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Prediction Research on Irregularly Cavitied Components Volume Based on Gray Correlation and PSO-SVM

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Abstract: The use of a micro-compressed air-volume-detection method to detect the volume of irregularly cavitied components has the characteristics of multi-variable coupling and nonlinearity. To solve this problem, a volume-prediction model of irregularly cavitied components based on gray correlation and a particle-swarm-optimization support-vector machine is proposed. In this paper, the gray-correlation method was used to extract the detection parameters that have the greatest correlation with the cavity volume. On the basis of the obtained detection parameters, the SVM algorithm was used to build an irregularly cavitied components volume-prediction model. During model training, since the regression accuracy and generalization performance of the SVM model depend on the proper setting of its two parameters (the penalty-parameter C and the kernel-parameter σ), and especially on the interaction of the parameters, this paper presents an optimal-selection approach towards the SVM parameters, based on the particle-swarm-optimization (PSO) algorithm. Experiments showed that the prediction model can better predict the volume of irregularly cavitied components, and the prediction accuracy was high, which played a guiding role in intellectual nondestructive testing of the volume of the irregularly cavitied components.

Keywords: volume-detection; micro-compressed air; gray-correlation analysis; support vector machine

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1. Introduction

For irregularly cavitied components such as the combustion chamber, liquid storage tank, supercharging device and vacuum-pump device of an automobile engine, it is difficult to measure their volume by conventional measurement methods, due to their complex profile or cavity. The traditional method is to use the water-injection method [1] to calculate volume. This method is mainly operated manually, and the medium generally used is liquid. There are the following problems when using liquid to measure volume: (1) if the internal shape of the tested part is complex, it is difficult to ensure that the liquid fills the entire space or the liquid is completely poured out, which will affect the accurate measurement of the volume; (2) the use of liquids may affect the performance of the parts in the future; (3) it involves many processes, the detection efficiency is low, and the accuracy is not high. At present, in addition to the traditional water-injection method, there is laser measurement [2–4], orthogonal double-grating [5], vibration measurement [6–11], the ultrasonic-measurement method [12], and so on.

In recent years, some volume-detection methods based on the ideal gas equation-of-state, such as the gas-calibration method [13], the gas-static-expansion method [14], the gas-pressure method [15–17], etc., have been continuously applied to volume detection of irregularly cavitied components. These methods are usually based on the conservation of mass, use the gas equation-of-state or combine the linear-regression method to obtain the volume calculation formula of the tested components. These methods will lead to large errors, and cannot measure precision containers. In addition, these methods have relatively high requirements for test conditions, and do not consider the influence of air humidity and temperature on the measurement results; however, it is difficult to meet these conditions in the actual application process.

In view of the practical problems of the above detection-methods, this paper analyzed the structural characteristics of the irregularly cavitied components, applied the ideal-gas equation-of-state, adopted the volume-measurement method of micro-compressed air, and, fully considering the influence of environmental factors such as temperature, humidity, pressure and gas-equilibrium time on volume measurement, a volume-prediction algorithm for irregularly cavitied components based on gray correlation and particle-swarm-optimization support vector machine was proposed, which was used for volume detection of irregularly cavitied components. The method has the characteristics of high efficiency and high precision, and has reference significance for the volume-prediction and detection of irregularly cavitied components.

The main contributions of this paper are three aspects. Firstly, collecting the parameters related to the volume of the irregularly cavitied components by using the micro-compressed-air method, under the premise of ensuring that the components to be tested are not damaged, this method micro-compresses the atmospheric pressure of the air sealed in the irregularly cavitied components, and collects the measurement parameters. Secondly, the main control-factors affecting the irregularly cavitied components' volume-measurement are analyzed by gray correlation, and we screen pressure, temperature, humidity, and air-equilibrium time, etc., as the main characteristic parameters. Thirdly, there is the development of a PSO-SVM model, to improve the accuracy and stability of the volume-prediction model of irregularly cavitied components. Finally, obtaining the volume-prediction value of the irregularly cavitied components, means that the volume of irregularly cavitied components can be measured quickly and accurately.

