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Original Article

# Research on prediction and analysis of supercritical water heat transfer coefficient based on support vector machine

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ABSTRACT

In order to better perform thermal hydraulic calculation and analysis of supercritical water reactor, based on the experimental data of supercritical water, the model training and predictive analysis of the heat transfer coefficient of supercritical water were carried out by using the support vector machine (SVM) algorithm. The changes in the prediction accuracy of the supercritical water heat transfer coefficient are analyzed by the changes of the regularization penalty parameter C, the slack variable epsilon and the Gaussian kernel function parameter gamma. The predicted value of the SVM model obtained after parameter optimization and the actual experimental test data are analyzed for data verification. The research results show that: the normalization of the data has a great influence on the prediction results. The slack variable has a relatively small influence on the accuracy change range of the predicted heat transfer coefficient. The change of gamma has the greatest impact on the accuracy of the heat transfer coefficient. Compared with the calculation results of traditional empirical formula methods, the trained algorithm model using SVM has smaller average error and standard deviations. Using the SVM trained algorithm model, the heat transfer coefficient of supercritical water can be effectively predicted and analyzed.

## 1. Introduction

The heat transfer coefficient (HTC) is an important parameter in the thermal hydraulic calculations of nuclear reactors and the related heat exchange system calculations, because the magnitude of the heat transfer coefficient affects the power output of the heat exchange system. The current results show [1]: under supercritical pressure, heat transfer enhancement (HTE) may occur, and heat transfer deterioration (HTD) may also occur. The occurrence of heat transfer deterioration of supercritical water is closely related to the magnitude of the actual heat transfer coefficient. At present, the research on heat transfer coefficient under supercritical pressure [2,3] is mainly limited to the corresponding supercritical water heat transfer experiment, and each researcher fit the corresponding empirical correlation according to the experimental data. However, these formulas tend to be too complicated, and the influence of each parameter on the heat transfer coefficient is not intuitive. H. Zahlan [4] et al. calculated the heat transfer coefficient within the supercritical pressure range by a look-up table, and the heat transfer coefficient obtained by this method reached high accuracy, but the limitation of the method was the range of experimental parameters. Therefore, at present, due to the actual limitations of the experimental conditions, under supercritical pressure, it is difficult to predict the change of heat transfer coefficient accurately with unified working conditions. Wadim Jager [5] et al. systematically evaluated the heat transfer capacity of the TRACE program in the supercritical water environment, and assessed the prediction capability of different empirical correlations, and in most cases it showed the discrepancies of the predicted heat transfer coefficient near the pseudocritical point compared with experimental results.

With the continuous improvement of machine learning algorithms and the continuous improvement of the performance of modern computer solvers, various machine learning algorithms can be used to effectively predict and analyze the working condition parameters of the actual thermal system. Alessandro Mazzola [6] used an artificial neural network system to predict critical heat flux (CHF), showing that the method of artificial neural network can achieve a satisfactory accuracy

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value when dealing with thermal hydraulic heat transfer parameters. HaoPeng [7] et al. analyzed the thermal-hydraulic performance of compact heat exchangers (CHEs) with the use of two methods: support vector machine (SVM) and artificial neural network (ANN). Based on the algorithm of Bayesian support vector regression, Wang Jinsheng [8] et al. proposed an adaptive reliability analysis method in engineering structure. Yao Pengchuan [9] established an abnormal condition monitoring system based on the typical data-driven algorithms such as support vector machine and local outlier factor, which can timely predict the abnormal state of nuclear power plant with high accuracy. Based on support vector machine, Yi Lingfan [10] et al. used an algorithm to effectively locate analog circuit faults effectively which could perform feature extraction and failure mode recognition of discrete data. Wang Xiaolong [11] et al. used support vector machine and BP neural network to carry out numerical experiments on the variable load operation conditions of nuclear power plant. The results showed that methods based on data statistical learning, especially the one based on support vector machine, could obtain a load prediction training model which met the requirement of accuracy. It can be seen that support vector machines (SVMs) and related machine learning algorithms have been more and more widely and deeply applied in various fields such as thermal hydraulics and failure mode recognition diagnosis. When using machine learning algorithm models to predict the parameters of thermal hydraulics, it is generally essential to analyze the sample distribution characteristics of the data set. When the distribution in different categories is unbalanced, it will lead to sampling bias in the final prediction results. For sample-balanced datasets, adjustments of model optimization are required for the hyper-parameters of the model. The hyper-parameters of the model need to be set in advance before model training, so the rationality of the setting has a large impact on the prediction results. Appropriate model hyper-parameters can improve the prediction accuracy of thermal-hydraulic parameters. Machine learning algorithms use the data-driven prediction model, and the prediction result is closely related to the actual data characteristics; while for the traditional relational prediction model, it is based on certain physical analytical formulae. It has clear physical meanings, and the formula structure and parameters are fixed after they are determined. However, with the enrichment and expansion of experimental data, the calculation results of different traditional predictive models will be quite different.

In the research related to supercritical water experiments, the experiments are limited to some specific experimental working conditions. The operating cost of experiments under different variable working conditions is very high. On the basis of the experimental data of supercritical water heat transfer, the general preliminary work is analyzing parameter sensitivity and the influence of the measurement error caused by experimental facilities. The data-driven statistical analysis method is a necessary and useful approach to make a quantitative analysis of the parameters which affect the heat transfer coefficient of supercritical water. On the basis of the widely collected experimental data related to the heat transfer coefficient of supercritical water, effective machine learning algorithms such as support vector machine (SVM) are used to train and learn from the existing experimental data. The algorithm help to better analyze the actual influence of different model parameters on the prediction accuracy of the heat transfer coefficient of supercritical water, thereby better predicting the characteristics of the coefficient change under different working conditions. It provides a new research method for the study of the heat transfer coefficient characteristics of supercritical water.

