INTRODUCTION

A valve is the control device of a fluid pipeline with many types and wide applications. However, insufficient sealing of the valve sealing surface because of frequent opening, wear and corrosion may cause valve leakage. There are three possible leakage places in the valve: the contact between the valve core and valve seat; the connection between the valve stem and the stuffing box; the connection between the valve body and valve cover. Among them, the first leakage place is called internal leakage, which will affect the ability of the valve to cut off the medium. The leakage at the last two places is called external leakage, that is, the medium leaks from the inside of the valve to the outside. Internal leakage will cause damage to the equipment, and the fluid leakage will affect the product quality or cause safety accidents; external leakage will cause material loss and environmental pollution. Compared with the external leakage, the internal leakage has strong concealment and cannot be observed directly. If it is not found in time, it will cause serious losses [1–3].

In order to judge whether the valve is internal leakage, the valve needs to be removed from the pipeline system regularly and installed on the hydraulic valve test bench for testing. The specific method is to apply a certain pressure of water or air to the front of the valve after closing the valve, and observe whether there is any medium flowing out of the rear of the valve. This detection method requires the pipeline system to stop working, and the detection time is long, which affects the production and causes economic losses. Therefore, some online detection technologies have been studied, such as acoustic emission (AE), ultrasonic and radiographic inspection technologies. Among them, AE technology is based on the principle that the transient elastic wave will be generated when the valve leaks and the AE signal will be sent out. The health state of the valve could be judged by collecting and analysing the valve internal leakage AE signal (VILAES) [4, 5]. As a dynamic detection method, the energy detected by AE technology comes from the measured object itself rather than provided by the detection instruments like ultrasonic and radiographic inspection technologies.
It can be used in high and low temperature, nuclear radiation, flammable, explosive and other environments, which is suitable for online detection of industrial processes. However, in order to realise this technology, it is necessary to first determine the quantitative relationship between the characteristics of VILAES and leakage rates, that is, to establish the mathematical model of VILAES. It is the basis and foundation for the application of AE technology in valve internal leakage detection. In recent years, some achievements have been made in establishing a mathematical model of VILAES.

According to the number of variables, VILAES models can be classified into single-variable and multiple-variable models.

The so-called single-variable model refers to the mathematical relationship between the characteristics of VILAES and leakage rates aiming at a certain calibre valve and under a certain pressure. The single-variable model is concise and clear and can be used to express the relationship between them conveniently, which is the basis of valve internal leakage detection.

Kaewwaewnoi et al. studied the relationship between the characteristics of VILAES and leakage rates for 25.4 50.8 and 76.2 mm diameter ball and globe valves when the leakage rates were 1000–6000 ml/min, and the pressures were 100, 300 and 700 kPa, respectively. The relationship between the root mean square of VILAES and leakage rates was deduced theoretically, and the effects of a single factor among pressure, mean square of VILAES and leakage rates was deduced theoretically, and the effects of a single factor among pressure, mean square of VILAES and leakage rates was deduced theoretically. However, the root mean square error (RMSE) of the model in the test set data was 22.12 ml/min [9]. However, when establishing the multiple-variable model, they only carried out experiments on two types of valves, and the number of each type of valve was very small, which was only one valve. For each type of valve, there were many calibres, and for the same calibre, there were some different flow coefficients. These parameters and variables are not considered in the modelling.

Zhu et al. conducted experiments on two types of 76.2 mm calibre valves, including a ball and a plug valve. Experimental data of 520 sets were collected under multiple pressures when the experimental medium was nitrogen, and the leakage rates were 5000–80,000 ml/min. Two-thirds of the experimental data were used for modelling, and one-third was used for testing. The multiple-variable model was established by taking the pressure, valve type and leakage rate as independent variables. The root mean square error (RMSE) of the model in the test set data was 22.12 ml/min [9]. However, when establishing the multiple-variable model, they only carried out experiments on two types of valves, and the number of each type of valve was very small, which was only one valve. For each type of valve, there were many calibres, and for the same calibre, there were some different flow coefficients. These parameters and variables are not considered in the modelling.