2. Preliminary

By applying the ideal-gas equation-of-state, a volume-measurement device for irregularly cavitied components using micro-compressed air was designed. The principle of volume measurement for irregularly cavitied components is shown in Figure 1. During detection, the irregularly cavitied components to be detected were filled with air at normal temperature and pressure, and after sealing the air inlet, the precision cylindrical-compression-rod was driven by a servo motor, and extended into the interior of the irregularly cavitied components to be tested for a certain length, in order to micro-compress the air inside the cavity. The mass of the fixed group of gas in the cavity before and after micro-compression remained constant. By measuring the pressure and temperature of the air in the irregular cavity before and after micro-compression, and the volume of the compression-rod extending into the cavity, the cavity volume of the irregularly cavitied components to be measured can be obtained, following the ideal-gas equation-of- state, which can be written as follows:

$$PV = Z\mathrm{m}RT \tag{1}$$

where P is the gas pressure, the unit of gas pressure is the pascal (Pa), V is the volume, the unit of volume is milliliter (mL), Z is the compression coefficient (dimension is 1), m is the mass (mol), T is the absolute temperature, the unit of temperature is the kelvin (K), and R is the gas constant (R = 8.31 J/(mol·K)).

However, the detection accuracy of the volume of irregularly cavitied components obtained by the above method was still low. Through experiments and analysis of past detection methods, it was found that there were many influencing factors when using this method to detect the volume of irregularly cavitied components. In addition to the pressure and temperature in the cavity to be measured, environmental factors such as air-equilibrium time after micro-compression, ambient atmospheric-pressure and humidity will also lead to some deviations in the equation-of-state for gas, which will have a certain impact on the accuracy and stability of volume detection of irregularly cavitied components. To attack these problems mentioned above, a volume-prediction model of irregularly-cavitied components based on gray correlation and particle-swarm-optimization support vector machine was proposed in this paper. Firstly, gray correlation analysis was used, and then several key factors related to the volume of irregularly cavitied components in the process of volume measurement using micro-compressed air were extracted, so as to reduce the dimensions to be considered in modeling. Then, using the support vector machine to train the extracted detection-values of important factors, a volume-prediction model of irregularly cavitied components was established simultaneously. In order to obtain a solution to the precision requirements of SVM calculation and modeling which may have problems caused by parameter errors, the research used the particle-swarm algorithm to optimize SVM parameters. The prediction accuracy of SVM was reduced, and the convergence speed of SVM was increased, the volume-prediction value of irregularly cavitied components was obtained, and fast and accurate volume-measurement of irregularly cavitied components was realized.

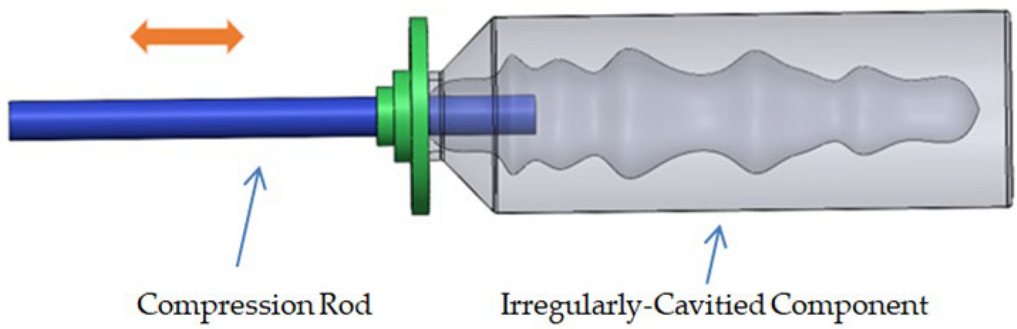

Figure 1. Schematic diagram of the volume-measurement method using micro-compressed air.

3. Gray Correlation Analysis

A gray relationship refers to the uncertain relationships between things or the system factors or the factors and the main behavior. Gray-correlation analysis [18,19] judges whether the relationship between data sequences is close by the similarity of the geometric shapes of the data curves; a modified algorithm finds out the main factors that affect the target value through correlation calculation, and evaluates the influence of various factors. There are some deficiencies in the samples of traditional mathematical-statistics methods, such as large demand and large computational-volume, and there may be inconsistencies between quantitative results and qualitative analysis. This analysis method overcomes these deficiencies and becomes a simple and unique system-analysis method [20].