The main progress and innovative features of the paper are as follows: the first chapter is to explain the source of experimental data and analyze the statistical characteristics of the main experimental data. The second chapter mainly introduces the model calculation principles of the support vector machine algorithm, the main methods of parameter setting and adjustment optimization, and the main evaluation indicators. The third chapter includes the trend change characteristics of supercritical water heat transfer coefficient predicted by different support vector machine parameters, the error analysis of the prediction results of different heat transfer types, the comparison verification of results between different algorithm models, and the range expansion analysis of prediction results. The last chapter focuses on the main conclusion.

## 2. Data source

The data selected for the prediction and analysis of the heat transfer coefficient of supercritical water is from the experimental data of supercritical water in a smooth round tube vertically upwards published in the public journal (1965–2015). The parameters selected which are related to the heat transfer coefficient of supercritical water include specific enthalpy value, pipe diameter, mass flow, heating power and system pressure. In the process of data selection, the experimental figures of supercritical water heat transfer coefficient changing with specific enthalpy under different states were obtained from various literatures at first. Then, set the upper and lower limits of the image range by GetData software, the curve graphical files are extracted and converted into the actual numerical type files through the data point capture function in GetData software. Finally summarize the heat transfer coefficient data which are obtained in numerical type. The statistics of the main experimental data are shown in Table 1.

After the correlation analysis of the experimental data in Table 1, the correlation matrix of the heat transfer coefficient of supercritical water is shown in Fig. 1.

Fig. 1 shows the correlation statistics of the parameters obtained from the experimental data in supercritical water. The numbers in Fig. 1 are called the Pearson correlation coefficient, which is used to measure the degree of linear correlation between two statistical variables x and y, ranging between −1 and 1. Pearson correlation coefficient is a result obtained from statistical calculation based on the actual experimental data. The experimental data used for the coefficient come from Table 1. The correlation coefficient in Fig. 1 is only a statistical result of the experimental data. While the actual experimental data changes, the correlation coefficient may change to some extent. The relevant information expressed in Fig. 1 is only used as a macro statistical reference, reflecting the degree of positive or negative correlation between the currently selected heat transfer coefficients. The calculation formula for Pearson correlation coefficient is as follows:

$$P_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{1}$$

In formula 1, x and y are any two different parameters in Fig. 1 i represents the sequence number of the actual samples, and n represents the number of all samples. $\bar{x}$ and $\bar{y}$ are the average values of these two experimental parameters, respectively.

When the value approaches 1, it indicates a stronger positive correlation between the two statistical variables. When the value approaches −1, it indicates a stronger negative correlation between the two statistical variables. In Fig. 1, different colors are used to indicate the correlation between parameters. The greener the rectangle is, the stronger the positive correlation is between the two variables. The redder the rectangle is, the stronger the negative correlation is. As can be seen from Fig. 1, the positive correlation between mass flow and heating power, and that between mass flow and heat transfer coefficient are relatively strong. The negative correlation between heating power and specific enthalpy is strong.

**Table 1**
Supercritical water experiment statistical data.

| Dataset | *Hb [kJ/kg]* | *D [mm]* | *G [kg/m²s]* | *q [kW/m²]* | *p [MPa]* | *Htc [kW/m²K]* | Point number |
|---|---|---|---|---|---|---|---|
| Ackerman [2] | 1012.96–2551.31 | 9.40 | 1220 | 1260 | 22.75 | 5.72–11.70 | 15 |
| Glushchenko [3] | 512.97–1977.11 | 1.00 | 2200 | 1150–2960 | 23.50 | 10.35–44.39 | 63 |
| Griem,H [17] | 1521.87–2410.25 | 14.00 | 500–1000 | 300–400 | 25.00 | 7.26–26.66 | 71 |
| H.Y. Gu [25] | 1343.44–2451.43 | 7.60–10 | 600–1000 | 700–1000 | 23–25 | 3.25–23.86 | 359 |
| Han wang [16] | 889.80–3135.87 | 2.00 | 400–1000 | 200–400 | 23–28 | 3.42–55.76 | 266 |
| Herkenrath [18] | 1512.39–2755.58 | 10.0–20.0 | 1000 | 500–750 | 24–25 | 6.60–20.21 | 69 |
| JianguoWang [26] | 1253.78–2557.11 | 26.00 | 900 | 300–500 | 26.00 | 2.05–22.48 | 37 |
| Jie Pan [27] | 1428.87–3043.12 | 17.00 | 400–1200 | 284–663 | 22.5–30 | 1.41–20.82 | 305 |
| Kirillov [19] | 1551.88–2204.54 | 10.00 | 496 | 239 | 24.03 | 7.17–14.26 | 42 |
| Lee [20] | 1165.69–2108.35 | 38.10 | 542–1627 | 252–1101 | 24.10 | 4.38–22.30 | 105 |
| Ornatskiy [21] | 451.30–2639.13 | 0.70 | 3000 | 1180–2960 | 23.50 | 10.22–98.08 | 104 |
| Pan jie [30] | 1349.30–3162.85 | 17.00 | 1009–1626 | 216–649 | 22.5–30 | 2.46–157.55 | 266 |
| Sarah Mokry [14] | 1570.37–3142.97 | 10.00 | 203–1499 | 166–884 | 23.9–24.2 | 1.25–48.84 | 1323 |
| Shitsman [22] | 1381.38–2934.82 | 10.00 | 430 | 210–386 | 23.30 | 1.72–24.90 | 106 |
| Swenson [23] | 659.64–3053.54 | 9.42 | 2150 | 786–1730 | 23–31 | 13.07–63.63 | 110 |
| Vikhrev [13] | 624.77–2679.82 | 20.40 | 1400 | 700–1160 | 26.50 | 6.47–39.36 | 72 |
| Wang Fei [31] | 1322.94–2479.42 | 10.00 | 450–1500 | 450–1250 | 23–26 | 1.54–29.91 | 679 |
| Xu feng [32] | 1194.61–2781.18 | 12.00 | 600–1200 | 200–600 | 23–30 | 10.21–171.08 | 353 |
| Yamagata [15] | 1089.93–2996.40 | 7.5–10 | 1114–1260 | 233–930 | 22.6–29.4 | 7.91–78.22 | 507 |
| Yoshida [28] | 1233.30–2707.81 | 10.00 | 1180 | 698 | 24.50 | 14.43–38.33 | 40 |
| Zhu Xiaojing [29] | 1239.79–2852.95 | 26.00 | 600–1200 | 200–400 | 26–30 | 1.04–41.87 | 78 |
| Zhu, X.J [24] | 1621.69–2677.27 | 26.00 | 600 | 200 | 26–30 | 4.48–18.92 | 76 |
| Total | 451.30–3162.85 | 0.7–38.1 | 203–3000 | 166–2960 | 22.50–31 | 1.04–171.08 | 5130 |

