A New Application of Support Vector Machine Method: Condition Monitoring and Analysis of Reactor Coolant Pump

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Abstract. Fukushima nuclear power plant accident caused huge losses and pollution and it showed that the reactor coolant pump is very important in a nuclear power plant. Therefore, to keep the safety and reliability, the condition of the coolant pump needs to be online condition monitored and fault analyzed. In this paper, condition monitoring and analysis based on support vector machine (SVM) is proposed. This method is just to aim at the small sample studies such as reactor coolant pump. Both experiment data and field data are analyzed. In order to eliminate the noise and useless frequency, these data are disposed through a multi-band FIR filter. After that, a fault feature selection method based on principal component analysis is proposed. The related variable quantity is changed into unrelated variable quantity, and the dimension is descended. Then the SVM method is used to separate different fault characteristics. Firstly, this method is used as a two-kind classifier to separate each two different running conditions. Then the SVM is used as a multiple classifier to separate all of the different condition types. The SVM could separate these conditions successfully. After that, software based on SVM was designed for reactor coolant pump condition analysis. This software is installed on the reactor plant control system of Qinshan nuclear power plant in China. It could monitor the online data and find the pump mechanical fault automatically.

1. Introduction
In March 2011, a magnitude 9.0 earthquake struck off the northeastern coast of Japan and setting off a devastating tsunami. The earthquake and tsunami destroyed the power supply of the coolant system of Fukushima nuclear power plant. Although the remaining decay heat of the fuel was being cooled through emergency system as soon as possible, without enough power, the reactor coolant pump could not take all of the decay heat from the reactor. In the next few weeks, the rising temperature caused several explosions and thousands of tons of pollutants all over the East Asia.

In this disaster, it shows that the reactor coolant pump is very important in a nuclear power plant. If the pump losses efficacy, it could cause a major accident and the damage could be very disastrous. The coolant pump in a reactor is placed in the work environment of high temperature and high pressure with long hours. Because of its special work environment, it needs very high requirements in the reliability and security. [1]- [3] Therefore, in order to keep the safety and reliability of the equipment, the condition of the coolant pump needs to be online condition monitored and fault...
analyzed. [4]

Currently, there are two different ways for system condition analysis. One is the traditional methods which based on the time series, the other one is the artificial intelligence methods which take neural network method as a representative. The traditional methods got very good effects in the system fault diagnosis but need plenty of fault samples and prior knowledge. As equipment with high reliability and security, we can not obtain so many fault samples from the reactor coolant pump. So here a method was chosen to aim at the small sample studies: Support Vector Machine (SVM). [5]-[8]

The method of SVM is based on the principle of statistical learning theory, VC dimension and structural risk minimization theory. The essence of SVM is looking for the best compromise between the complexity of the model and the study ability according to limited information. In this paper, through the validation of experiment data and field data, SVM-based fault classifier can distinguish a variety of types of rotating machinery fault.

2. Principle of condition analysis based on SVM

In this paper, we use the method of Least Squares Support Vector Machine (LSSVM), a method based on SVM. Comparing with regular SVM forecast method, the advantage of this method is to use quadratic loss function instead of the insensitive loss function in SVM. It could change the secondary optimal problem in SVM to linear equations through constructing the loss function. So the computational complexity could be simplified.

For condition analysis, a group of linear separable training samples could be described as follows:

\[
D = \{(x_i, y_i) : (x_i, y_i) \in (x_1, y_1) \ldots (x_n, y_n)\}; \\
x \in R^d; y \in \{+1, -1\};
\]

The classification line equation could be described as:

\[
x \cdot \omega + b = 0; \\
y_i[(\omega \cdot x_i) + b] - 1 \geq 0, \ i = 1, \ldots, n.
\]

The Lagrange multiplier method could be used to solve constrained optimization problem. The Lagrange function is set as follows:

\[
L(\alpha, b, \alpha) = \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) - \sum_{i=1}^{n} \alpha_i \{y_i[\omega \cdot x_i + b] - 1\}
\]