When the micro-compression air method is used to detect the volume of irregularly cavitied components, the volume-prediction model of irregularly cavitied components is affected by various factors such as atmospheric pressure, pressure before and after air micro-compression, temperature, and equilibrium time. In addition, the relationship between most of the influencing factors and the volume of the irregular-cavity parts is nonlinear, so the effect of these influencing factors on the volume of the irregular-cavity parts is not clear, which is gray. The gray-correlation analysis can quantitatively reflect the degree of correlation between the volume of irregular cavity parts and various influencing factors. Through comparative analysis, the main factors with higher correlation were selected from the factors that affect the volume of irregularly-cavitied components. As input variables for SVM modeling, SVM was then used for prediction. Here are the specific steps of gray relational analysis:

Step 1. determine the referential data sequence as

$$x'_0(k) = \{x'_0(1), x'_0(2), \cdots, x'_0(n)\} \tag{2}$$

Step 2. determine the comparative data series as

$$x'_i(k) = \{x'_i(1), x'_i(2), \cdots, x'_i(n)\} \tag{3}$$

Step 3. the data is processed in a dimensionless manner. Since the parameters of different properties (such as pressure, temperature, humidity, equilibration-time, etc.) are measured at each test point during the volume test, and these parameters have different orders of magnitude, to make sure the correlation analysis result between parameters of each detection point and the volume is reliable, the original sequence needs to be processed in a dimensionless manner. Therefore, $x_0'(k)$ and $x_i'(k)$ sequences are processed in a dimensionless manner, and the reference sequence $x_0(k)$ and the comparative data $x_i(k)$ are obtained, as in Equations (4) and (5).

$$x_0(k) = \frac{x_0'(k)}{x_0'(1)} = \{x_0(1), x_0(2), \cdots, x_0(n)\} \tag{4}$$

$$x_i(k) = \frac{x_i'(k)}{x_i'(1)} = \{x_i(1), x_i(2), \cdots, x_i(n)\} \tag{5}$$

Step 4. find the absolute-difference sequence. The absolute value of the difference between the reference sequence $x_0(k)$ and the comparative data $x_i(k)$ constitutes an absolute-difference sequence, as in Equation (6).

$$\begin{aligned} \Delta_{0i}(k) &= |x_0(k) - x_i(k)| \\ &= \{\Delta_i(1), \Delta_i(2), \cdots \Delta_i(n)\} \end{aligned} \tag{6}$$

Step 5. find the maximum difference and the minimum difference in the absolute-difference sequence, as in Equations (7) and (8).

$$\Delta_{\max} = \max \left| \begin{matrix} \Delta_{oi}(k) \\ 1 \le i \le m \\ 1 \le k \le n \end{matrix} \right| \tag{7}$$

$$\Delta_{\min} = \min \left| \begin{matrix} \Delta_{oi}(k) \\ 1 \le i \le m \\ 1 \le k \le n \end{matrix} \right| \tag{8}$$

Step 6. find the grey correlation coefficient, which is shown as:

$$\gamma_{0i}(k) = \frac{\min\limits_i \min\limits_k |x_0(k) - x_i(k)| + \rho \max\limits_i \max\limits_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max\limits_i \max\limits_k |x_0(k) - x_i(k)|} = \frac{\Delta_{\min} + \rho \Delta_{\max}}{\Delta_{0i}(k) + \rho \Delta_{\max}} \tag{9}$$

where $\gamma_{0i}(k)$ is the correlation coefficient between the kth object of the comparative data and the reference sequence; ρ is the resolution coefficient in the range of $[0, 1]$, usually 0.5 [21].

Step 7. find the grey correlation degree of each factor, as in Equation (10).

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \gamma_{0i}(k) \tag{10}$$

Step 8. sort, according to the gray correlation degree.

γ_i is the reflected correlation between the comparative data $x_i(k)$ and reference sequence $x_0(k)$; the larger the value, the greater the impact on $x_0(k)$. According to the above steps, gray-correlation analysis was carried out on parameters such as atmospheric pressure and stable differential-pressure before and after micro-compression. The results are shown in Table 1, the most important factors which affect the volume of irregularly cavitied components are gas-equilibration time (the correlation coefficient is 0.9993), atmospheric pressure before micro-compression (the correlation coefficient is 0.9896) and stable differential-pressure after micro-compression (the correlation coefficient is 0.9989), followed by temperature after micro-compression and atmospheric pressure after micro-compression.