## 3. Calculation model

### 3.1. Introduction of support vector machine

Support Vector Machine (SVM) is one of the most popular algorithms in modern machine learning, and this algorithm [12] was proposed by Vapnik in 1992 which can handle complex physics problems with high nonlinearity. The fundamental idea is to map a feature space to another feature space at higher latitudes by the means of nonlinear transformation, so as to obtain the optimal linear delimitation hyperplane. Support vector machine can directly calculate the distance between different data points in the extended feature model through the kernel functions processing. According to different mapping methods, kernel functions are mainly divided into linear kernel functions, polynomial kernel functions and radial basis kernel functions. In the process of finding the optimal linear demarcation hyperplane, which means the error loss function is minimal, the minimized function is calculated as follows:

$$L(\omega,\varepsilon)=\omega^{T}\omega+C\sum_{i=1}^{n}\varepsilon_i \tag{2}$$

In the equation, $\omega$ is the weight coefficient of the input variable. C is the regularization penalty parameter. $\varepsilon$ is the relaxation variable which is used to implement the soft margin classifier, which allows a certain prediction error in order to achieve the better generalization ability.

The calculation of the radial basis kernel function is based on the following formula:

$$K\left(\overline{x_i},\overline{x_j}\right)=\exp\left(-\gamma\left|\overline{x_i}-\overline{x_j}\right|^2\right) \tag{3}$$

In the process of calculating the distance between data points, because the kernel functions are very sensitive to the selection range of the initial data value, the input data need to be normalized first. In the Python language, data normalization can be achieved with the use of MinMaxScaler() function. The normalization is calculated as follows:

$$x_{new}=\frac{x-x_{\min}}{x_{\max}-x_{\min}} \tag{4}$$

### 3.2. Parameters of the model

When using a support vector regression machine to predict the parameters of supercritical water, the main parameters used are shown in the following table.

The parameter range of the support vector machine selected in Table 2 is set according to the actual characteristics of the supercritical water experimental data. Based on the sample size of the supercritical

| | Specific enthalpy | Pipe diameter | Mass flow | Heating power | System pressure |
|---|---|---|---|---|---|
| Specific enthalpy | - | | | | |
| Pipe diameter | 0.0734 | - | | | |
| Mass flow | -0.1606 | -0.2161 | - | | |
| Heating power | -0.3315 | -0.2587 | 0.6832 | - | |
| System pressure | 0.1067 | 0.2746 | 0.1235 | -0.0865 | - |
| Heat transfer coefficient | -0.0361 | -0.1124 | 0.4468 | 0.0715 | -0.0776 |

**Fig. 1.** The correlation matrix of the heat transfer coefficient in supercritical water.

**Table 2**
Ranges of the main parameters.

| Parameter | Meaning | Range |
|---|---|---|
| C | Regularization penalty parameter | 1–50000 |
| $\varepsilon$ | Slack variable | 0.01–5.0 |
| $\gamma$ | The reciprocal of the width of the Gaussian kernel | 0.01–200 |
| kernel | Kernel function option | RBF |
| tol | The stop conditions of algorithm | 0.001 |
| cache_size | Size of the kernel cache | 200 |

water test data in Table 1, it was randomly divided into training set and test set according to the ratio of 7:3. Among the model parameters, parameter C is the regularization penalty parameter. The smaller the C value is, the smaller the predicted penalty is while the more corresponding interval violations are. The bigger the C value is, the greater the penalty predicted is while the less the corresponding interval violations are. Epsilon is a slack variable parameter, the size of which determines the size of the support vector width of the support vector machine model. The larger the epsilon is, the larger the model support vector width is, and the smaller the support vector width is. Gamma is the coefficient of the kernel function which determines the width of the bell-shaped curve assumed by the Gaussian distribution of the characteristic data. The larger the gamma is, the narrower the curve is and the higher the complexity of the model is, otherwise the wider the bell curve is and the smaller the complexity of the model is. Kernel is the type of kernel function used in the algorithm. RBF kernel function with the best performance is used by default within the range allowed by training time complexity. TOL is the residual convergence condition, and training is stopped when the error reaches the specified condition value. Cache_size is used to limit the size of each calculation.

### 3.3. Calculation process

The main calculation process is mainly shown in Fig. 2:

It can be seen from the calculation flow chart in Fig. 2 that the parameters such as specific enthalpy, pipe diameter, flow, and power pressure in Table 1, are first normalized and set as the input parameters of SVM model. The target variable is the heat transfer coefficient of supercritical water. When performing the calculation of the support vector machine, the corresponding kernel function and kernel parameters are first determined, and the kernel distance between different sample points is calculated according to the training data. During the model training, the constraint set of the samples is assembled into a matrix to be solved, and the corresponding solution is carried out by the solver. During the calculation, the vector within a certain distance from the nearest point of the target variable is continuously looked for and identified as the corresponding support vector. After the training model satisfies the corresponding algorithm stopping conditions, the optimal support vector obtained is used to make further regression prediction of the test data. In the process of model training, the prediction ability of the model is mainly improved by optimizing hyperparameters. The hyperparameters for optimization mainly include C, epsilon, and gamma. In the process of hyperparameter optimization, random search and Bayesian search are used to optimize the hyperparameter. In random search process, each search parameter is completely random and has no relationship with the performance of previous search