From the perspective of the modelling process, it can be divided into two steps: Modelling and verification. Due to the complexity and non-uniformity of the transmission path of VILAES, there is a great uncertainty when the AE signal is transmitted from the inside of the valve through the thick metal valve wall and then picked up by the sensor, and the absolute error of detection is relatively large. Although leakage detection is to judge the state of the valve, it is not necessary and impossible to meet the requirements for metrological measurement, but it also requires that the detection results have certain repeatability. Therefore, before establishing the multiple-variable model for the same type of valves, it is necessary to verify the mathematical model built by the experimental data of a single valve. The validation data include the experimental data of a new round of experiments for the same valve; the experimental data after moving the sensor installation position for the same valve; the experimental data of another valve of the same type, calibre and flow coefficient. There are few reports on this verification work in the existing papers. This work is the basis of setting up a mathematical model for the same type of valves.

If the model established for the single valve has no repeatability, the practical significance of establishing the valve mathematical model will be lost.

In addition, the existing papers paid more attention to the VILAES modelling of large leakage rate. The valve leakage rate is generally divided into six levels, the allowable leakage rate of the first level is the largest, and the allowable leakage rate of the sixth level is the smallest. Generally speaking, when the medium is liquid, the fourth-level leakage standard is used to judge whether the valve is qualified. According to the American ANSIB16•104-1976 valve leakage rate standard, for medium and small valves with a calibre less than 80 mm, the allowable leakage rate of fourth-level leakage standard is less than 200 ml/min, which is called small leakage rate. For example, for HTS valve with a calibre of 50 mm and a flow coefficient of 17, the fourth-level allowable leakage rate at 0.35 MPa is 45 ml/min. When the leakage rate is greater than 45 ml/min, it indicates that the valve does not meet the fourth-level leakage standard and needs to be repaired or replaced. At present, AE technology is mainly used to detect the large leakage rate of valves, and the leakage rate is mostly greater than 1000 ml/min. For
example, the minimum detectable leakage rate of the VPAC5131 valve leak detector developed by an American physical acoustics company is 1000 ml/min. There are few researches on detecting small leakage of the valve by AE technology. At the same time, it did not disclose the specific technical details of data processing. Therefore, the research of small leakage rate detection has more practical application value. However, the smaller the leakage rate is, the more difficult it is to detect.

To this end, the same type of valve with different calibres and flow coefficients are selected to conduct experiments and collect data under the condition of a small leakage rate; the frequency range of VILAES is determined by spectrum analysis, and the best filtering frequency band is selected for Butterworth band-pass filter to preprocess the signal to reduce the interference of environmental and pump noises; the standard deviation that can best represent the VILAES is calculated as the characteristic; the mixed multiple-variable model between the characteristics of VILAES and leakage rates, pressures, valve calibres and flow coefficients for the same type of valve is built by least-squares SVM (LSSVM). In the process of modelling, the results of each step are verified.

2 | MODEL ANALYSIS

According to the AE principle of valve internal leakage, in the process of leakage, the medium in the valve flows out at a high speed from the leak hole under the action of the pressure at the front end of the valve forming a jet stream. The jet stream will cause turbulence in the normal flow of fluid and interact with the valve wall to generate an elastic wave on the valve wall. The elastic wave will carry the information of the leak point and spread it around. The information is picked up by using an AE sensor and processed by some methods. It is possible to judge the valve internal leakage.

Through theoretical analysis, Kaewwaewnoi et al. built a qualitative relationship between the root mean square of VILAES and leakage rate, pressure for the ball and globe valves [6] as shown in Equation (1):

\[
AE_{RAMS}^2 = C_1 \cdot \frac{\rho}{\alpha^5 D^{14}} \left( \frac{Q}{\Delta P} \right)^8 \left( \frac{R_1}{\Delta P} \right)^4
\]

(1)

where \(AE_{RAMS}^2\) is the root mean square of VILAES, and its unit is \(V\); \(C_1\) is a simplified function of fluid variables, which neglects the influences of some factors, including AE sensor, instrument gain, reference voltage, signal attenuation, AE acquisition system and valve material; \(\alpha\) is the sound velocity in the fluid, and its unit is \(m/s\); \(D\) is the valve size, and its unit is \(m\); \(Q\) is the theoretical leakage rate of valve, and its unit is \(m^3/s\); \(\Delta P\) is the pressure drop across the valve. According to Equation (1), the leakage rate of the valve can be estimated only by calculating the characteristic of VILAES and combining with test parameters.