Table 1. Correlation coefficients of the variables.

Serial Number	Variable Name	Input-Feature Parameters	Correlation Coefficient
1	x_1	Atmospheric pressure before micro-compression	0.9896
2	x_2	Stable differential-pressure before micro-compression	0.5735
3	x_3	Temperature before micro-compression	0.5948
4	x_4	Stable differential-pressure after micro-compression	0.9989
5	x_5	Temperature after micro-compression	0.8689
6	x_6	Atmospheric humidity	0.5285
7	x_7	Gas-equilibration time	0.9993
8	x_8	Atmospheric pressure after micro-compression	0.8678

4. Parameter Optimization of Volume-Prediction Model Based on SVM

The support vector machine (SVM) is based on statistical learning theory and structural-risk minimization [22]. The SVM algorithm has strong learning-functions and characteristics, good adaptability to small samples and limited samples, and strong stability and generalization-ability [23]. It can better deal with the problem of nonlinear regression.

We used gray-correlation analysis to develop the support-vector-machine predictive modeling for the main influencing factors of multiple variables related to the volume of irregular-cavity parts after processing in this paper. In the given sample set $\{(x_i, y_j), (i = 1, 2, 3, \cdots, m)\}$, x_i was a attribute vector of two-dimensional space, with characteristic input-values such as atmospheric pressure, atmospheric humidity, temperature before micro-compression, stable differential-pressure before micro-compression, stable differential-pressure after micro-compression, gas-equilibrium time, and temperature after micro-compression, etc.; y_j was the corresponding predicted-target value, and m was the number of samples. For the volume model of irregularly cavitied components in the low-dimensional nonlinear space [24], the sample data set, x, was mapped to the high-dimensional linear space through the nonlinear function, $\phi(x)$, and the decision function was established in the high-dimensional linear space, as in Equation (11).

$$\phi(x) = \omega \cdot (x) + b \tag{11}$$

where ω is the weight vector, and b is the bias parameter.

The algorithm uses the minimization-optimization model to establish a decision function, as in Equations (12) and (13).

$$\min \frac{1}{2}\omega^2 + C\sum_{i=1}^{m}(\xi_i + \xi_i^*) \tag{12}$$

$$S.T.\begin{cases} y_i - \omega \cdot \varphi(x) - b \leq \varepsilon + \xi_i \\ [\omega \cdot \varphi(x)] + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 (i = 1, 2, 3, \cdots, m) \end{cases} \tag{13}$$

where C is the penalty factor; ξ_i, ξ_i^* are the relaxation factors; and ε is the upper limit of the error.

We introduced the Lagrangian multipliers a_i and α_i^*, and then transformed the minimization-optimization model into a dual optimization, in order to solve it, by finding the maximum value of $Q(\alpha)$, as in Equations (14) and (15).

$$\max : Q(\alpha) = -\frac{1}{2}\sum_{i,j=1}^{m}(\alpha_i - \alpha_i^*)\left(\alpha_j - \alpha_j^*\right) \cdot K\left(x_i, x_j\right) + \sum_{i=1}^{m} y_i(\alpha_i - \alpha_i^*) - \varepsilon\sum_{i=1}^{m}(\alpha_i + \alpha_i^*) \quad (14)$$

$$S.T.\begin{cases} \sum_{i=1}^{m} \alpha_i = \sum_{i=1}^{m} \alpha_i^* \\ 0 \leq \alpha_i, \alpha_i^* \leq C(i = 1, 2, 3, \cdots, m) \end{cases} \quad (15)$$

where $Q(\alpha)$ is the dual objective function of the Lagrangian function, $K\left(x_i, x_j\right) = \varphi(x_i) \cdot \varphi\left(x_j\right)$ is the kernel function when $\alpha_i \times \alpha_i^* = 0$ and α_i, α_i^* are not 0 at the same time, and the corresponding x_i is a support vector (SV).

