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Adaptive threshold method for intelligent ship power system equipment

GAO Zeyu, ZHANG Peng, ZHANG Boshen, ZHANG Yuewen, SUN Peiting*

Marine Engineering College, Dalian Maritime University, Dalian 116026, China

Abstract: [**Objective**] In light of problems such as the untimely condition monitoring and alarm, excessively large threshold bandwidth, and inaccurate condition evaluation parameters of intelligent ship power system equipment, an adaptive threshold method is proposed to monitor, alarm, and evaluate the conditions of such equipment. [**Methods**] First, a simulated annealing algorithm is used to optimize the support vector regression (SVR) prediction model and simulate the general state characteristic parameters of the power system equipment. Then, after the normal transformation of the modeling residual, in combination with the sliding time window, the adaptive threshold model is constructed. Finally, the exhaust gas temperature of the ship's main propulsion diesel engine is selected as the research object for example verification. [**Results**] The results show that compared with the traditional fixed threshold, the adaptive threshold model has more compact bandwidth and good adaptability, and can identify abnormal phenomena in power system equipment in advance. [**Conclusions**] This method improves the efficiency and threshold accuracy of monitoring and alarm systems and provides an effective means of early fault diagnosis and a more accurate basis for system status evaluation.

Key words: intelligent ships; adaptive threshold; support vector regression (SVR); simulated annealing; state characteristic parameters

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0 Introduction

As an important part of an intelligent ship, an intelligent engine room needs to use the monitoring parameters of equipment states in the ship engine-room system to give an alarm about anomalies and intelligently analyze and evaluate its operation and health conditions. Thus, decision-making support can be provided for the use, manipulation, maintenance, and management of system equipment [1].

At present, fixed thresholds are generally used for judgment in the equipment-state evaluation and monitoring alarm of a ship power system. The fixed thresholds can be determined according to delivery tests, real-ship tests, and empirical analysis. Common methods for threshold determination include confidence-interval based, mean-variance based [2], and threshold corridor based methods [3]. Over-high thresholds will reduce alarm sensitivity, disenabling normal operation of alarm systems. Too-low thresholds will increase false alarm rates, resulting in excessive alarms. In addition, support-vector-machine based prediction models have been widely used in state monitoring [4], and intelligent diagnosis systems of ship power plants have also been developed and applied to state evaluation of ships [5]. However, none of the above work can adaptively update thresholds according to actual situation of equipment in operation. This will cause false alarms from monitoring systems and judgment deviations of op-

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Authors: GAO Zeyu, male, born in 1994, master degree candidate. Research interests: intelligent operation and maintenance of ships. E-mail: 13309865896@163.com

ZHANG Peng, male, born in 1983, master, lecturer. Research interests: intelligent operation and maintenance of ships. E-mail: zhangpenglunji@dlmu.edu.cn

***Corresponding author:** ZHANG Peng

erational benchmarks and parameters. Thus, accurate intelligent control and auxiliary decision-making will fail.

In response to the above problem and actual requirements of intelligent ships, this paper proposed an adaptive-threshold model combining a support-vector-regression (SVR) -based prediction model with sliding time window. First, a simulated annealing (SA) algorithm was used to optimize the hyper parameters C and g in the SVR model, and on this basis, conventional state characteristic parameters of ship power-system equipment were modeled for prediction. Then, modeling residuals were transformed into normal data through Johnson distribution, and adaptive thresholds were calculated by using a sliding time window in order for monitoring alarm and state evaluation of power-system equipment of intelligent ships. This method can determine adaptive thresholds according to real-time state parameters of equipment in operation, so as to reduce threshold bandwidth and false alarm rates. Thus, the accuracy of state evaluation of ship power-system equipment can be improved.

