P_\mathrm{g2}}{x_1-x_2}. \tag{9}$$

Therefore, for the missing data of valve displacement x_m, there is

$$x_\mathrm{m}=\frac{A_\mathrm{e}}{k_\mathrm{s}}(P_\mathrm{m}-P_\mathrm{im})+x_\mathrm{im}, \tag{10}$$

where x_im is the valve stem displacement information that is not missing. The valve stem stroke x=16 mm, the spring stiffness coefficient k_s=52330 N/m, and the diaphragm area A_e=0.032 m^2. P_m and P_im are the chamber pressures when the valve stem displacements are x_m and x_im, respectively.

Dealing with the problem of missing data can be seen as a problem of predictive modeling. A combined control valve is integrated with an MM and data-driven fault diagnosis. This kind of fault diagnosis method based on the MM closely links the fault characteristics with the parameters of the MM. Using the MM calculates the system's internal state and can effectively reduce the requirements for model correction data and simultaneously play a positive role in the interpolation of missing data.

2.3 Fault diagnosis model based on MDRST

For the deep learning model, the non-linear expression ability of the model becomes more robust as the number of network layers increases. However, with the increase of the network, the model will have the problem of network degradation. In addition, the valve action and the operation of the automatic control system usually result in a sharp increase and decrease in pressure of the control valve (Tripathy et al., 2015; Dutta et al., 2020). Not only that air is often mixed in water hydraulic systems. The air in the fluid causes the hydraulic system to work unstably, and the pressure fluctuates, thus affecting the quality of the data.

The deep residual shrinkage network (DRSN) is a deep learning method for noisy data. When the deep residual network performs model training based on backpropagation, its loss can be backpropagated layer by layer through convolutional layers. It can be back-propagated more conveniently through the identity mapping of residual items. By introducing the soft threshold and attention mechanism into the DRSN, a threshold-sharing deep residual shrinkage unit is constructed to overcome the noise of data samples generated by pressure fluctuations. The working principle of DRSN is to find out the interference characteristics of the input sample according to the attention mechanism and use the soft threshold function to set it to zero thus reducing the influence of noise interference on the pattern recognition effect (Zhao et al., 2020).

Based on the research of Zhao et al. (2020), combined with the control valve's data volume and characteristics, the proposed MDRSN is shown in Fig. 3. The overall structure includes an input layer, a convolutional layer (Conv), residual shrinkage building units (RSBUs), a batch normalization layer (BN), an activation function (rectifier linear unit (ReLU)), global average pooling (GAP), and a fully connected layer (FC). Specifically, the critical feature is converted into a larger absolute value through the previous convolutional layer. The feature corresponding to the redundant information is converted into a smaller absolute value. In this way, the feature of any interval can be set to zero through soft thresholding, and the feature of a certain value range can be flexibly deleted to better characterize the non-linear mapping.

The soft threshold function is widely used in the field of signal denoising. The operating mechanism is

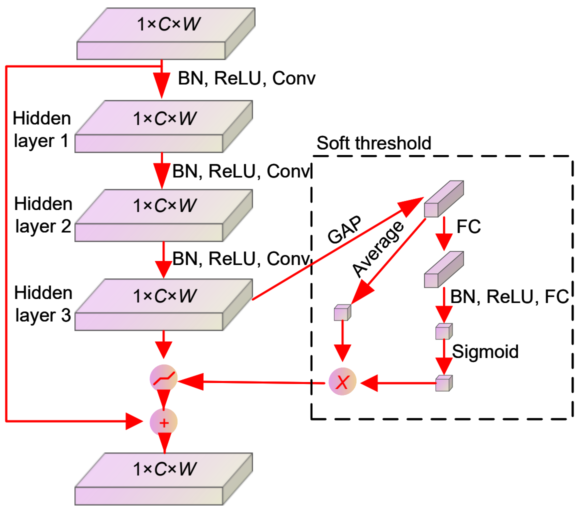

Fig. 3 Deep residual shrinkage network with channel-shared thresholds. *C* is the number of channels, and *W*×1 is the width and height of feature

as follows: the convolutional neural network automatically performs filter learning, maps the original data to another space, and performs soft thresholding. The soft thresholding sets the features in the threshold interval to zero. The feature X further from zero shrinks toward zero. However, the estimation deviation of the soft threshold method is large, the data of helpful information is compressed, and the phenomenon of over-smoothing is prone to appear. To reduce excessive contraction in the pre-training period of the model, this study sets the threshold interval to $[-\tau^2, \tau^2]$, and the soft threshold formula is