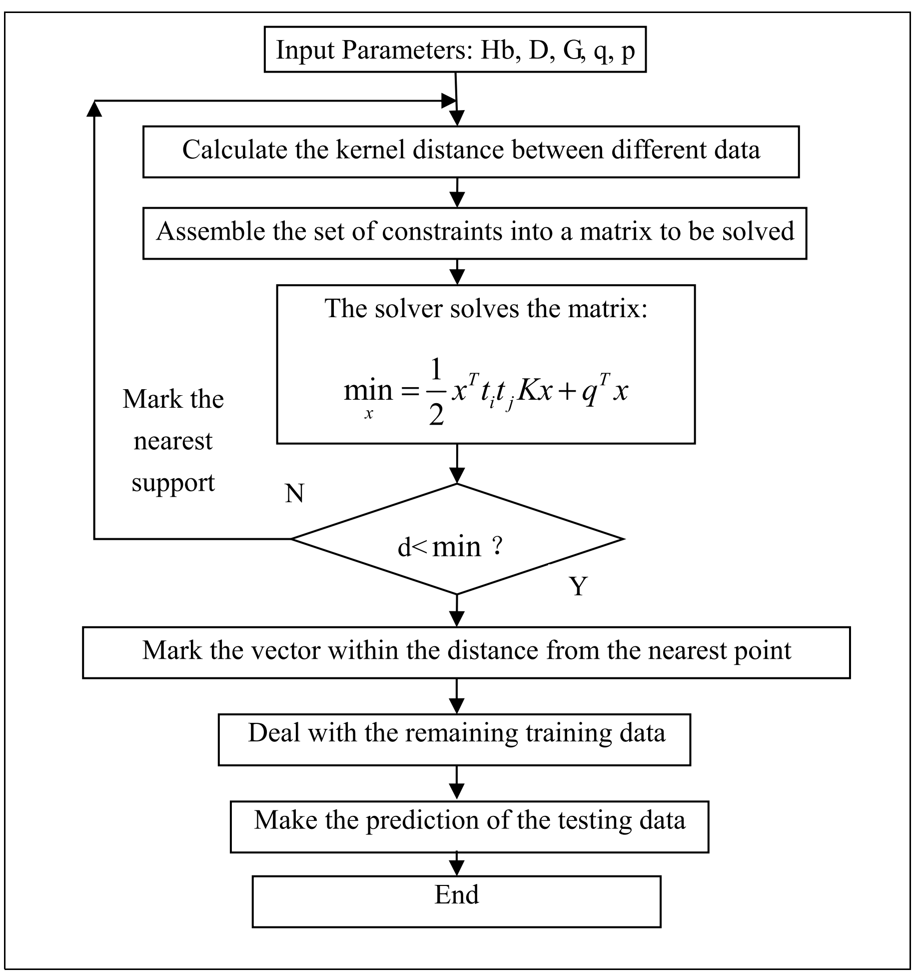
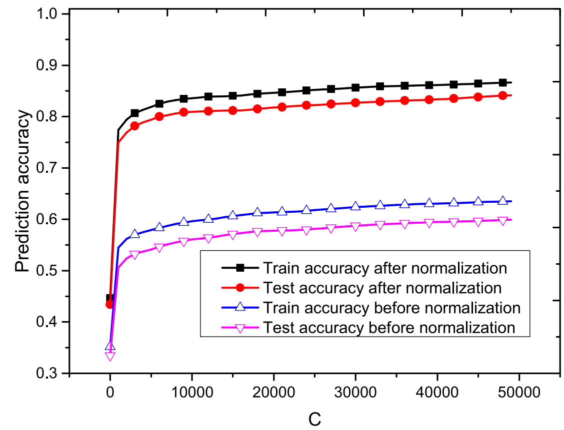
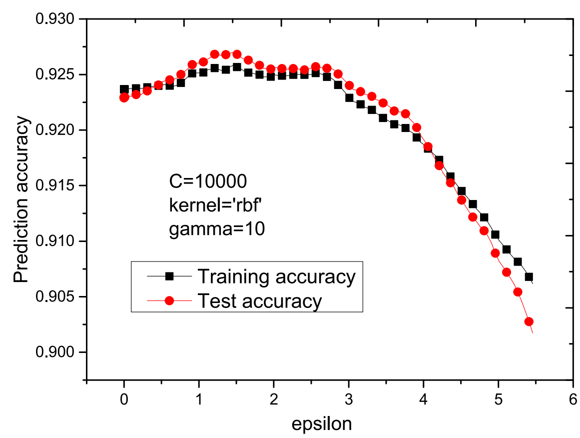


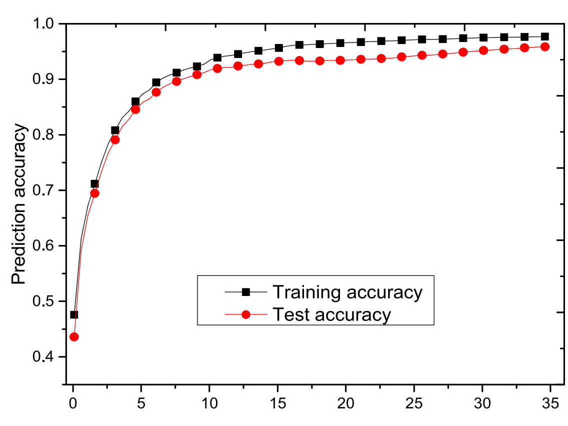

**Fig. 2.** SVM Calculating flowchart.




a Normalization of data and C value




b Epsilon value




c Gamma value

**Fig. 3.** The effects different parameters had on SVM prediction results.

parameter results. Unlike the process of random search, Bayesian search process uses Bayesian optimization technology to model the hyperparameter search space. During each process of optimizing hyperparameter, the model structure of the search space is evaluated based on the performance results of historical searches, in order to determine the next parameter combination which is more likely to provide better performance results as a new candidate parameter.

