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Critical power prediction using SVM algorithms

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Abstract

This article discusses the application of the support vector method to predict the critical heat load.

Keywords: Machine learning; prediction; technical diagnostic; Group Method of Data Handling; Support Vector Machine.

1. Introduction

The crisis of heat transfer during boiling is the phenomenon of a sharp deterioration in heat transfer on a heat transfer surface, leading to a rapid increase in its temperature. The thermal load W_{cr} at which this phenomenon occurs is called the critical thermal load.

To predict the heat transfer crisis, research was conducted on the SVD-2 high-pressure thermophysical bench at the "State Scientific Centre of the Russian Federation Institute for Physics and Power Engineering named after A.I. Leypunsky". The experimental section was a square-shaped rod inscribed in a cylinder with a diameter of 7.0 mm - simulating a fuel element. Fig. 1 (a) shows the cross section of a fuel element with the position of eight sensors for measuring the temperature of the wall of a fuel element located along the perimeter.

The mode was set as the three main parameters P, G, T:

- Pressure (P);
- Flow rate (G);
- Temperature (T).

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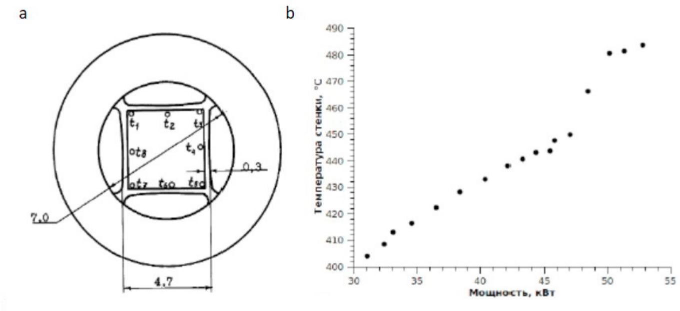

Fig. 1. Experimental determination of critical power at the SVD-2 stand: (a) cross section of a fuel rod and the location of thermocouples; (b) the dependence of the temperature of the wall of the fuel rod on the power.

From the first during the experiment, the power was set specially less than critical, then the power was increased in increments of 1 kW. Fig. 1 (b) shows that up to a certain value the temperature of the fuel rod wall linearly depended on the increase in power, but at a certain value (48 kW) there was a jump in the temperature of the fuel rod wall (heat transfer crisis) associated with the formation of a vapor film in the heated section.

The dependence of the critical power (W_{cr}) on the main parameters pressure, flow rate, and temperature was sought in the form of a nonlinear function $W_{cr} = f(P, G, T)$. To determine the optimal structure of an unknown function, the support vector machine (SVM, Support Vector Machine) was used.

SVM with both linear and nonlinear nuclear functions is one of the promising data analysis algorithms [2, 11, 7, 8]. Initially, the algorithm was used to solve the classification problem, but later they began to use it to perform regression analysis. To distinguish between two applications, the abbreviation SVR (Support Vector Regression) was added [9].

To predict critical heat load, the scikit-learn [5] library of the python programming language was chosen [6, 1].

For preliminary data processing and execution of the method of group accounting of arguments, Dyalog APL was used [3].

2. Support-vector machine

The support-vector method is models that have powerful predictive power and work well on various data sets. They work well on low- and high-dimensional data, but they do not scale well with the growth of the data volume [4]. Let's learn more about the main parameters of SVR:

- Regularization parameter C;
- Allowable regression error;
- Kernel type, as well as parameters determined by the kernel.

In SVR, the initial data array is first displayed in the m-dimensional feature space using a special nonlinear function called the kernel for this, and only then a linear regression model is constructed. Using mathematical notation, we write a linear model (in the space of features):

$$f(\mathbf{x}, \omega) = \sum_{j=1}^{m} \omega_j g_j(\mathbf{x}) + b \tag{1}$$

where $g_j(x)$, $j = 1, .., m$ denotes a set of nonlinear transformations, and b is the displacement. The coefficient b can be discarded if the average value in the data is zero (due to the data nature or preprocessing).

The quality of the estimate can be measured using the loss function $L_\epsilon(y, f(x, \omega)$, which in SVR is called ϵ the insensitive loss function introduced by Vapnik:

$$L_\epsilon(y, f(x, \omega) = \begin{cases} 0 \text{ if } |y - f(x, \omega| - \epsilon \leq \epsilon \\ \text{if } |y - f(x, \omega| - \epsilon \text{ otherwise} \end{cases} \tag{2}$$

The empirical risk or the average error of the algorithm in the training set is calculated as:

$$R_{emp}(\omega) = \frac{1}{n}\sum_{i=1}^{n} L_{\epsilon}(y_i, f(\mathbf{x_i}, \omega)) \tag{3}$$

As mentioned above, SVR performs linear regression in a high-dimensional space of attributes and at the same time tries to reduce the complexity of the model by minimizing $||\omega^2||$. This solution can be described by introducing new non-negative variables $\xi_i, \xi_i^*, i = 1, .., n$ in order to calculate the deviation of the training sample from the ϵ non-sensitive zone. Thus, SVR is formulated as minimizing the following functionality:

$$\mathbf{min}\frac{1}{2}||\omega^2|| + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{4}$$