The above is based on the AE mechanism of valve internal leakage, and by analysing the features of VILAES, the mathematical model is established to describe the relationship between the characteristics of VILAES and leakage rates. However, the propagation path of VILAES is complicated, and VILAES will be attenuated in the process of propagation. These factors make that the \(C_1\) in this model cannot be accurately calculated. Therefore, the health state of the valve can only be judged qualitatively. In order to quantitatively calculate the valve leakage rate, it is necessary to build the mathematical model between the characteristic of VILAES and the leakage rate by the experimental modelling method.

The VILAES is related to leakage rate, front pressure of valve, valve type, valve calibre and valve flow coefficient. However, the workload of building a multiple-variable model to describe the relationship between the characteristics of VILAES and leakage rates, pressures, valve types, valve calibres and flow coefficients by the experimental modelling method is very large. At the same time, considering the mechanical structure and working principle are different for different types of valves; therefore, for different types of valves, a multiple-variable model between the characteristics of VILAES and leakage rates, pressures, valve calibres and flow coefficients is built, which fully meets the needs of practical applications. Since the valve calibre and flow coefficient are designed and manufactured according to the national standards, they cannot take values arbitrarily and can only be discrete values, which belong to discrete variables, while the leakage rate and pressure belong to continuous variables. Therefore, these parameters are mixed multiple-variable. Next, we will establish a hybrid multivariable model for the HTS pneumatic control valve.

3 | EXPERIMENTAL STUDY

In order to build the mixed multiple-variable model for describing the relationship between the characteristics of VILAES and leakage rates, pressures, valve calibres and flow coefficients, a large amount of experimental data is needed. For this reason, the valve leakage detection experiments were performed at the valve production site of Chongqing Chuanyi Automation Co., Ltd. in Chongqing city, China. A hydraulic valve test bench that inspects the valve leakage in the production site is used to set up a valve leakage detection experimental platform based on an AE sensor, and a large number of experimental data are collected by utilising the advantage of many valves with various parameters in the production site.

First, a round of experiments is performed for a valve, and a mathematical model between the standard deviation of VILAES and leakage rates is built according to the experimental data. This model is verified by the experimental data of a new round of experiments for the same valve and the experimental data after moving the sensor installation position for the same valve. Second, another valve with the same type, calibre and flow coefficient is selected to verify the consistency of the mathematical model for the valve with the same type, calibre and flow
Finally, aiming at the same type of valves with different calibres and flow coefficients, two rounds of experiments are performed under multiple pressures to collect a large amount of data. The first round of experimental data are used to build the mixed multiple-variable model, and the second round of experimental data are used to verify the effect of the model.

### 3.1 Experimental setup

The experimental platform of valve leakage detection based on AE detection technology consists of two parts. One is the hydraulic valve test bench provided by Chongqing Chuanyi Automation Co., Ltd., and the other is the AE sensor, data acquisition and signal processing system built by us.

The hydraulic valve test bench is produced by Shanghai Zengxin Electromechanical Equipment Manufacturing Co., Ltd., which is composed of a bench, a water pump, a pressure console, a sealing blind plate, a clamping disk and a water tank. The water pump in the hydraulic valve test bench is a variable frequency medium pressure pump. The maximum pressure produced by the medium pressure pump can reach 10 MPa. Therefore, the front pressure of the valve can be set according to the nominal pressure, which is more in line with the actual situation. In addition, the medium pressure pump can keep pressure stable through feedback control at small leakage rate. After the valve is fixed on the hydraulic valve test bench, the water in the water tank is extracted by the pump to provide the front pressure of the valve. When the valve leaks, the water flows out from the sealing surface and generates the AE signal that can reflect the leakage rate. Finally, the water flows back to the water tank through the hole in the baffle. The schematic of the valve leakage channel of the hydraulic valve test bench is shown in Figure 1.

The AE sensor, data acquisition and signal processing system is composed of an AE sensor, a voltage amplifier, an anti-aliasing filter, a data acquisition card and a laptop as shown in Figure 2. The AE sensor is the R15a piezoelectric AE sensor produced by an American physical acoustics company, and its frequency response range is 50–400 kHz. The amplification factor of the voltage amplifier is 40 dB. The anti-aliasing filter with a cutoff frequency of 600 kHz is used to reduce the aliasing frequency component to a negligible level. The data acquisition card is a multifunctional data acquisition card USB-6255 produced by American National Instruments. The maximum sampling frequency of data acquisition card is 1.25 MHz. In the experiments, the sampling frequency of the data acquisition card was set to 1.25 MHz.