### 3.4. Evaluation parameters

In the process of training the support vector regression machine model of supercritical water heat transfer coefficient, the determination coefficient is used as the evaluation index of the predictive accuracy performance of the model. The determination coefficient is also called $R^2$, and the coefficient is between 0 and 1. When the coefficient is getting closer to 1, it indicates that the regression prediction performance of the overall model gets better, otherwise the performance gets worse in turn. This parameter is determined by the variance of the prediction results of the data set. The determination coefficient is calculated as follows:

$$R^2 = 1 - \frac{RSS}{TSS} = 1 - \frac{\sum_{i=1}^{n} \left( htc_{pre} - htc_{\exp} \right)^2}{\sum_{i=1}^{n} \left( htc_{\exp} - htc_{avg} \right)^2} \tag{5}$$

In the above equation, RSS is the residual sum of squares of the calculating data. TSS is the overall square error of calculating data. The parameter n is the number of data collection sample size. $htc_{pre}$ is the output value of the super critical water heat transfer coefficient predicted by the model. $htc_{\exp}$ is the actual experimental value of the supercritical water heat transfer coefficient, and $htc_{avg}$ is the average of all the experimental values of the supercritical water heat transfer coefficient.

## 4. Calculating results

### 4.1. The effects parameter changes had on SVM prediction

Using the supercritical water experimental data in Table 1, the optimal parameters of the support vector regression machine were analyzed, and calculation results changes of SVM prediction of supercritical water heat transfer coefficient caused by different parameters were shown in the figure below.

Fig. 3 shows the change of heat transfer coefficient in supercritical water predicted by the support vector regression machine before and after the data are normalized when different regularization parameters C, epsilon parameters and gamma parameters change respectively. In Fig. 3a–c, the ordinates are all prediction accuracy values. The abscissa axes are the C value of the regularization penalty parameter, the epsilon value of the relaxation variable, and the gamma value of the Gamma parameter of the width parameter of the Gaussian kernel function respectively. In Fig. 3a, the two curves consisting of hollow triangles are the effect of the change in C value on the prediction accuracy before the data is normalized. The two curves consisting of solid squares and circles are the changes in the C value obtained after data normalization. As can be seen from Fig. 3a, data normalization has a great influence on the accuracy of SVM prediction results. Before data normalization, the average prediction accuracy was only about 0.5894, and after data normalization, the average prediction accuracy reached about 0.8247. However, with the increase of the C value, the penalty parameter, the prediction accuracy increases rapidly at the beginning, and then gradually increases steadily. Fig. 3b shows how the prediction accuracy changes with the relaxation variable epsilon when the C value remains constant. It can be seen that with the gradual increase of the relaxation variable, the prediction accuracy improves to a certain extent first, but when the relaxation variable increases to about 1.7, the prediction accuracy gradually remains stable and fluctuates within a certain range. In general, the magnitude of changes in relaxation variables has a relatively small effect on prediction accuracy. Fig. 3c shows how the prediction accuracy changes with the change of gamma parameter when both the C value and the relaxation variable remain constant. When the gamma parameter is smaller, the prediction accuracy is also lower. As the gamma parameter gradually increases, the prediction accuracy increases rapidly at the beginning, and then increases gradually and slowly. When the gamma parameter reaches 10, both the prediction accuracy of the training set and the prediction accuracy of the test set increase slightly. By comparing and adjusting the above three parameters, it can be seen that after adjusting the gamma parameters, the prediction accuracy achieves the highest value.