$$Y=\begin{cases} X-\tau^2, & X>\tau^2, \\ 0, & -\tau^2\leqslant X\leqslant\tau^2, \\ X+\tau^2, & X<-\tau^2, \end{cases} \tag{11}$$

where X is the input feature, Y is the output feature, and τ^2 is the soft threshold. Eq. (11) takes the derivative of X to obtain Eq. (12). It can be seen that the derivative of the soft threshold function is 1 or 0, which is helpful in preventing the gradient from disappearing or exploding.

$$\frac{\partial Y}{\partial X}=\begin{cases} 1, & X>\tau^2, \\ 0, & -\tau^2\leqslant X\leqslant\tau^2, \\ 1, & X<-\tau^2. \end{cases} \tag{12}$$

Fig. 4 shows the 3D implicit function diagram of the improved soft threshold formula. Compared with the threshold formulas $Y=X-\tau$ and $Y=X+\tau$, the improved soft threshold contains more abundant output features in the same threshold interval. This is helpful in preventing excessive contraction in the pre-training period and in retaining the effective features in the training set as much as possible.

According to the above method, combined with the working data set of the control valve, we finally determined the model parameters of the network, as shown in Table 1. This study takes the DRSN as a benchmark to be further compared. The RSM and MRSM represent residual shrinkage modules and improved residual shrinkage modules, respectively. Table 1 illustrates the number of layers, convolutional kernels, and the size of convolutional kernels. The first numbers in the brackets in the first and second columns are the number of convolutional kernels, and the second numbers in those brackets are the width of those kernels.

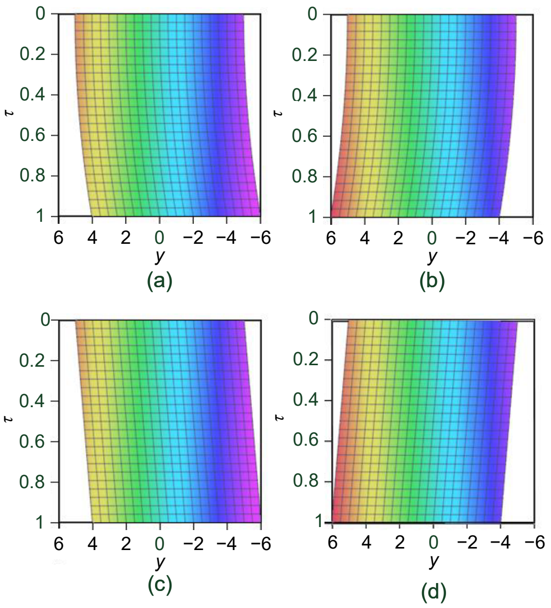

Fig. 4 3D implicit function diagram of the modified soft threshold: (a) $Y=X-\tau^2$; (b) $Y=X+\tau^2$; (c) $Y=X-\tau$; (d) $Y=X+\tau$

Table 1 Experiment-related model parameters of DRSN and MDRSN

DRSN	MDRSN	Output size
Input	Input	1×5×16
Conv (16, 3)	Conv (16, 3)	16×5×16
RSM (16, 3, /2)	MRSM (16, 3, /2)	16×3×8
RSM (16, 3, /2)	MRSM (16, 3, /2)	16×2×4
BN	BN	16×2×4
ReLU	ReLU	16×2×4
GAP	GAP	16×1×1
FC	FC	4

The third numbers represent the down-sampling operation.

3 Case study

A data acquisition system for the control valve was constructed to verify the effectiveness of the proposed method in the fault diagnosis of a control valve with missing data. The diagnostic data was the original experimental data of the sensor. All fault diagnosis experiments are built-in Python 3.7 in the TensorFlow 2.1.0 environment.

Due to technical confidentiality, the commercial valve positioner is usually inaccessible to users. Hence, the study chooses a Siemens smart valve positioner

(SIPART PS2, Germany) as the electric-pneumatic conversion device. The physical map of the test system (water hydraulic system, test control valve, and sensors) can be seen in Fig. 2b. The control system is connected to the current control signal directly to the electric-pneumatic conversion device. The control loop block diagram is illustrated in Fig. 2c. Our concern in this research is the MM of the control valve and the evaluation of its working condition.