The experimental picture is shown in Figure 3.

### 3.2 Experimental steps

Since the experimental site is the valve production, assembly and testing workshop, for the same type of valve, valves of different calibres and flow coefficients can be found, which provides more data to improve the modelling effect of the mixed multiple-variable model. At present, most scholars simulate the leakage of a healthy valve by adjusting the handwheel in the valve leakage detection experiments. This is mainly because for unhealthy valves, the leakage rate is constant at a certain pressure so that it is difficult to collect data under multiple leakage rates and build the mixed multiple-variable model to describe the relationship between the characteristics of VILAES and leakage rates, pressures, valve calibres and flow coefficients.
In the experiments, the HTS-regulating valve widely used in the field of industrial automation was selected. Its valve core adopts the upper-guide structure, the valve structure is compact, and the internal channel of the valve body is streamlined, which has some features, such as small pressure drop loss, wide adjustable range, and high accuracy of flow control. Since the HTS regulating valve has only one valve core, it is easy to ensure the seal of the valve. However, the unbalanced thrust of the medium to the valve core is large, resulting in the instability of the AE signal when the pressure or leakage rate is large. Figures 4 and 5 show the experimental results of HTS valves at 1 and 5 MPa. When the leakage rate is less than 250 ml/min, the standard deviation of VILAES increases with the increase of the leakage rate. However, when the leakage rate is greater than 250 ml/min, the standard deviation of VILAES fluctuates greatly with the increase of the leakage rate. Therefore, the maximum leakage rate is set to 250 ml/min in the experiments, which is more in line with the actual application requirements.

The experimental steps are as follows. The valve was closed by the handwheel, and the front pressure of the valve was adjusted. When the pressure stabled at 1 MPa, the experiments were started. First, the handwheel was adjusted to open the valve, which made the leakage rate about 250 ml/min. After the leakage rate was stable, the VILAES was collected. Then, the valve was closed gradually through the handwheel to reduce the leakage rate. When adjusting the handwheel each time, it was necessary to wait for the leakage rate to stabilise before collecting the VILAES. The leakage rate was measured by a measuring cup and a stopwatch.

After this round of experiment had been completed, another round of experiment was performed under the same experimental conditions, and the collected data was used for verification. After these experiments, the pressure of the valve inlet was changed according to the nominal pressure of the valve, and the experiments were continued at other pressures. In the experiments, six HTS valves were selected and were denoted as HTS50-17, HTS50-44, HTS50-24, HTS40-24, HTS65-24 and HTS32-17, respectively. Among them, 50, 40, 65 and 32 are the calibres of the valve, and their unit is in mm; 17, 44 and 24 are the flow coefficient of the valve, respectively. Since the nominal pressure of HTS50-17 valve is 5 MPa, in order to make the experiments more in line with the actual situation, the pressures set in the experiments were 1, 3, 5, and 7 MPa, respectively. For the HTS50-17 valve, the maximum pressure was set to 7 MPa so as to observe the effect of pressure on the VILAES. The experimental time was short, and the valve was not damaged. The nominal pressures of the other five valves were 1.6 MPa, and the pressures set in the experiments were 0.5, 1 and 1.5 MPa, respectively. The number of datasets collected under each pressure is shown in Table 1.

Since the collected data needs to be segmented in the subsequent data processing, two rounds of data were collected at the sampling frequency of 1.25 MHz, totalling 2,500,000 points, in order to ensure the accuracy of the analysis results.
In order to verify the repeatability of AE detection of valve leakage, it is necessary to verify the mathematical model built by the experimental data of a single valve. It includes a validation of the new round of experimental data, and a validation of the experimental data after moving the sensor installation position. This also involves verifications of experimental data from another valve of the same type, calibre and flow coefficient.

(1) Validation of the new round of experimental data

After the AE sensor was installed on the HTS50-17 valve, two rounds of experiments were performed under the pressure of 1 MPa. For the first round of experimental data, the Butterworth band-pass filter with a band-pass bandwidth of 140 to 180 kHz is selected to preprocess the VILAES, and then the standard deviation of the filtered signal is calculated as the characteristic. Next, the mathematical model between the standard deviation of VILAES and leakage rate is built by using the least-squares linear fitting as shown in Figure 6. The relationship between standard deviation and leakage rate is as follows:

$$Q = 4.8875 \times 10^3 \sigma + 15.5274$$  \hspace{1cm} (2)

where $Q$ is the leakage rate, and $\sigma$ is the standard deviation.