Or:

$$\begin{cases} y - f(\mathbf{x_i}, \omega) \leq \epsilon + \xi_i^* \\ f(\mathbf{x_i}, \omega) - y_i \leq \epsilon + \xi_i \\ \xi_i, \xi_i^* \leq 0, i = 1, ..., n \end{cases} \tag{5}$$

The solution to this optimization problem can be written as follows:

$$f(x) = \sum_{i=1}^{n_{sv}}(\alpha_i - \alpha_i^*)K(\mathbf{x_i}, \mathbf{x}) \tag{6}$$

With that $0 \leq \alpha_i^* \leq C, 0 \leq \alpha_i \leq C$, where n_{sv} and $K(\mathbf{x_i}, \mathbf{x})$ is the number of support vectors and the kernel function.

$$K(\mathbf{x_i}, \mathbf{x}) = \sum_{j=1}^{m} g_j(\mathbf{x_i})g_j(\mathbf{x}) \tag{7}$$

The following kernel types are available in the scikit-learn library:

- linear;
- polynomial;
- radial basis (RBF);
- sigmoid.

3. Implementation of the SVR technique in python

In this paper, to solve the critical heat load prediction problem, we chose the RBF core (radial basis function), also known as the Gaussian core, which has only one γ parameter. The Gaussian kernel can be explained as follows: it considers all possible polynomials of all degrees, but the importance of the features decreases with increasing degree.

Parameters γ and C control the complexity of the model, higher values of these parameters give a more complex model. Thus, the optimal settings of both parameters are interconnected and therefore C and γ must be adjusted together [4].

To predict the critical heat load using the SVR method, real experimental data were used, to which the group method of data handling (GMDH) was applied in [10]. A total of 211 points were used. The input variables were pressure (P), coolant flow rate (G) and temperature (T). The output value was power (W).

The input dataset was divided into three subsets:

- training for the selection of parameters of the SVR model;
- test to select the best sets of parameters;

- exam to assess the quality of the final model.

For training the model, 60 points were taken at random, representing less than 30 % of the entire data set. The sizes of the training and testing subsets were 40 and 20 points, respectively. The support vector method is very sensitive to data preprocessing, so before training the model, the data were normalized:

$$x_{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{8}$$

To select the parameters of the SVR model, we used the GridSearchCV function of the sklearn library, which allows you to choose the best one from the proposed set of parameters. For training and assessing the quality of the model, the data were divided into training, verification and examination sequences in the ratio of 40, 20 and 151 points, respectively.

Table 1. Results of learning model.

	Train	Test	Exam	All
N	40	20	151	211
MIN	-0.27	-0.37	-0.85	-0.77
MAX	0.26	0.35	0.78	0.85
SSQ	0.43	0.64	8.04	9.11
MIN,	-4.5	-6.79	-16.09	15.42
MAX,	4.63	7.24	17.70	16.97
MEAN,	1.59	2.75	3.60	3.09

4. Conclusion

The results can be considered good. The error in predicting the heat transfer crisis was 3.60 % in the test sequence of 151 experimental points that were not used to train the model. In this paper, we considered the application of the support vector method for the problem of regression analysis using the python programming language and its sklearn library. The python programming language is a good tool for solving the critical power prediction problem due to the large number of tunable parameters and ease of use.

The support vector method has several advantages already described earlier, such as high accuracy, a large number of adjustable parameters, a large number of examples. However, as a drawback, I would like to note the difficulty in selecting optimal hyperparameters, which depends on the nature of the data, their preprocessing, and other factors. In this work, the application of this algorithm was demonstrated, which made it possible to predict the critical power of a nuclear power reactor with sufficiently high accuracy.

References

[1] Anaconda Distribution, . URL: https://www.anaconda.com/.
[2] Bzdok, D., Krzywinski, M., Altman, N., 2018. Points of significance: Machine learning: supervised methods.
[3] Dyalog, . URL: https://www.dyalog.com/.
[4] Müller, A.C., Guido, S., et al., 2016. Introduction to machine learning with Python: a guide for data scientists. " O'Reilly Media, Inc.".
[5] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., et al., 2011. Scikit-learn: Machine learning in python. Journal of machine learning research 12, 2825–2830.
[6] Python, . URL: https://python.org.
[7] Ramaswamy, S., Rastogi, R., Shim, K., 2000. Efficient algorithms for mining outliers from large data sets, in: ACM Sigmod Record, ACM. pp. 427–438.
[8] Settouti, N., Bechar, M.E.A., Chikh, M.A., 2016. Statistical comparisons of the top 10 algorithms in data mining for classification task. International Journal of Interactive Multimedia and Artificial Intelligence 4, 46–51.
[9] Sheremet, O., Sadovoy, O., 2016. Using the support vector regression method for telecommunication networks monitoring, in: 2016 Third International Scientific-Practical Conference Problems of Infocommunications Science and Technology (PIC S&T), IEEE. pp. 8–10.

[10] Skomorokhov, A.O., 1993. Adaptive learning networks in apl2. ACM SIGAPL APL Quote Quad 24, 219–229.
[11] Wu, X., Kumar, V., Quinlan, J.R., Ghosh, J., Yang, Q., Motoda, H., McLachlan, G.J., Ng, A., Liu, B., Philip, S.Y., et al., 2008. Top 10 algorithms in data mining. Knowledge and information systems 14, 1–37.