The control valve experimental system is composed of the following parts: pump, control valve, filter, water tank, pipeline, and control system. The control valve under test is from Jiangsu Evalve Co. Ltd. (B102B, DN20, China). The maximum displacement of the valve stem is 16 mm. The proposed control system is connected to sensors and controls the valve opening. The collected data contains the valve opening, time, flow, pressure, and temperature. The trained data set contains four parts: the standard working data of the control valve and three types of faults (blockages before and after the valve, and bypass valve leakage). All the recorded working data have the same length.

3.1 Data description

The data set includes four working states at 10%–28% valve opening: fault-free, blockages before and after the valve, and leakage of the bypass valve. Each data set consists of 72000 samples. The ratio of training samples to test samples is 8:2. The four working conditions of the data set and the corresponding numbers of long-term series are shown in Table 2.

Table 2 Dataset of control valve

No.	Work condition	Number
1	Fault-free	1.2×10^4
2	Blockage before valve	1.2×10^4
3	Blockage after valve	1.2×10^4
4	Bypass valve leakage	1.2×10^4

3.2 Data imputation performance comparison

Without loss of generality, two typical statistical imputation methods are selected for comparison: random imputation (Rand) and k-nearest neighbor (KNN) imputation.

1. Random imputation

Random imputation randomly selects some values from the known data of this missing variable to make the sample closer to the actual distribution. Suppose the total number of samples is n and the number of missing samples is n_{m}, then the number of available non-missing samples is $n-n_{\mathrm{m}}$. Random imputation is to select from $n-n_{\mathrm{m}}$ samples to replace missing data randomly.

2. KNN imputation

The KNN imputation uses the similarity between missing and complete data to select imputed data sets. Suppose the number of missing samples is i and the number of non-missing samples is j. $y(i)$ and $y(j)$ are the data corresponding to i and j, respectively. The Euclidean distance between the data can be expressed as

$$\mathrm{dist}[y(i),y(j)]=\sqrt{\sum(y(i)-y(j))^2}. \tag{13}$$

The distances are sorted, and the k distances corresponding to the smallest distances are selected as the KNN of the target data. The corresponding missing data is:

$$y(i)^*=\frac{1}{k}\sum_{i=1}^{k}y(i). \tag{14}$$

The following performance indicators are calculated to evaluate data interpolation performance: mean squared error (MSE) and mean absolute error (MAE).

MSE is the mean value of the sum of squares of the corresponding point errors between the predicted and original data. The closer the value is to zero, the better the fitting effect is. The function can be expressed as

$$\mathrm{MSE}=\frac{1}{n_{\mathrm{m}}}\sum_{i=1}^{n_{\mathrm{m}}}(y_{\mathrm{o}}-y_{\mathrm{i}})^2, \tag{15}$$

where y_{o} and y_{i} are the original data and the imputation data, respectively.

MAE is the average absolute value of the error between the observed and actual values. The closer the MAE is to zero, the better the fitting effect is. The MAE can be expressed as

$$\mathrm{MAE}=\frac{1}{n_{\mathrm{m}}}\sum_{i=1}^{n_{\mathrm{m}}}\left|y_{\mathrm{o}}-y_{\mathrm{i}}\right|. \tag{16}$$

The valve displacement data in the test sample of the control valve is treated with random data missing at a rate of 20%. Then, we use random, KNN, and MM imputation to deal with missing data. Twenty groups of interpolation data are randomly selected for comparison (Table 3).

Table 3 Valve opening comparison between the actual value and the partial imputation of various imputation methods

No.	Valve opening (%)			
	Real	Rand*	KNN	MM
1	10.1375	**10.8750**	26.4025	6.0244
2	16.1625	11.3375	**16.2066**	16.2844
3	21.4687	15.8562	**20.3383**	19.2732
4	10.0750	15.8750	26.4025	**7.6081**
5	10.6062	25.3156	14.0125	**9.7545**
6	11.5250	16.1562	13.9454	**11.9594**
7	11.5687	16.2125	13.2841	**9.9409**
8	11.5250	13.9812	**12.7808**	13.2072
9	11.2187	14.1687	13.1008	**9.9837**
10	11.5687	**10.8562**	14.6729	13.2338
11	11.2312	20.8500	14.0125	**12.0430**
12	11.2312	**10.7062**	13.1433	10.3620
13	14.1875	15.8750	12.9512	**13.9058**
14	16.4000	15.3625	14.9587	**17.1932**
15	16.2437	13.8437	15.8204	**15.9258**
16	10.6562	24.8375	11.7870	**10.6342**
17	10.6812	13.5937	13.1433	**11.6436**
18	11.8125	16.2125	16.3679	**14.5748**
19	15.9687	20.9125	23.3550	**16.0006**
20	20.5375	15.1812	19.7862	**19.6793**