Then, the second round of experimental data is used for validation. The verification results are shown in Figure 6, and the absolute errors are listed in Table 2. It can be seen that for the same valve, the results of the two rounds of experiments are the same when the sensor is installed in the same position.

(2) Validation of the experimental data after moving the AE sensor

The AE sensor was fixed on the platform in the middle of the valve body, and the fixed position was denoted as A. After one round of experiments, the sensor was moved horizontally to the left by 21 mm, and the fixed position was denoted as B as shown in Figure 7. Then, another round of experiments was performed.

The data collected in position A is used for modelling, and then the data collected in position B is used for validation. The verification results are shown in Figure 8, and the absolute errors are shown in Table 3, which shows that the results of collecting data at a similar position are the same. Therefore, the precise installation position of the sensor is not required, which increases the practicality of AE detection technology.

(3) Verification of experimental data for another valve with the same type, calibre and flow coefficient

Two valves of the same type, calibre and flow coefficient were selected. One valve was calibrated first, and then the other was
TABLE 3  Verification results of experimental data at position B

| Actual (ml/min) | Predicted (ml/min) | Absolute errors (ml/min) | Actual (ml/min) | Predicted (ml/min) | Absolute errors (ml/min) |
|----------------|--------------------|--------------------------|----------------|--------------------|--------------------------|
| 173            | 160                | 13                       | 80             | 71                 | 9                        |
| 154            | 154                | 0                        | 87             | 73                 | 14                       |
| 144            | 139                | 5                        | 74             | 65                 | 9                        |
| 135            | 127                | 8                        | 52             | 77                 | 25                       |
| 120            | 70                 | 50                       | 48             | 40                 | 8                        |
| 112            | 71                 | 41                       | 40             | 32                 | 8                        |
| 107            | 74                 | 33                       | 32             | 25                 | 7                        |
| 93             | 72                 | 21                       | 0              | 19                 | 19                       |
| 86             | 79                 | 7                        | —              | —                  | —                        |

FIGURE 9  Experimental results of two HTS valves of the same type, calibre and flow coefficient

used for examination. The verification results are shown in Figure 9, and the absolute errors are shown in Table 4, which indicates that the experimental results of two valves with the same type, calibre and flow coefficient are similar.

Through the repetition experiment of valve leakage AE detection, it is shown that for the valve with the same type, calibre and flow coefficient, the data collected after moving the sensor position and the data collected for another valve with the same parameters, the results of two rounds of experiments are similar. The good repeatability lays the foundation for building the mixed multiple-variable model to describe the relationship between the characteristics of VLAES and leakage rates, pressures, valve calibres and flow coefficients.

4  | MODELING PROCESS

In the modelling process, the frequency range of VLAES is determined by spectrum analysis first, and the best frequency band of the Butterworth band-pass filter is selected to prepro-

cess the VILAES for reducing the interference of environmental noise and pump noise. Then, the standard deviation that can best represent the VILAES is calculated as the characteristic. Finally, the mixed multiple-variable model between the characteristics of VILAES and leakage rates, pressures, valve calibres and flow coefficients for the same type of valve is built by LSSVM. In order to illustrate the effectiveness of LSSVM, the least-squares polynomial regression and SVM are used to build the mixed multiple-variable model, and the modelling results of the three methods are compared.

4.1  | Preprocessing of VILAES

The VILAES is greatly disturbed by the high noise of the environment in the valve production workshop and water pump in the valve test producer. It is necessary to preprocess the VILAES first so as to remove the interference of noise and to better extract the characteristic of VILAES that reflects the valve leakage rate.

In the hydraulic valve test bench, the water pump is used to realise water circulation and provide the front pressure of the valve, and in the valve production workshop, there are various motor noises and assembly knocking noises; therefore, the collected VILAES contains a lot of noises as shown in Figure 10.

In order to reduce the interference of noise and effectively extract the characteristic of VILAES, it is necessary to analyse the spectrum of VILAES and select the Butterworth band-pass filter with optimal frequency band for preprocessing the VILAES.