Based on Wofle’s duality theory, this problem could be changed to:

\[
Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j); \\
\alpha \geq 0, \ i = 1, \ldots, n;
\]

The optimal classification function is as follows:

\[
f(x) = \text{sgn}\{\sum_{i=1}^{n} \alpha_i y_i (x \cdot x_i) + b\}
\]

If this group of data could not be linear separable, we could create a new feature vector. By this vector, the nonlinear problem could be changed to a linear problem in a high-dimensional space through a non-linear transform. The optimal classification surface could be found in this high-dimensional space. By defining a kernel function, SVM could calculate the optimal classification surface in the input space plane. And the equation (3) to (5) could be changed as:
Through method of LSSVM, equation (4) could be changed as:

\[
\phi(\omega, \zeta) = \frac{1}{2} (\omega \cdot \omega) + C \left( \sum_{i=1}^{n} \zeta_i \right)
\]

\[
\text{st. } y_i (\omega \cdot x_i + b) = 1 - \xi_i, \xi_i \geq 0, i = 1, 2, ..., I
\]

And the optimization problem could be changed as:

\[
\min \frac{1}{2} \|\omega\|^2 + \frac{1}{2} \gamma \sum_{i=1}^{I} \xi_i^2
\]

\[
\text{s.t. } y_i (\omega \cdot \psi(x_i) + b) + \xi_i = 1, i = 1, 2, ..., I
\]

The kernel function could be defined as:

\[K(x_i, x_j) = \psi(x_i) \cdot \psi(x_j)\]

And the nonlinear classifier function is as follows:

\[y = \text{sign} \left\{ \sum_{i=1}^{I} \alpha_i y_i K(x_i, x) + b \right\}\]

In this paper, the mechanical signal from reactor coolant pump could be created into a feature vector and the different conditions of pump could be separated by classification surface in high-dimensional space.

3. Condition analysis of reactor coolant pump

3.1. Construction of multi-band FIR filter

In the field of rotating machinery condition analysis, frequency domain information can directly reflect the operational status of equipment, but sometimes it could be lost in background noise. In this paper, a multi-band FIR filter is constructed for feature extraction of the equipment status. Through this multi-band FIR filter, the useful periodic component which drowns in the noise could be extracted effectively.

The FIR filter is with linear phase property and the system structure is always stable, it could achieve a zero phase shift filtering between the fundamental frequency and the doubling frequency, the design of the filter is as follows:

Firstly, define the ideal frequency characteristics of the multi-band filter. This multi-band filter needs to keep the frequency around the fundamental frequency and the doubling frequency, the ideal frequency characteristics could be as follows:

\[H_0(f) = \begin{cases} 1 & k = 0, \pm 1, \pm 2, \ldots \\ 0 & \text{others} \end{cases}\]

Secondly, calculate the unit sampling response:
\[ h_d(n) = \Gamma^{-1}[H_d(f)] \]
\[ = \frac{\sin(PnT)}{2n\pi} \sum_{k=1}^{K} \cos(kf_0nT) \]

(12)

Where \( K \) is the number of band-pass of filter, \( T \) is the sampling period, and \( f_0 \) is the fundamental frequency.

Thirdly, select the window function and calculate the unit step response. In this paper, Hanning window is selected as the window function. The unit step response is as follows:

\[ h(n) = h_d(n)\omega(n) \]
\[ h(n) = \sum_{k=1}^{K} \frac{\sin(2\pi(f_k+P)nT-\sin(2\pi(f_k-P)nT))}{\pi n} \ast (1 + \cos(\pi n / N)) \]

(13)

After the signal passes through the multi-band filter, the useful frequency and its doubling frequency could be maintained, and the other frequency could be repressed and eliminated powerfully.

The following signals are achieved through our gear fault simulation test bench, the revolving speed is 800 rev, the sampling frequency is 5120 Hz, and the gear meshing parameter is 26/64. Figure 1 and 2 are the time domain waveform and frequency domain waveform. Figure 3 and figure 4 are the time domain waveform and frequency domain waveform passed through the multi-band filter. Through these four figures, this method could eliminate the noise and useless frequency, and improve the SNR (signal to noise ratio).