The bold text indicates the imputed data close to the actual value. It can be seen from Table 3 that the interpolation data based on the MM of the control valve is the closest to the actual value.

Further, MSE and MAE are calculated according to the imputation value and the real value in Table 3. The calculation results are illustrated in Table 4. According to the results, the MM imputation method has the best effect, and the interpolation value is closer to the real value, followed by KNN imputation and random imputation. Compared with random and KNN imputations, the accuracies of MM-based imputation are improved by 17.87% and 21.18%, in the circumstances of a 20% data missing rate at a valve opening from 10% to 28%. Consequently, according to Tables 3 and 4, the proposed MM interpolation method has good interpolation results.

Table 4 Comparison of the MAE and MSE between the interpolation and actual value of various interpolation methods

Method	MAE	MSE
Rand	4.7070	37.4073
KNN	3.5815	33.2983
MM	1.2052	2.5024

3.3 Fault diagnosis performance comparison

To analyze and compare different processing methods for missing data and fault diagnosis algorithms, three factors that may affect the test results are selected: handling incomplete data, fault diagnosis algorithms, and data missing rate. Each factor has four levels, and an experimental design is carried out. Incomplete data processing includes direct deletion, random imputation, KNN imputation, and MM imputation. Fault diagnosis algorithms include support vector machine (SVM), convolutional neural network (CNN), DRSN, and MDRSN. Data missing rates are 20%, 40%, 60%, and 80%. The experimental design of missing feature fault diagnosis with various methods and missing rates can be seen in Table 5.

Table 5 Measured data of the experiments in four states

No.	Handling missing data	Fault diagnosis algorithm	Missing rate	Accuracy
1	Del*	SVM	20%	0.8700
2	Del	CNN	40%	0.8175
3	Del	DRSN	60%	0.7640
4	Del	MDRSN	80%	0.7275
5	Rand	SVM	40%	0.8520
6	Rand	CNN	20%	0.8750
7	Rand	DRSN	80%	0.8901
8	Rand	MDRSN	60%	0.9440
9	KNN	SVM	60%	0.8610
10	KNN	CNN	80%	0.8574
11	KNN	DRSN	20%	0.9601
12	KNN	MDRSN	40%	0.9700
13	MM	SVM	80%	0.8730
14	MM	CNN	60%	0.9150
15	MM	DRSN	40%	0.9603
16	MM	MDRSN	20%	0.9750

* Deletion

The Taguchi experimental designs (Sheesley, 1990; Sharif et al., 2014) were applied to determine the average response results of Table 5. Furthermore, as shown in Table 6, the maximum values of the mean values of the three factors appear respectively in MM imputation, MDRSN, and 20% missing rate.

Table 6 Mean main effect of the Taguchi design of the performance comparison

Handle missing data	Accuracy	Fault diagnosis algorithm	Accuracy	Missing rate	Accuracy
Del	0.7948	SVM	0.8640	20%	0.9200
Rand	0.8903	CNN	0.8662	40%	0.9000
KNN	0.9121	DRSN	0.8936	60%	0.8710
MM	0.9308	MDRSN	0.9041	80%	0.8370
Δ	0.1361	Δ	0.0401	Δ	0.0830
Rank	1		3		2

Δ: difference between the maximum and minimum

The ranking MAE of the mean response table shows that dealing with missing data has the most significant impact on fault diagnosis accuracy. Next followed the feature data missing rate and fault diagnosis algorithm. Fig. 5 visually shows the results in the mean corresponding table. It can be seen intuitively from Fig. 5 that the MM has the best imputation effect. The DRSN and MDRSN are relatively effective in fault diagnosis of the missing feature data. The accuracy of fault diagnosis decreases with the increase of the missing rate.