The spectrum of VILAES is shown in Figure 11. It can be seen that the energy of VILAES is mainly concentrated in 30–180 kHz, but it is also distributed in 210–450 kHz. In order to determine the frequency band of VILAES, which can best

TABLE 4  Verification results of experimental data of the second valve

| Actual (ml/min) | Predicted (ml/min) | Absolute errors (ml/min) | Actual (ml/min) | Predicted (ml/min) | Absolute errors (ml/min) |
|----------------|--------------------|--------------------------|----------------|--------------------|--------------------------|
| 248            | 267                | 19                       | 127            | 63                 | 64                       |
| 251            | 251                | 0                        | 126            | 68                 | 58                       |
| 247            | 215                | 32                       | 127            | 67                 | 60                       |
| 247            | 201                | 46                       | 80             | 44                 | 36                       |
| 245            | 208                | 37                       | 75             | 44                 | 31                       |
| 243            | 210                | 33                       | 80             | 44                 | 36                       |
| 239            | 234                | 5                        | 69             | 37                 | 32                       |
| 236            | 222                | 14                       | 60             | 39                 | 21                       |
| 224            | 220                | 4                        | 60             | 39                 | 21                       |
| 227            | 217                | 10                       | 43             | 35                 | 8                        |
| 230            | 204                | 26                       | 40             | 37                 | 3                        |
| 233            | 200                | 33                       | 39             | 34                 | 5                        |
| 177            | 155                | 22                       | 0              | 32                 | 32                       |
| 177            | 165                | 12                       | 0              | 33                 | 33                       |
reflect the valve leakage rate, the Butterworth band-pass filter with a bandwidth of 10 kHz is used to filter the VILAES. The band-pass frequency ranges of the filter are 30–40 kHz, 40–50 kHz, 50–60 kHz, 60–70 kHz, 70–80 kHz, and 80–90 kHz, respectively. Then, the standard deviations of the filtered signals are calculated as the characteristics of VILAES as shown in Figure 12.

As can be seen from Figure 12, the standard deviation of VILAES increases with the increase of leakage rate in the five frequency bands of 60–110 kHz, 110–140 kHz, 140–180 kHz, 210–260 kHz and 260–450 kHz, respectively. Therefore, we select these filter bands to filter the signal and then calculate their standard deviations.

The relationship between standard deviation and leakage rate is linearly fitted, and the quality of the filter frequency band is evaluated by fitting degree.

The fitting degree \( r^{\text{square}} \) is

\[
r^{\text{square}} = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}
\]

where \( y_i \) is the actual value, and \( \hat{y}_i \) is the predicted value. The closer \( r^{\text{square}} \) is to 1, the better the fitting effect is. The filter frequency band whose standard deviation is of a good linear fitting is selected to calculate the characteristic of VILAES.

The experimental data of the HTS50-17 valve under various pressures are preprocessed by Butterworth bandpass filter with different filter bands. The fitting degrees of analysis results are shown in Table 5. It can be seen that when the filter frequency band is 140–180 kHz, the fitting degree of the analysis results is the best. It indicates that in this frequency band, the VILAES is less interfered by environmental and pump noises, and its characteristic reflecting valve leakage rate can be best extracted. The VILAES after preprocessing is shown in Figure 13.
4.2 Calculate the characteristic of VILAES

Currently the characteristics calculated for VILAES include the standard deviation, root mean square, variance, energy, spectrum peak, wavelet packet entropy, kurtosis, and so forth. Among them, the standard deviation and root mean square can best characterise the VILAES [5–9].

The equations of root mean square and variance of VILAES are as follows:

\[
A_{E_{RMS}} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2}
\]

(4)

\[
\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2}
\]

(5)

where \(A_{E_{RMS}}\) is the root mean square of VILAES, \(x_i\) is the VILAES, \(\sigma\) is the variance of VILAES, and \(\mu\) is the mean value of VILAES.

Since the mean value of VILAES is close to 0, we can obtain

\[
A_{E_{RMS}}^2 = N \cdot \sigma^2
\]

(6)

Moreover, in the process of data analysis, it is also found that the fitting degree is the same when the root mean square and variance of the preprocessed signal are modelled, respectively. To this end, the standard deviation is selected as the characteristic of VILAES, and the calculation process is introduced in detail.