Since the volume-prediction of irregularly cavitied components belongs to nonlinear prediction, to improve the model's veracity we selected the radial-basis function (RBF) as the kernel function of the SVM, and used the particle-swarm-optimization method to optimize the initial parameters of the support vector machine, as in Equation (16).

$$K\left(x_i, x_j\right) = exp\left(-\frac{x - x_i}{2\sigma^2}\right) \quad (16)$$

The correct selection of the penalty parameter C and the kernel parameter σ of the nonlinear SVM is very important for the support-vector algorithm; this not only affects the complexity of the model algorithm, but also has a great impact on the generalization performance and robustness of the model prediction, which further influences the prediction precision of the SVM model. Whether the selection of model parameters is appropriate or not, this will have a greater impact on the volume-prediction effect of irregular-cavitied components. The traditional SVM adopts the grid-search cross-validation method to optimize the parameters, but when using this method, subjective factors have a great influence, the search and verification process takes a long time, and a considerable number of training samples are wasted for verification. In the case of limited samples, its defects are more obvious. However, particle-swarm-optimization (PSO) is an optimization algorithm, which has the simplicity characteristics, strong global-search ability, fast convergence-speed and high solution-accuracy. In addition, it is easy to implement because it does not have to adjust too many parameters [25,26]. In this paper, particle-swarm-optimization was used to optimize the parameters of SVM. For the volume-prediction process of PSO-SVM based on the grey correlation, see Figure 2.

As an effective algorithm in the field of optimization, particle-swarm-optimization can achieve good results in the optimization process of SVM parameters. Particle-swarm-optimization (PSO) is a random-search algorithm-based group collaboration which works by simulating the behavior of birds foraging, where each "bird" represents a particle, and the "food" that the flock is looking for is the optimal solution. In the volume-prediction of the irregularly cavitied components, the PSO algorithm was used to initialize the two particles of "penalty-factor C and kernel-function parameter σ"; the coordinate of the i-th particle was $x_i^i = (x)_{i1}^i, x_{i2}^i, \cdots, x_{\mathrm{iD}}^i, x_{\mathrm{iD}}^i \in [L_D, U_D]$, and the coordinates of the D target solutions were the target solutions before optimization. The running speed of the i-th particle was $v_i^i = \left(v_{i1}^i, v_{i2}^i, \cdots, v_{\mathrm{iD}}^i\right), v_{\mathrm{iD}}^i \in [v_{\min,D}, v_{\max,D}]$, the optimal position of the i-th particle was $p_i^i = \left(p_{i1}^i, p_{i2}^i, \cdots, p_{\mathrm{iD}}^i\right)$, and the optimal position of the population was $p_g^i = \left(p_{g1}^i, p_{g2}^i, \cdots, p_{\mathrm{gD}}^i\right)$. Therefore, the iterative result of particle-motion velocity and particle coordinates in the s-th dimension can be expressed as in Equations (17) and (18).

$$v_{iD,s}^i = \beta v_{iD,s}^i + c_1 r_1\left(p_{iD,s}^i - v_{iD,s}^i\right) + c_2 r_2\left(p_{gD,s}^i - v_{gD,s}^i\right) \quad (17)$$

$$x_{iD,s}^{i+1} = x_{iD,s}^i + v_{iD,s}^{i+1} \quad (18)$$

where v is the particle velocity, β is the inertia weight, c_1, c_1 are the learning factors, and r_1 and r_2 are random numbers in [0, 1].