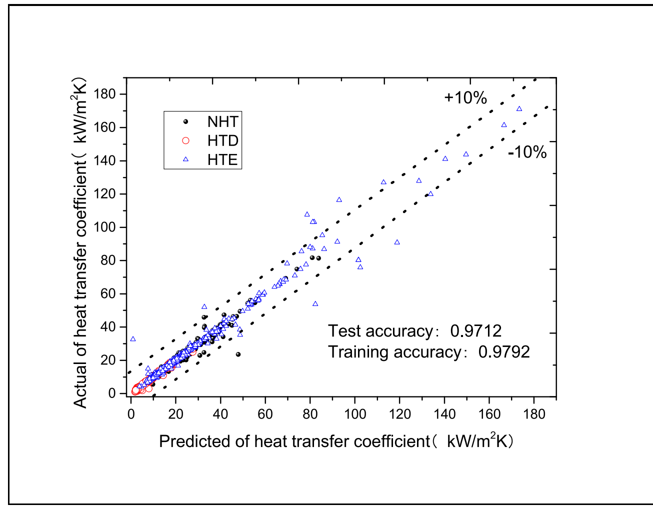



**Fig. 4.** The comparison between predictive values by SVM and actual values.

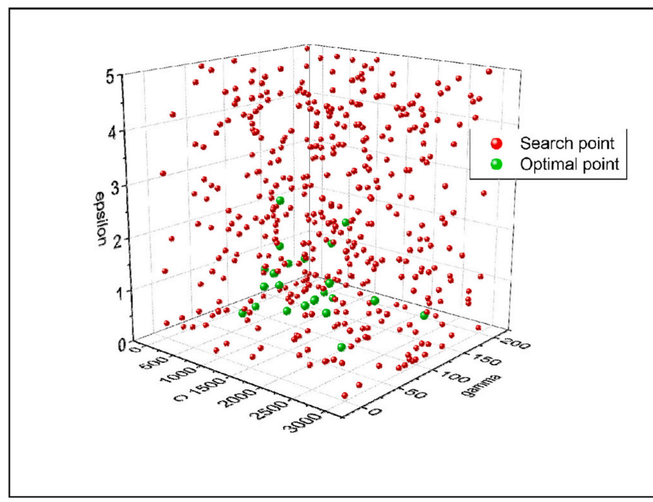



**Fig. 5.** Comparison of hyperparameter space search points and optimal points.

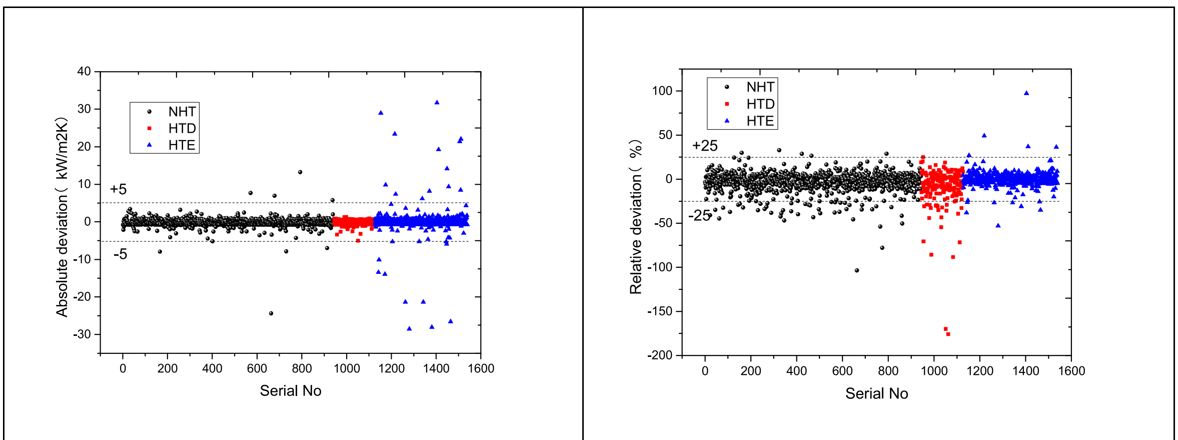
### 4.2. Model verification

The predictive value of the heat transfer coefficient obtained after parameter optimization is compared with the actual value, and the comparative change of the obtained verification result is shown in Fig. 4.

Fig. 4 shows the comparative change distribution of the actual and predicted values of the heat transfer coefficient. The abscissa axis refers to the actual experimental value of the heat transfer coefficient, and the vertical axis is the predicted value of the heat transfer coefficient obtained by SVM after parameter optimization. It can be seen that most of

**Table 3**
Optimal hyperparameters points for spatial search.

| Random search optimal points | | | | Bayesian search optimal points | | | |
|---|---|---|---|---|---|---|---|
| C | gamma | epsilon | test accuracy | C | gamma | epsilon | test accuracy |
| 338.2947 | 144.4140 | 0.8394 | 0.9686 | 2026.4206 | 63.5176 | 1.4077 | 0.9605 |
| 518.0101 | 154.0656 | 0.9506 | 0.9683 | 2050.1148 | 78.8360 | 0.1000 | 0.9599 |
| 419.5296 | 71.4495 | 0.2274 | 0.9643 | 495.7310 | 197.9199 | 1.0489 | 0.9469 |
| 315.1745 | 111.0549 | 0.8813 | 0.9666 | 1609.9130 | 77.5771 | 0.8595 | 0.9563 |
| 922.1496 | 63.4902 | 0.9783 | 0.9615 | 729.2056 | 200.0000 | 1.5579 | 0.9410 |
| 2483.0844 | 86.8318 | 1.1029 | 0.9451 | 1627.2387 | 63.3273 | 0.8449 | 0.9574 |
| 1651.6495 | 91.3406 | 0.5496 | 0.9470 | 2454.5712 | 166.3109 | 0.3501 | 0.9541 |
| 906.0821 | 87.8153 | 2.5376 | 0.9649 | 309.4458 | 133.9968 | 1.2453 | 0.9504 |
| 915.4069 | 84.9628 | 0.8883 | 0.9752 | 1142.5376 | 117.7618 | 0.5000 | 0.9587 |
| 245.9282 | 102.8989 | 0.1237 | 0.9744 | 803.5004 | 173.6569 | 0.1000 | 0.9652 |
| 1102.3410 | 80.5425 | 0.4608 | 0.9740 | 568.0877 | 180.4795 | 0.1000 | 0.9655 |
| 1107.0718 | 62.6604 | 1.3022 | 0.9722 | 1256.0696 | 132.1258 | 0.7377 | 0.9712 |




a Distribution changes of absolute error | b Distribution changes of relative error

**Fig. 6.** Distribution changes of errors.

the prediction errors are within the range of 10% comparing predicted value and the actual value. When the actual heat transfer coefficient is relatively smaller, the predicted value obtained by SVM is closer to the actual value. When the actual heat transfer coefficient is relatively larger, especially after the actual heat transfer coefficient exceeds 100, the predicted value obtained by SVM is relatively consistent compared with the actual value. Therefore, by optimizing the hyperparameters of the model, the prediction performance can be significantly improved. In the process of optimizing the hyperparameters, the final determined model hyperparameters are: C is 1256.0696, epsilon is 0.7377, and gamma is 132.1258. Because the optimal hyperparameters of the model are within a range, they are not limited to a particular hyperparameter. In order to display the distribution characteristics of the optimal hyperparameters points, the spatial distribution of the optimal