![Figure 1. The time domain waveform of the original signal.](image1.png)

![Figure 2. The frequency domain waveform of the original signal.](image2.png)

![Figure 3. The time domain waveform of the processed signal.](image3.png)

![Figure 4. The frequency domain waveform of the processed signal.](image4.png)
3.2. Principal component analysis-based fault feature extraction

In mechanical fault analysis, various characteristics, such as the amplitude spectrum and power spectrum, could be extracted from the frequency domain of the vibration signal. In the research of fault diagnosis, the fault features of rotating machinery could be divided through the energy distribution in different frequency bands. The most common and useful characteristic parameters of rotating machinery fault analysis is to analyze the total frequency peak of a number of different frequency bands extracted from the vibration signals. In this paper, the frequency spectrum of the vibration signal is divided into several section spectrums through a multi-band FIR filter, and then composed to multi-dimensional feature vectors. The spectrum bands are divided as below:

| Characteristic frequency | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   |
|-------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Frequency range         | 0.01| 0.4 to 0.49f₀ | 0.5 to 0.51f₀ | f₀  | 2f₀ | 3f₀ | Odd multiples | High multiples |
|                         | 0.39f₀ | 0.99f₀ |

f₀ is the working frequency of the rotor.

As shown in figure 1, the friction fault and unbalanced fault could be separated by this nine Section Spectrums method. The X-axis and the Y-axis is the fourth dimension and the eighth dimension of the nine Section Spectrums.

To reduce the computational complexity of the fault classifier, and to improve the separability of the failure mode, it is necessary to make a selection of the fault characteristic vectors extracted. In this paper, a fault feature selection method based on principal component analysis is proposed. In this PCA method, the related variable quantity is changed into some new unrelated variable quantity, and the dimension is descending during this process. The essence of this method is to remain the bigger variance and ignore the smaller, linear parts. In this paper, this method is generalized to nonlinear area: PCA based on kernel functions.

Assume the function \( \phi \) could achieve the nonlinear mapping from the input space \( \mathbb{R}^m \) to the characteristic space \( F \). Makes changes to the function as follows:
\[ x_i = (x_{i1}, x_{i2}, \ldots, x_{ip})^T, \quad i = 1, 2, \ldots, n \]

\[ x^*_i = \frac{x_i - \mu_k}{\sigma_{ik}^{1/2}} \quad k = 1, 2, \ldots, n; \]

And the correlation coefficient matrix is shown as follows:

\[ R = (r_{jk})_{p \times p} = \left( \frac{s_{jk}}{(s_{jk}^2)^{1/2}} \right)_{p \times p} \]

\[ s_{jk} = \frac{1}{n-1} \sum_{i=1}^{n} (x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k), \quad j, k = 1, 2, \ldots, p \]

Where, the contribution rate of the Kth sample principal component is \( \lambda_k / \sum \lambda_j \), the cumulative contribution rate of the first m-th sample principal component is \( \sum_{k=1}^{m} \lambda_k / \sum \lambda_j \). The principal component could be selected though this method.

Figure 5 and figure 6 show that: the distance between the vectors could be changed smaller and the distance between different types could be changed bigger. So this method could improve the distinction between different faults.

3.3. Condition analysis and fault classification of reactor coolant pump

In the following, the SVM and SVM based on PCA are used to analyze the condition of the reactor coolant pump system and separate different fault characteristics.

Through the experience of reactor system operation in the last 10 years, the fault of the reactor coolant pump is mainly about the rotor system. In the rotor system, the condition could be separated into normal, unbalance fault, friction fault, misalignments fault, and cracked fault. In this paper, both experiment data and field data are used in this SVM-based condition classifier. These condition characteristic vectors are prepared by Spectrums.

The experiment based on reactor coolant pump is shown as figure 7. Similar as a reactor coolant pump, the system contains an electromotor, an oil lubrication bearing, a water lubrication bearing and a quality dish. In this experiment, the speed of the rotor was maintained to an initial values, 1500 round/min (157 rad/sec), just the same speed as reactor coolant pump. In this test bench, the system could simulate the condition of normal, unbalance fault, friction fault, misalignments fault, and cracked fault. The experiment data are prepared by spectrums through multi-band filter.