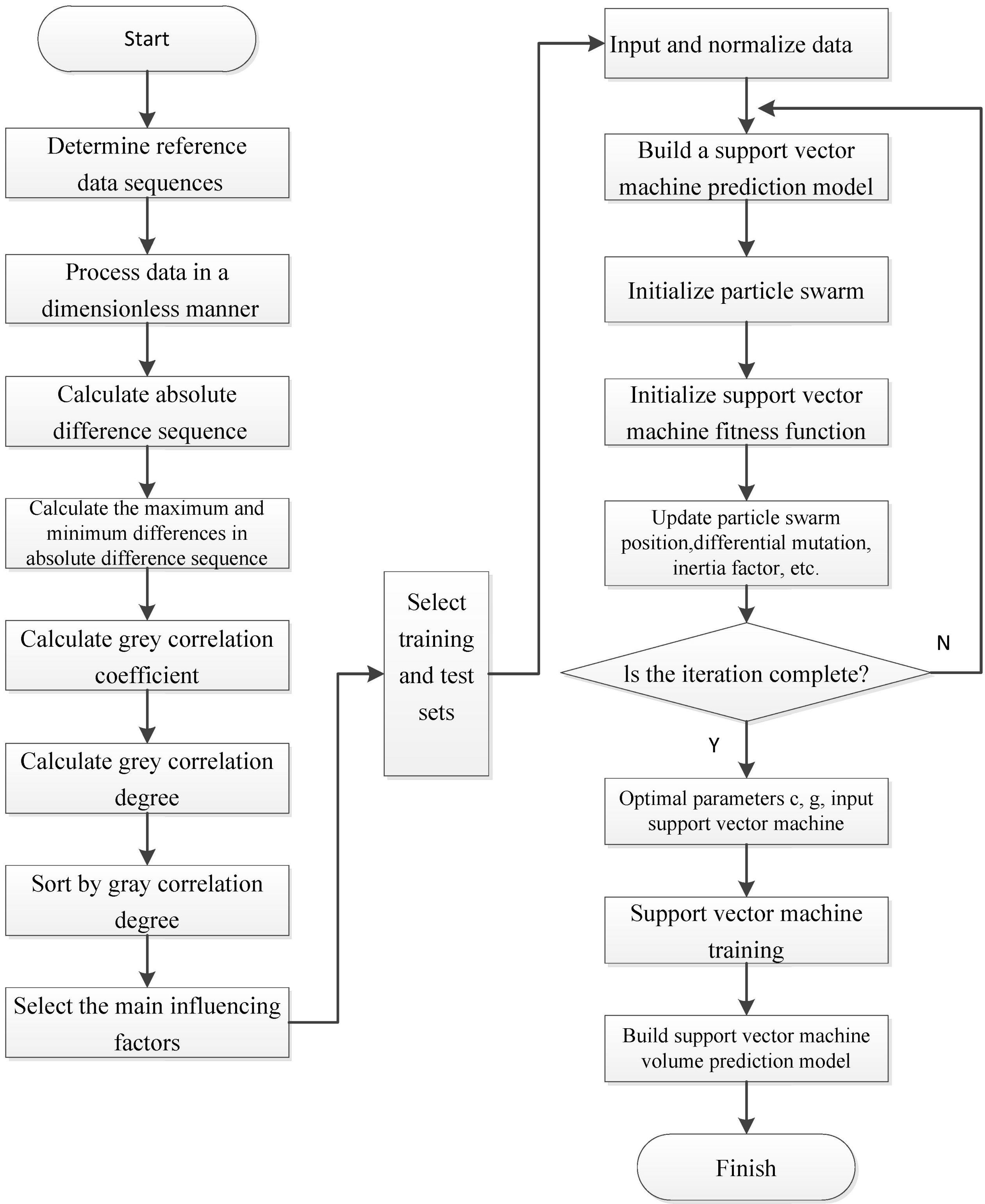

Figure 2. Flowchart of GRA-PSO-SVM model.

β has the ability to balance local and global searches. The larger the value of β, the stronger the global-convergence ability; otherwise, it has a stronger local-convergence ability. The learning factors c_1 and c_2 control the ability of the particle to find the individual optimal-position and the global optimal-position, respectively [27]. The optimal selection of parameters includes atmospheric pressure, stable differential-pressure before or after micro-compression, atmospheric humidity, gas equilibrium time etc. In addition, they were used as input variables to predict the volume of the irregularly cavitied components, by regression. If the error between the predicted and the measured irregular-cavitied-component volume is within the error range, the optimal parameter-selection procedure is ended. At this time, the optimal position of the particle swarm is the optimal solution of parameter C and σ. If the predicted volume of the irregularly cavitied components and the volume of the irregularly cavitied components exceed the set error range, the program should be executed until the error between the two values is within the set error-range.

The optimization steps with the PSO-optimization algorithm are as follows:

Step 1: Define the fitness function. The prediction error of the training sample is defined as the fitness function of the model; that is, the optimal solution corresponding to the function is the particle position corresponding to the minimum prediction error;
Step 2: Normalization. Read the sample data and normalize the sample data, set the parameter-motion range, set the acceleration constants c_1 and c_2, the dimension, n, of the individual particle, the inertia-weight coefficient, ω, the number of particles in the population, m, the penalty factor, C, and the kernel parameter, σ;
Step 3: Initialization. Initialize particle-swarm position and particle velocity;
Step 4: Evaluate fitness. Calculate the individual fitness-value of each particle, initialize the optimal individual particle and the optimal global particle;
Step 5: Compare the optimization. Generate new populations by updating particle velocities and positions, calculate the individual fitness-degree of the new populations, compare the fitness degree of the current parameters, C and σ, with their own historical optimal-values and the optimum populations, and update the optimal global values of the population's parameters, C and σ;
Step 6: Check the end condition. When the optimization reaches the maximum evolutionary algebra, end the optimization, and output the optimal parameters, C and σ; otherwise, return to step 2, and retrain;
Step 7: Perform SVM-algorithm training on the optimal parameters, C and σ, values, and then use the validation set to verify the prediction accuracy of the network and obtain the prediction-value of the volume of the irregularly cavitied components.

5. Comparative Analysis of Predicted Results

In this paper, we analyzed the various influencing indicators that affect the volume of the irregularly cavitied components using the grey-relational-analysis method; the eight indicators with the greatest influence were selected as the input-feature components for the training of the SVM model, and the volume of the irregularly cavitied components to be measured is the output variable. In the experiment, a total of 100 sets of data were collected; 90 data sets were selected as the training set, and 10 sets of data were selected as the test set after shuffling the order, and these were used to verify the prediction-performance of the model. In the support-vector-machine model optimized by PSO, the kernel function adopted a radial-basis function (RBF). According to the performance of the model algorithm, the initial size of the particle-swarm algorithm was set to 25 and the maximum evolutionary-generation of the particle swarm was set to 400, through multiple attempts. Since the range of the penalty-factor and kernel-function parameters will affect the accuracy and prediction-rate of the algorithm, to ensure the stability and efficiency of the algorithm, the optimal parameters c = 58.039, σ = 6.109,and the learning factors c_1 = 2, c_2 = 2 were set. Then, the optimal searched parameter was brought into the support-vector-machine algorithm, and the PSO-SVM algorithm was used to train the training set. The predicted values of the model for the training-sample data and test-sample data are shown in Figure 3. The prediction-accuracy rate of the volume of irregularly cavitied components was as high as 99%, which indicated that the setting of the algorithm parameters was reasonable. By predicting the volume of irregular-cavity parts, higher accuracy can be obtained.

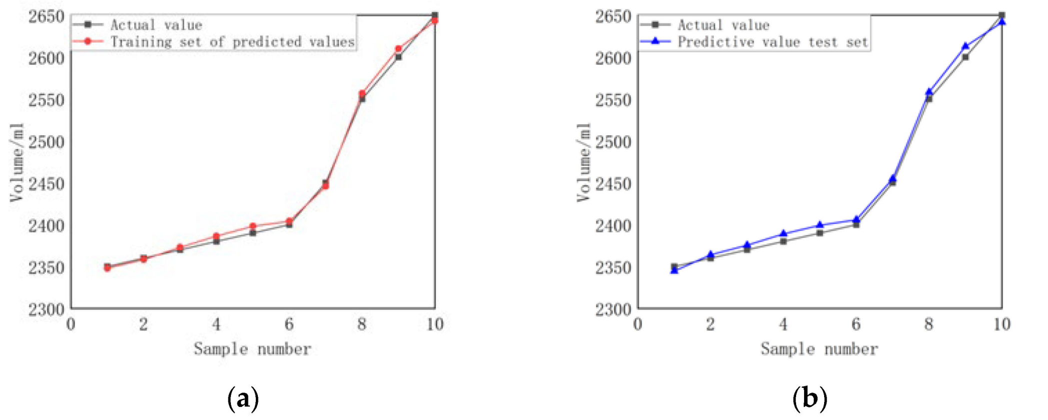

Figure 3. Results of the particle-swarm-optimization support-vector-machine algorithm. (**a**) Results of training set; (**b**) Results of test set.

For the mean squared error (MSE), mean absolute error (MAE), and R squared (R^2) predicted by the model, please refer to Table 2.

Table 2. Results of MSE, MAE and R^2.

Parameter Names	MSE	MAE	R^2
Values	0.0046	0.035	0.9704

From Table 2, we can see that R^2 is as high as 0.9704, MSE is 0.0046 and MAE is 0.035, indicating the good generalization-ability of the established support-vector-regression model. In order to test the feasibility and effectiveness of the proposed prediction-algorithm, the prediction results obtained by traditional SVM and GRA-PSO-SVM were compared, and the comparison results between the predicted and actual values obtained by these three models are shown in Figure 4 and Table 3.