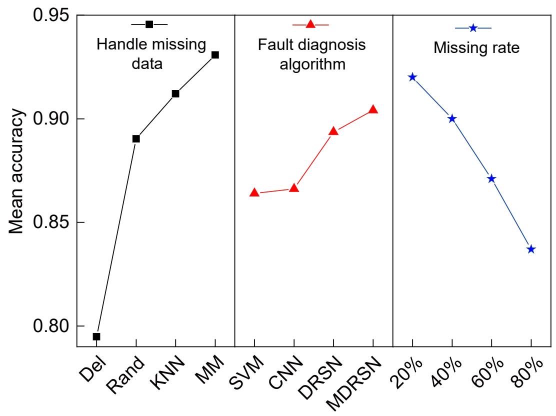

Fig. 5 Mean main effect diagram of different types of missing feature fault diagnosis with various methods and missing rates

According to the experimental design results in the previous part, the DRSN and MDRSN algorithms have better fault diagnosis effects for imputation models with different data missing rates. Furthermore, to verify the validity of the proposed MDRSN, the fault diagnosis accuracy rates of DRSN and MDRSN were compared under different imputed data sets as shown in Fig. 6.

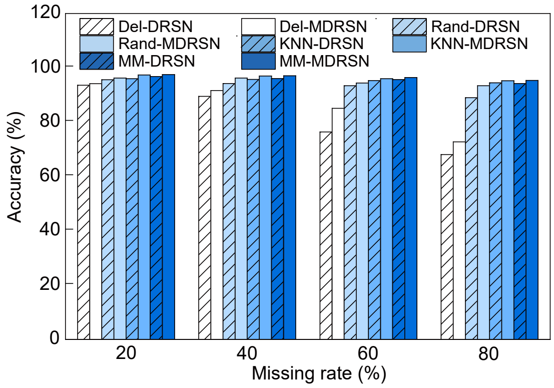

Fig. 6 Comparison of classification accuracies for DRSN and MDRSN with variable handling incomplete data and missing rates

It can be seen from Fig. 6 that the accuracy fault diagnosis of MDRSN has some improvement compared with DRSN. Compared with DRSN, MDRSN deletes missing data sets, random imputation data sets, KNN imputation data sets, and MM imputation data sets. The fault diagnosis accuracies have increased by 4.90%, 2.14%, 1.06%, and 0.95%, respectively.

4 Online fault diagnosis of control valve

The fault diagnosis model based on MDRSN is shown in Fig. 7a. We assume that the abnormal process state is well sensed in online fault diagnosis. The pressure before and after the control valve, the air chamber pressure, and information on the control valve's position were obtained and processed into a standard data set through the controller. We divided the data set into a training set and a test set for model training and testing. The online evaluation part involves collecting the data mentioned above in real-time and then passing it to the fault diagnosis model for online fault classification. The detailed processes of the control valve online fault diagnosis are offline part and outline part.