1. The preprocessed VILAES is shown in Figure 13. It is divided into 416 sections, and each section contains 6000 points.
2. The standard deviation of each segment signal is calculated, and a total of 416 standard deviations are obtained as shown in Figure 14.
3. In order to further reduce the influence of noise on the analysis results, the 416 standard deviations are sorted from small to large as shown in Figure 15, and the average value of the first 20 standard deviations after sorting is taken as the characteristic of VILAES. This is because the standard deviation is the arithmetic square root of the variance, and it reflects the dispersion degree of the data. The values of the first 20 standard deviations are relatively smaller than those of other standard deviations. It indicates that these data suffer little interference and can better characterise the VILAES.

4.3 Establishing the mixed multiple-variable model of VILAES

The VILAES is related to the leakage rate, pressure, valve calibre and flow coefficient. When the conventional least-squares polynomial regression is used for building the multiple-variable model, it is difficult to select an appropriate polynomial accurately. Compared with the conventional modelling method, the LSSVM based on SVM has higher accuracy. It not only preserves the characteristics of SVM but also transforms the inequality constraints into linear equations to reduce the complexity of the solution, which makes more efficient calculation speed and more accurate prediction results [10–12]. In order to illustrate the effect of LSSVM, both the least-squares polynomial regression and SVM are used to build the multiple-variable model.

The mixed multiple-variable model between the characteristics of VILAES and leakage rates, pressures, valve calibres and flow coefficient cannot be described by a two-dimensional or a three-dimensional graph because there are one dependent and four independent variables in this model. Therefore, in the model between the characteristics of VILAES and leakage rates, pressures are built first, and its three-dimensional graph model is drawn to show the modelling effect intuitively. Then, the mixed multiple-variable model is built on this basis.

The experimental results of HTS50-17 valve under different pressures are shown in Figure 16. It can be seen that at the same pressure, as the leakage rate increases, the standard deviation of VILAES increases; at the same leakage rate, as the pressure increases, the standard deviation also increases.
The characteristic of VILAES is calculated. First, the band-pass Butterworth filter with a passband frequency of 140 to 180 kHz is adopted to preprocess the VILAES, and then the preprocessed data is segmented so as to calculate their standard deviations. The average value of the minimum 20 standard deviations is taken as the characteristic. The standard deviations under each pressure and leakage rate are shown in Figure 16.

2. The LSSVM is utilised to build the model between characteristics of VILAES, leakage rates and pressures. The characteristic of VILAES and pressure are taken as inputs, and the leakage rate is taken as an output. The modelling result is shown in Figure 17. The blue points in the figure are the preprocessed data is segmented so as to calculate their standard deviations. The average value of the minimum 20 standard deviations is taken as the characteristic. The standard deviations under each pressure and leakage rate are shown in Figure 16.

The main process of building the mathematical model to describe the relationship between the characteristics of VILAES and pressures, leakage rates by the LSSVM are as follows:

1. The LSSVM is utilised to build the model between characteristics of VILAES, leakage rates and pressures. The characteristic of VILAES and pressure are taken as inputs, and the leakage rate is taken as an output. The modelling result is shown in Figure 17. The blue points in the figure are the training data, and the meshed surface is the mathematical model between characteristics of VILAES, pressures, and leakage rates. The colour of the grid reflects the leakage rate. The redder the grid colour is, the larger the leakage rate is; the bluer the grid colour is, the smaller the leakage rate is. The fitting degree of the model is 0.9542. It can be seen that the LSSVM could well build the mathematical model between characteristics of VILAES, leakage rates and pressures. On this basis, the mixed multiple-variable model could be built for describing the relationship between characteristics of VILAES and valve leakage rates, pressures, valve calibres and flow coefficients.

It is similar to the above process to build the mixed multiple-variable model between the characteristics of VILAES and leakage rates, pressures, valve calibres and flow coefficients, which is only necessary to increase valve calibre and flow coefficient as inputs. The multiple-variable model built by the LSSVM is as the following:

\[
Q = \sum_{i=1}^{n} \alpha_i K(x_i, x_j) + b
\]  

(7)

where \( Q \) is the leakage rate; \( K(x_i, x_j) \) is the kernel function, and the radial basis function with good modelling effect is selected as the kernel function in this paper; \( x_i \) and \( x_j \) are the vector composed of the characteristic of VILAES, pressure, valve calibre and flow coefficients; \( \alpha \) is a vector of 398*1, and the specific value of the vector \( \alpha \) has been placed in the attachment; \( b = -0.3937 \).