Figure 7. Structure of the experiment equipment.
Firstly, SVM is used to separate two different conditions of rotor system. Table 2 shows the data taken from experiment test bench; first 10 training samples are friction fault. Second 10 training samples are unbalance. The multi-band filter is used to eliminate the noise and useless frequency. Then SVM program is used to extract the eigenvalue of the samples and construct the separation model. After that, the test data is used to test this model and the program could be used to separate different two types as trained before. In table 3, friction fault and unbalance fault data are input to the SVM separation program randomly. The test result shows that the SVM separation program could separate different types successfully.

| Fault type         | Characteristic frequency 1 | Characteristic frequency 2 | Characteristic frequency 3 | Characteristic frequency 4 | Characteristic frequency 5 |
|--------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Friction fault     | 0.0265                      | 0.0271                      | 0.0098                      | 0.3569                      | 0.2689                      |
|                    | ...                         | ...                         | ...                         | ...                         | ...                         |
| Unbalance fault    | 0.0270                      | 0.0276                      | 0.0100                      | 0.3610                      | 0.2706                      |

| Fault type         | Characteristic frequency 6 | Characteristic frequency 7 | Characteristic frequency 8 | Characteristic frequency 9 |
|--------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Friction fault     | 0.0032                      | 0.0253                      | 0.2754                      | 0.0068                      |
|                    | ...                         | ...                         | ...                         | ...                         |
| Unbalance fault    | 0.0025                      | 0.0234                      | 0.2757                      | 0.0021                      |

| Fault type         | Characteristic frequency 1 | Characteristic frequency 2 | Characteristic frequency 3 | Characteristic frequency 4 | Characteristic frequency 5 |
|--------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Friction fault     | 0.0264                      | 0.0271                      | 0.0098                      | 0.3569                      | 0.2687                      |
| Unbalance fault    | 0.0266                      | 0.0275                      | 0.0100                      | 0.3623                      | 0.2734                      |
| Friction fault     | 0.0267                      | 0.0273                      | 0.0099                      | 0.3575                      | 0.2682                      |
| Friction fault     | 0.0269                      | 0.0274                      | 0.0099                      | 0.3580                      | 0.2684                      |
| Unbalance fault    | 0.0264                      | 0.0272                      | 0.0099                      | 0.3595                      | 0.2714                      |
| Unbalance fault    | 0.0266                      | 0.0274                      | 0.0099                      | 0.3620                      | 0.2735                      |

| Fault type         | Characteristic frequency 6 | Characteristic frequency 7 | Characteristic frequency 8 | Characteristic frequency 9 |
|--------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Friction fault     | 0.0038                      | 0.0292                      | 0.2742                      | 0.0037                      |
| Unbalance fault    | 0.0026                      | 0.0181                      | 0.2773                      | 0.0024                      |
| Friction fault     | 0.0038                      | 0.0287                      | 0.2735                      | 0.0043                      |
| Friction fault     | 0.0030                      | 0.0248                      | 0.2746                      | 0.0070                      |
| Unbalance fault    | 0.0026                      | 0.0239                      | 0.2766                      | 0.0025                      |
| Unbalance fault    | 0.0025                      | 0.0182                      | 0.2774                      | 0.0025                      |
Secondly, this method is used to separate more than three different conditions of rotor system.
Table 4 is the training samples taken from experiment test bench, and table 5 is the test samples. The first fault type is friction fault. The second fault type is unbalance. The third type is the normal type. Each type has 10 samples. After training, the program is used to test the test sample. Only one classification of the 12 test samples is incorrect. The result has an accuracy rate of 91.67%.