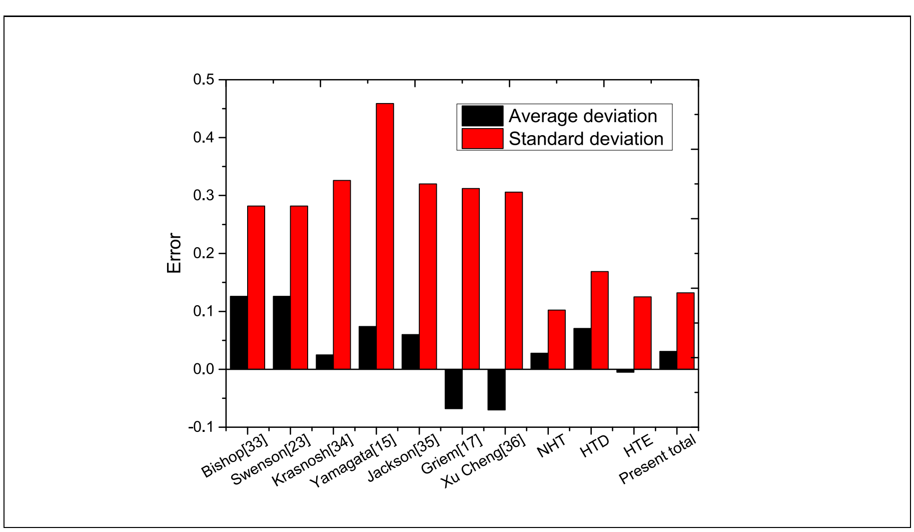
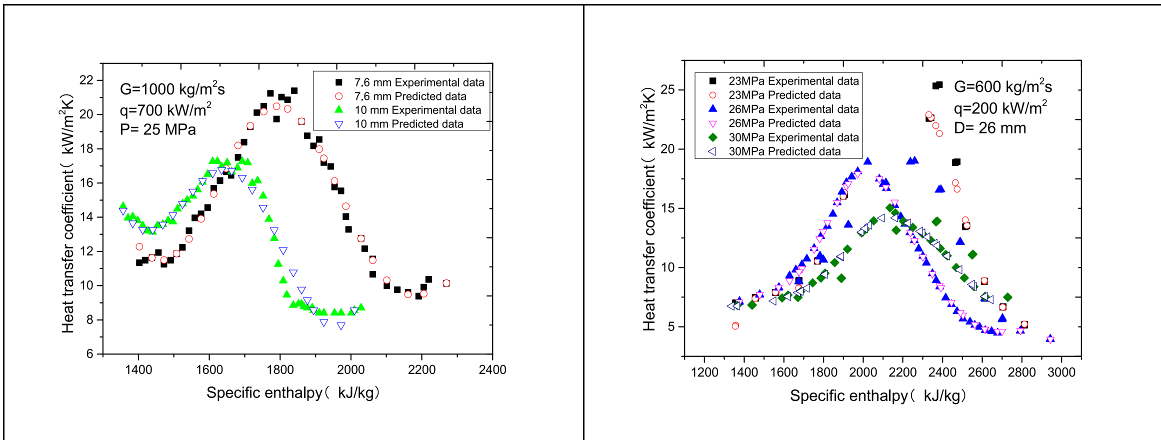



**Fig. 7.** Accuracy comparison of different calculation methods




a At different pipe diameters | b At different pressure

**Fig. 8.** The comparison of predicted and experimental value at different conditions.

hyperparameters points and all search points within the entire spatial range is shown in Fig. 5. This figure shows the position of all searched points and each optimal point in the hyperparameters space after more than 20 times optimizations. The red dots represent the position of all hyperparameters points in previous spatial searches. The green dots represent the position of optimal hyperparameters points obtained during each spatial search process. In Fig. 5, it can be seen the distribution characteristics of the optimal hyperparameters points in the overall space. The actual values of all optimal hyperparameters points in Fig. 5 are shown in Table 3.

### 4.3. Distribution of error

After statistical analysis of error at the sample points of the test data, the absolute error and relative error distribution changes obtained are shown in Fig. 6.

Fig. 6 shows the change in prediction error of experimental sample points in the test set. The abscissa axis refers to the sequence number of the actual experimental sample point, and the index of vertical axis is the absolute and relative deviation of the prediction, respectively. The absolute error is the actual deviation between the actual value and the predicted value, while the relative error is the percentage of the actual deviation and actual value. As can be seen from Fig. 6a, the absolute error generated during HTE is the largest, the absolute error generated during NHT comes second, and the absolute error of HTD is the smallest. The HTD absolute error is mainly distributed within $\pm 5$ (kW/m$^2$K), while the actual error excess is mainly the positive absolute error. As can be seen from Fig. 5b, the relative error is mainly distributed within $\pm 25\%$. The absolute error of HTE is mainly the relative error in the positive direction, and the relative error excess of NHT and HTD is mainly based on the relative error in the negative direction. It indicates that when the prediction error is mainly positive, the absolute value of the actual heat transfer coefficient is relatively large, so the relative value of the positive error is smaller compared with the absolute value. When the prediction error is mainly negative, the absolute value of the actual heat transfer coefficient is relatively lower, so the relative value of the negative error has a large deviation from the absolute value.

### 4.4. Comparison of the results of different calculation methods

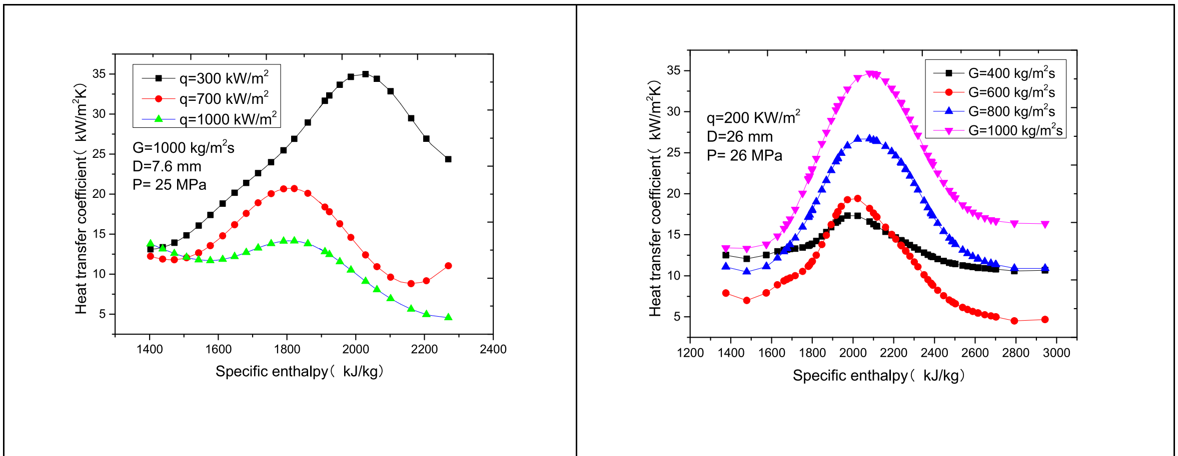
The accuracy results of supercritical water heat transfer coefficient prediction obtained by support vector machine are compared with those of other existing traditional calculation methods and the comparison is shown in Fig. 7.