In order to illustrate the effectiveness of LSSVM, the least-squares polynomial regression and SVM [13–16] are used to build the multiple-variable model for describing the relationship between the characteristics of VILAES and leakage rates, pressures, valve calibres and flow coefficients. The modelling results of the three methods are compared.

The mixed multiple-variable model established by least-squares polynomial regression is

\[
Q = -117.56 + 8931.27 \sigma - 48.04 D + 11.58 D^2 + 48.53 \sigma^2
- 214.76 \sigma^2 + 22.57 P^2 + 0.29 D^2 - 0.14 D^3 - 730.98 \sigma D
- 22.61 \sigma D - 144.94 \sigma^2 - 2.74 P + 0.73 P \sigma - 0.77 D \sigma
\]  

(8)

where \( Q \) is the leakage rate, \( \sigma \) is the standard deviation, \( P \) is the pressure, \( D \) is the valve calibre, and \( \zeta \) is the valve flow coefficient.

The mixed multiple-variable model built by SVM is as the following:

\[
Q = wX + b
\]  

(9)

where \( Q \) is the leakage rate; \( w \) is the weight vector; \( X = (x_1, x_2, ..., x_m) \) is the matrix composed of characteristics of VILAES, pressures, valve calibres and flow coefficients; \( b \) is the bias term.

Figure 18 is the SVM model, where \( rho \) is \( b \) in Equation (9), equal to –97.4489. The \textbf{sv_coef} is \( w \) in Equation (9), which is a vector of 385*1. \textbf{SVs} is a support vector, which is a matrix of 385*4.

Figures 19 and 20 are the prediction leakage rate of the test set by different modelling methods. It can be seen that the analysis
result of LSSVM is best, especially when the leakage rate is less than 50 ml/min.

In order to better reflect the prediction ability of different models, the advantages and disadvantages are evaluated by the fitting degree and RMSE, respectively.

Fitting degree is

\[ r^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{10} \]

RMSE is

\[ RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{11} \]

where \( y_i \) is the actual value, and \( \hat{y}_i \) is the predicted value.

Table 6 shows the analysis results of three regression models. It can be seen that the model adopting LSSVM has the smallest RMSE, which is 32.73 ml/min, indicating that the LSSVM can achieve better results for the VLAES.

### Table 6  Evaluation indexes of three regression methods

| Regression methods                          | Root mean square error (ml/min) | r-square |
|---------------------------------------------|---------------------------------|----------|
| Least-squares support                      | 32.73                           | 0.9326   |
| vector machine (SVM)                       |                                 |          |
| SVM                                         | 36.84                           | 0.8570   |
| Least-squares polynomial                    | 67.33                           | 0.4937   |
| regression                                  |                                 |          |

## 5  CONCLUSION

1. In order to improve the practicability of valve internal leakage detection technology, it is proposed to build the mixed multiple-variable model of VLAES for six valves of the same type with different calibres and flow coefficients. This model describes the relationship between the characteristics of VLAES and leakage rates, pressures, valve calibres and flow coefficients. Using this model can predict the leakage rate of valve with different calibres and flow coefficients under various pressures and greatly improve the practicability of valve leakage AE detection technology so as to meet the needs of the actual application.

2. The repetitive experiments of valve leakage AE detection are performed to examine the validity of the model. The mathematical model built by the experimental data of a single valve is verified. The validation data include the experimental data of a new round of experiments, the experimental data after moving the sensor installation position, and the experimental data of another valve of the same type, calibre, and flow coefficients. The experimental results are repetitive, which
verifies the practicability of valve leakage AE detection technology and lays a foundation to build the mixed multiple-variable model for the same type of valve. However, there are few reports on this verification work in the existing papers.

3. The Butterworth bandpass filter with a passband of 140–180 kHz is selected to preprocess the VILAES, and then the standard deviation of the preprocessed signal is calculated as the characteristic. The LSSVM is used to build the mixed multiple-variable model for the same type of valves. The results show that the RMSE of LSSVM model is the smallest, which is 32.73 ml/min, while the RMSE of SVM model is 36.84 ml/min, and that of the least-squares polynomial regression model is 67.33 ml/min. It indicates that when the leakage rate is lower than 250 ml/min, the LSSVM can build the mixed multiple-variable model well for the VLAES with liquid medium, which provides the theoretical basis to realise online leakage detection for a valve with different calibres and flow coefficients under various pressures.

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