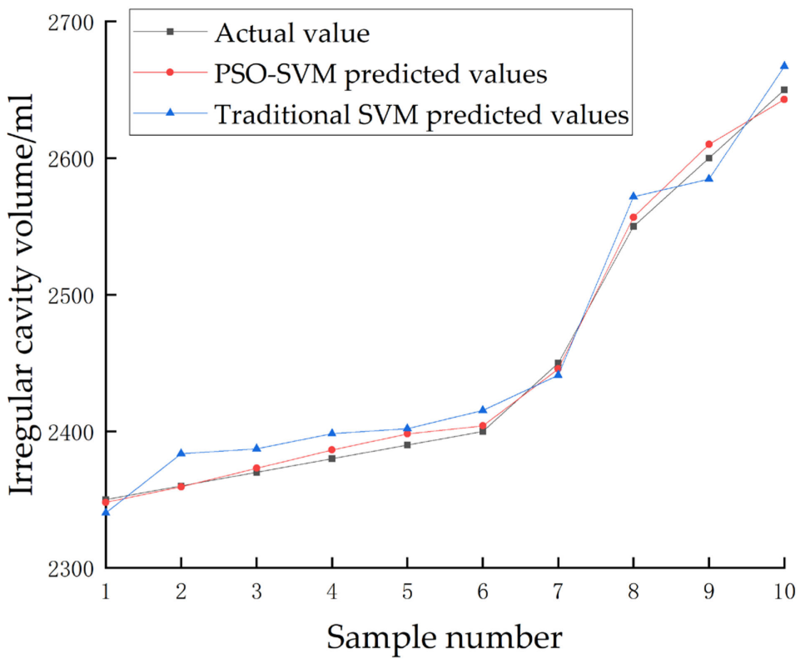

Figure 4. Simulation results from three models.

Table 3. Simulation results from three models.

Sample	Actual Value mL	GRA-PSO-SVM		Traditional SVM	
		Predicted Value	Relative Error	Predicted Value	Relative Error
		mL	%	mL	%
1	2350	2347.96	0.09	2340.35	0.41
2	2360	2357.30	0.11	2383.65	1.00
3	2370	2372.97	0.13	2387.32	0.73
4	2380	2386.38	0.27	2398.27	0.77
5	2390	2398.12	0.34	2401.93	0.50
6	2400	2404.05	0.17	2415.23	0.63
7	2450	2445.67	0.18	2440.98	0.37
8	2550	2556.65	0.26	2571.69	0.85
9	2600	2610.02	0.39	2584.54	0.59
10	2650	2642.97	0.27	2667.28	0.65

According to Table 3 and Figure 4, the maximum absolute error of the predicted value of the irregular-cavity-parts volume based on GRA-PSO-SVM, is 10.02 mL, the maximum relative error is 0.39%, the minimum absolute error is 2.04 mL, and the minimum relative error is 0.09%. Among GRA-PSO-SVM and traditional SVM prediction models, the GRA-PSO-SVM prediction model has the smallest absolute error and relative error, and the highest prediction-accuracy.

6. Conclusions

This research studies the regression method of GRA-PSO-SVM used to model and predict the volume of irregularly cavitied components. The volume of irregularly cavitied components was affected by a variety of influencing factors. Through the grey-correlation analysis of the influencing factors, this experiment selected eight main influencing factors on the volume of irregularly cavitied components, and sorted them according to the degree of influence on the volume of irregularly cavitied components, in descending order. A volume-prediction model of irregularly cavitied components with the strong search ability of PSO and the good generalization performance of a support-vector machine, was then established. The simulation results showed that, compared to the conventional SVM, the GRA-PSO-SVM showed its strength by generating more accurate and stable results, with R^2 as high as 0.9704, MSE of 0.0046 and MAE of 0.035. The volume change can be well predicted, and this prediction model provides a new idea for accurately predicting the volume of irregularly cavitied components. In the follow-up research, we will continue to search for factors that may affect the volume-prediction model of irregularly cavitied components through a large number of experiments, and further optimize the algorithm to improve the detection accuracy and reliability.

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