Fig. 7 shows that the average deviation, standard deviation and other parameters predicted by SVM on the heat transfer coefficient of supercritical water are compared with the indicators of other calculation methods [15,17,23,33–36]. Through the comparison, it can be seen that in the SVM method, the average deviation of HTE is the smallest, the average deviation of HTD is the largest, and the average deviation of NHT is moderate. The standard deviation of HTD is the largest, the standard deviation of NHT is the smallest, and the standard deviation of HTE is moderate. In general, the average and standard deviations of SVM method are smaller compared to other existing calculation methods. It shows that the SVM method can make a good prediction of the heat transfer coefficient of supercritical water, and has a better prediction accuracy.

### 4.5. Comparison of predicted and experimental value

The heat transfer coefficient in supercritical water is predicted by using the trained SVM model, and the changes of predicted and experimental values of heat transfer coefficient under different pipe diameters and different system pressure conditions are shown in Fig. 8.

Fig. 8 shows the comparison between the heat transfer coefficient predicted by the support vector machine model and the heat transfer coefficient under actual experimental conditions at different pipe diameters and different pressures. In Fig. 8a, the distribution of the heat transfer coefficient is shown with the change of enthalpy value under different pipe diameter conditions when the flow rate is 1000 kg/m$^2$ s, the pressure is 25 MPa, and the heating power is 700 kw/m$^2$. With the gradual increase of pipe diameter, the peak of heat transfer coefficient gradually increases, which indicates that when the pipe diameter becomes larger, it will inevitably bring about a rapid increase in the overall mass flow rate in the pipeline, so it will effectively strengthen the heat transfer in the pipeline. The heat transfer enhancement effect in this pipeline is most obvious when the diameter is with the range of 12–15 mm. With the further increase of the pipeline diameter, the heat transfer strengthening phenomenon of the heat transfer coefficient gradually weakens, indicating that the effect of heat transfer strengthening has become no longer greatly obvious when further increasing the diameter of the pipeline. Fig. 8b shows the distribution of heat transfer coefficient with the change of enthalpy.under different system pressure conditions when the flow rate is 600 kg/m$^2$ s, the pipe diameter is 26 mm, and the heating power is 200 kw/m$^2$. As the pressure of the system gradually increases, the peak value of the heat transfer coefficient becomes smaller in general. This phenomenon is closely related to the physical parameters of supercritical water near the critical point. Especially when the




a At different heating power | b At different mass velocity

**Fig. 9.** Changes of heat transfer coefficient predicted by the model at different parameters.

system pressure exceeds 25 MPa, the peak heat transfer coefficient drops very quickly. As the system pressure continues to increase, the peak process of the heat transfer coefficient is no longer obvious.

### 4.6. Extended prediction of model

The trained model is used to further predict and analyze the changes of the heat transfer coefficient of supercritical water under different parameters, and the prediction result changes of the heat transfer coefficient are obtained under different heating power conditions and different mass flow conditions, as shown in Fig. 9.

Fig. 9 shows the characteristics of the extended prediction results of the supercritical water heat transfer coefficient using the trained SVM model. Through the extended prediction, it can be seen that the change characteristics of the heat transfer coefficient in supercritical water are different when heating power and mass velocity are selected as the single variables in respective experiments. Due to the lack of experimental data when heating power and mass velocity change under the same parameter conditions, the output can be predicted by the model and it can be observed that the heat transfer coefficient changes at different heating power and mass velocity. Fig. 8a shows that under the same mass flow, pipe diameter and pressure conditions, as the heating power increases, the peak of the heat transfer coefficient moves towards the low specific enthalpy, and the peak of the heating power gradually decreases. It can be seen from Fig. 8b that under the same heating power, pipe diameter and pressure conditions, the peak of heat transfer coefficient gradually increases as the mass flow increases. Under these conditions the peak heat transfer coefficient at larger mass velocity gradually shifts towards the larger specific enthalpy. However, through comparison, it can be found that the change of peak shifting to a higher specific enthalpy value caused by increasing the mass velocity is significantly smaller than that caused by increasing heating power. Because it is limited by the parameter range of supercritical water heat transfer experimental data, the model can be further trained and optimized on the basis of increasing the supercritical water experimental data. On the premise of ensuring that the experimental parameters are set at the upper and lower limits of the unified range, the supercritical water test data with timestamps which meet the condition specifications can be further integrated into the model to improve the prediction performance of the training model.

## 5. Conclusion

Using the support vector machine algorithm, the prediction model of the heat transfer coefficient of supercritical water is trained and analyzed on the basis of the heat transfer experimental data of supercritical water, and the main conclusions are as follows:

(1) When the support vector machine algorithm is used to calculate and analyze the experimental data of supercritical water, the normalization of the data has a great impact on the prediction results. The average prediction accuracy before and after normalization of the data was 0.5894 and 0.8247, respectively.
(2) The influence of slack variables on the magnitude of the accuracy change in predicting the heat transfer coefficient is relatively small. The change of gamma parameter has the greatest influence on the accuracy prediction of heat transfer coefficient. When the gamma parameter reaches 10, the sequential increasing of the parameter no longer has a significant impact on the subsequent improvement of prediction accuracy. In the spatial distribution of hyperparameters, the optimal hyperparameters spatial distribution were obtained.
(3) In the optimized SVM prediction model, the absolute error is mainly distributed within $\pm 5$, and the actual error excess is mainly the positive absolute error. The relative error is mainly distributed within $\pm 25$, while the relative error excess is mainly based on the negative relative error, and the absolute value of the actual heat transfer coefficient is relatively low. Compared to other existing calculation methods, the SVM model has a better prediction accuracy.

## Declarartion of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled "**Research on Prediction and Analysis of Supercritical Water Heat Transfer Coefficient Based on** Support **Vector Machine**".

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