**Table 4. Spectrums of different running conditions (training samples).**

| Fault type   | Characteristic frequency 1 | Characteristic frequency 2 | Characteristic frequency 3 | Characteristic frequency 4 | Characteristic frequency 5 |
|--------------|---------------------------|----------------------------|---------------------------|---------------------------|---------------------------|
| Friction fault | 0.0265                    | 0.0271                     | 0.0098                    | 0.3569                    | 0.2689                    |
| ...           | ...                       | ...                        | ...                       | ...                       | ...                       |
| Unbalance fault | 0.0269                    | 0.0275                     | 0.01                      | 0.3603                    | 0.2709                    |
| ...           | ...                       | ...                        | ...                       | ...                       | ...                       |
| Normal type   | 0.027                      | 0.0277                     | 0.01                      | 0.363                     | 0.2726                    |

**Table 5. Spectrums of different running conditions (test samples).**

| Characteristic frequency | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    |
|--------------------------|------|------|------|------|------|------|------|------|------|
|                          | 0.0266 | 0.0272 | 0.0099 | 0.3575 | 0.2691 | 0.0031 | 0.0252 | 0.2754 | 0.006  |
|                          | 0.0264 | 0.0271 | 0.0098 | 0.3569 | 0.2687 | 0.0038 | 0.0292 | 0.2742 | 0.0037 |
|                          | 0.0269 | 0.0274 | 0.0099 | 0.358  | 0.2684 | 0.003  | 0.0248 | 0.2746 | 0.007  |
|                          | 0.0267 | 0.0273 | 0.0099 | 0.3575 | 0.2682 | 0.0038 | 0.0287 | 0.2735 | 0.0043 |
|                          | 0.027  | 0.0276 | 0.01   | 0.361  | 0.2706 | 0.0025 | 0.0234 | 0.2757 | 0.0021 |
|                          | 0.0273 | 0.0278 | 0.01   | 0.3631 | 0.272  | 0.0025 | 0.0185 | 0.2761 | 0.0026 |
|                          | 0.0269 | 0.0275 | 0.01   | 0.3603 | 0.2707 | 0.0026 | 0.0237 | 0.2759 | 0.0026 |
|                          | 0.0074 | 0.0013 | 0.0005 | 0.0192 | 0.2543 | 0.0226 | 0.1155 | 0.456  | 0.1232 |
|                          | 0.0267 | 0.0275 | 0.01   | 0.3625 | 0.2734 | 0.0024 | 0.0181 | 0.2775 | 0.002  |
|                          | 0.0269 | 0.0276 | 0.01   | 0.3644 | 0.2748 | 0.0023 | 0.014  | 0.2779 | 0.002  |
|                          | 0.0269 | 0.0275 | 0.01   | 0.3625 | 0.2733 | 0.0024 | 0.0181 | 0.2773 | 0.002  |
|                          | 0.0269 | 0.0276 | 0.01   | 0.3644 | 0.2748 | 0.0023 | 0.014  | 0.2779 | 0.002  |

Then this SVM classification method is used to separate the field data which are taken from the 4th reactor coolant pump of Qinshan nuclear power plant. The training samples are shown in table 6, ten samples for each fault. The test samples are shown in table 7, through the SVM classification method, the result of classification are misalignments fault, cracked fault, unbalance fault and unbalance fault. The result could fully consistent with the type of fault.
### Table 6. Fault feature samples of field data (training samples).

| Fault Type       | Characteristic frequency 1 | Characteristic frequency 2 | Characteristic frequency 3 | Characteristic frequency 4 | Characteristic frequency 5 |
|------------------|-----------------------------|----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Misalignments    | 0.1102                      | 0.0231                     | 0.0035                      | 0.0774                      | 0.2045                      |
| Cracked fault    | 0.0075                      | 0.0077                     | 0                           | 0.0584                      | 0.3428                      |
| Unbalance fault  | 0.0318                      | 0.009                      | 0.0017                      | 0.0717                      | 0.3931                      |
|                  | ...                         | ...                        | ...                         | ...                         | ...                         |