4.1 Offline part

1. Collect data, determine whether there is missing data, and invoke the MM of the regulator for interpolation.

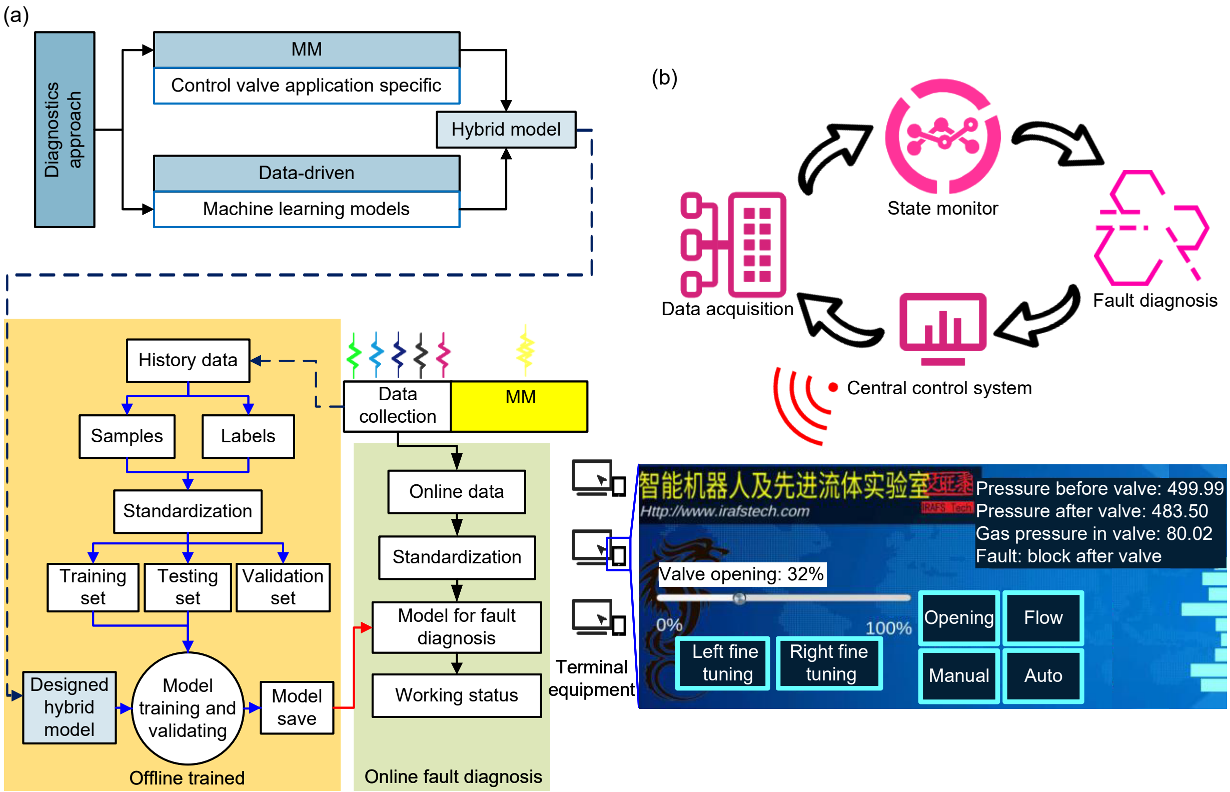

Fig. 7 Flowchart of the proposed online control valve fault diagnosis model (a); control valve online fault diagnosis system and terminal equipment operation interface (b) (pressure unit: kPa)

2. Set training parameters, including the number of iterations and learning rate.

3. Initialize network parameters.

4. Train the model in supervised learning.

5. Store the trained fault diagnosis model.

4.2 Online part

1. Retrieve the trained fault diagnosis model.

2. Collect sensor data online and standardized.

3. If missing data is detected, invoke MM-based imputation and complete test data.

4. Input the test sample set and get the diagnosis result.

In addition, we have further improved the application of the fault diagnosis method proposed in actual production. Fig. 7b shows the complete online fault diagnosis system and the terminal effect diagram of the control valve. The controller transmits the sensor information and diagnosis results to the mobile terminal in real-time via the wireless network. The mobile terminal is convenient for staff to check the operating status and key data of the control valve.

5 Conclusions

Data-acquisition plays an increasingly important role in control valve state detection. A vital premise of the control valve monitoring system is to build real-time and accurate data processing but the data-driven model of the control valve is susceptible both to changing working conditions and to missing data. This paper used an MM of the control valve to deal with missing data. Furthermore, we proposed the MDRSN for fault diagnosis. Based on the complete sample obtained after the imputation, the fault diagnosis model of the control valve was analyzed and trained to improve the accuracy of fault diagnosis. In addition, we used different fault diagnosis methods to identify faults in the completed data set. The data set with MM interpolation has better results under MDRSN fault diagnosis. The comparison with other methods proves the effectiveness and applicability of the proposed method in supplementing missing features and detecting valve faults. In addition, a diagnostic platform developed for practical engineering applications has been established. Data has become an inevitable part of diagnosis in complex engineering systems. Therefore, processing miscellaneous data with multiple characteristics is one of the main challenges. In the future, combining the MM of the control valve with the method based on a hybrid data-driven calculation will optimize the accuracy of fault diagnosis.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (No. 51875113), the Natural Science Joint Guidance Foundation of the Heilongjiang Province of China (No. LH2019E027), the PhD Student Research and Innovation Fund of the Fundamental Research Funds for the Central Universities (No. XK2070021009), China.

Author contributions

Feng SUN designed the research and wrote the draft of manuscript. He XU helped to supervise and administrate the project. Yu-han ZHAO carried out software and data processing and Yu-dong ZHANG helped to review the manuscript.

Conflict of interest

Feng SUN, He XU, Yu-han ZHAO, and Yu-dong ZHANG declare that they have no conflict of interest.

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