### Table 7. Fault feature samples of field data (test samples).

| Characteristic frequency 1 | Characteristic frequency 2 | Characteristic frequency 3 | Characteristic frequency 4 | Characteristic frequency 5 |
|-----------------------------|-----------------------------|----------------------------|-----------------------------|-----------------------------|
| 0.0946                      | 0.0157                      | 0.0035                     | 0.0805                      | 0.0969                      |
| 0.0666                      | 0.0119                      | 0.0196                     | 0.1436                      | 0.2244                      |
| 0.0309                      | 0.0082                      | 0.0017                     | 0.0679                      | 0.3838                      |
| 0.0315                      | 0.0088                      | 0.0019                     | 0.0694                      | 0.3825                      |

| Characteristic frequency 6 | Characteristic frequency 7 | Characteristic frequency 8 | Characteristic frequency 9 |
|-----------------------------|-----------------------------|----------------------------|----------------------------|
| 0.0214                      | 0.4999                      | 0.1354                     | 0.0521                     |
| 0.0132                      | 0.0891                      | 0.3081                     | 0.1236                     |
| 0.0143                      | 0.044                       | 0.4191                     | 0.0301                     |
| 0.0131                      | 0.0467                      | 0.4173                     | 0.0288                     |

### Table 8. Samples of different running conditions disposed through KPCA (Training samples).

| Characteristic frequency 1 | Characteristic frequency 2 | Characteristic frequency 3 | Characteristic frequency 4 |
|-----------------------------|-----------------------------|----------------------------|-----------------------------|
| 0                           | -0.0648                     | -0.0738                    | 0.1871                      |
| 1                           | 0.0745                      |                            |                            |
2 -0.0044 -0.0703 0.1647 0.234

3 -0.0443 -0.0716 0.1976 0.184

Table 9. Samples of different running conditions disposed through KPCA (Test samples).

| Characteristic | Characteristic | Characteristic | Characteristic |
|----------------|----------------|----------------|----------------|
| frequency 1    | frequency 2    | frequency 3    | frequency 4    |
| 0.3606         | -0.0826        | -0.046         | 0.0243         |
| 0.0939         | -0.1387        | 0.1366         | 0.1161         |
| -0.0309        | -0.0772        | 0.2032         | 0.1805         |
| -0.0285        | -0.0772        | 0.2018         | 0.1779         |

To reduce the computational complexity of the fault classifier, and improve the separability of the failure mode, it is necessary to extract the feature from the fault feature vectors. Table 8 and table 9 are characteristic tables of K-PCA, the data of the table 8 are the field data disposed through K-PCA. Each type of table 8 also has ten training samples Table 9 is the test sample. The characteristic dimension of the vector is decreased from 9 dimensions to 4 dimensions. So the information of calculation could be decreased and the speed could be increased. Then the SVM is used to separate the test samples and analyze the conditions of the reactor coolant pump rotor system, the accuracy rate of this test sample is 100%.

4. Software of reactor coolant pump condition monitoring and analysis based on SVM

After the analysis of the experiment data and field data, the software for reactor coolant pump condition monitoring and analysis was designed. This software could not only test the online data, but also find the pump mechanical fault automatically. The following figures are about this software.

Then this software was installed on the reactor plant control system of Qinshan nuclear power plant in China. In the past 6 months, the system worked properly. In March 2011, a non-normal system temperature rise caused by drain valve damage was monitored and analyzed before the temperature reached the warning level.

Figure 8. System login interface.

Figure 9. Multi-band filter of the system.
5. Conclusion
This paper has presented a new condition monitoring and analysis method of reactor coolant pump based on support vector machine. SVM is an artificial intelligence method based on the principle of statistical learning theory.

Through this SVM method, the system condition characteristic of the reactor coolant pump was extracted and analyzed. The data are disposed through multi-band FIR filter to eliminate the noise and useless frequency. Then the characteristics of the system condition are improved by kernel principal component analysis, the SVM based on K-PCA decreased the dimension of the vector and increased the calculation speed and accuracy. This method is used as both two-kind classifier and multiple classifier, it could separate the different running conditions successfully.

After that, analysis software based on SVM for Qinshan nuclear power plant was proposed. This software could both monitor and analyze the system current condition. Through this software, a failure caused by drain valve damage was monitored and analyzed before a huge damage was done in March 2011.

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