1 Adaptive-threshold model

1.1 State characteristic parameters

As an important part of a ship engine room, an intelligent-ship power system mainly includes a main propulsion diesel engine, a diesel genset, propulsion shafting, a fuel system, a lubricating oil system, and a cooling water system. Conventional state characteristic parameters of power-system equipment include pressure, temperature, flow, and rotational speed. However, for vibration-related data, due to their over-high frequency and the insufficient timeliness of the model in this paper, such data are not considered. Operation states of equipment can be described by a single-parameter or multi-parameter method. For example, operation states of the main propulsion diesel engine can be described by the single parameter of exhaust temperature, while those of the cooling system are described by multiple parameters including pressure, pressure difference, and temperature. Due to complex and changeable working conditions, ship power systems are affected by their own inherent uncertainties and uncertainties caused by loads, manipulation, and working-environment changes. As a result, thresholds of conventional state characteristic parameters of intelligent-ship power-system equipment vary in a wide range. Thus, the use of fixed thresholds for monitoring alarm and state evaluation in such a case will lead to a great evaluation deviation. In order to solve this problem, this paper selected conventional state characteristic parameters of intelligent-ship power systems as the sample set, and then analyzed the adaptive-threshold method.

1.2 SVR-based prediction model

SVR is developed on the basis of support vector machine (SVM). Considering the influences of multiple factors like degradation and working conditions on samples, SVR is of strong robustness and suitable for regression prediction. In this paper, an ε-SVR model is used to predict the state parameters of an intelligent-ship power system [6-7].

Suppose that a training sample set $\boldsymbol{D}$ and a function set $\boldsymbol{F}$ are given as follows:

$$\boldsymbol{D} = \{(x_i,\ y_i)|x_i \in \mathbf{R}^n,\ y_i \in \mathbf{R},\ i = 1,\ 2, \cdots, n\} \tag{1}$$

$$\boldsymbol{F} = \left\{ f \middle| f(x) = \boldsymbol{w}^{\mathrm{T}} \cdot x_i + b \right\} \tag{2}$$

where x_i and y_i are the i^{th} input and output sample data, respectively; $\mathbf{R}$ is a set of real numbers; n is the sample dimension; $f(x)$ is a nonlinear regression function; $\boldsymbol{w}$ is a weight vector; $\boldsymbol{w}^{\mathrm{T}}$ is the transpose of the weight vector; b is an offset.

The solving of a regression problem is to find a function $f(x) \in \boldsymbol{F}$, so that the error between the value $f(x)$ of the function at a training sample x ($x \in \mathbf{R}^n$) and the expected value y of the sample is less than or equal to the given deviation ε.

The following planning problem is optimized by selecting the weight vector $\boldsymbol{w}$ and the offset b:

$$\begin{cases} \min_{w,b,\xi_i,\xi_i^*} & \dfrac{1}{2}\|\boldsymbol{w}\|^2 + C\displaystyle\sum_{i=1}^{n}(\xi_i + \xi_i^*) \\ & (\boldsymbol{w}^{\mathrm{T}} \cdot x_i + b) - y_i \leqslant \varepsilon + \xi_i \\ \text{s.t.} & y_i - (\boldsymbol{w}^{\mathrm{T}} \cdot x_i + b) \leqslant \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \geqslant 0, \quad i = 1, 2, \cdots, n \end{cases} \tag{3}$$

Where ξ_i and ξ^*_i are slack variables; $C > 0$ is a penalty coefficient, indicating the degree of punishment for samples beyond ε.

Its dual problem can be derived by setting a kernel function $K(x_i, x_j)$ and using Lagrangian multipliers:

$$\begin{cases} \max & -\dfrac{1}{2}\displaystyle\sum_{i,j=1}^{n}(a_i^* - a_i)(a_j^* - a_j)K(x_i, x_j) - \\ & \displaystyle\sum_{i=1}^{n}(a_i^* - a_i)y_i + \varepsilon\sum_{i=1}^{n}(a_i^* + a_i) \\ \text{s.t.} & \displaystyle\sum_{i=1}^{n}(a_i^* - a_i) = 0 \\ & 0 \leqslant a_i^*, a_i \leqslant C \quad i, j = 1, 2, \cdots, n \end{cases} \tag{4}$$

where a_i and a_j are the Lagrangian multipliers corresponding to the i^{th} and j^{th} variables, respectively; a^*_i and a^*_j are optimal Lagrangian multipliers; x_j is the j^{th} sample variable during the training.

The weight vector $\boldsymbol{w}$ and the offset b can be solved after a_i and a^*_i are calculated. Then, the nonlinear regression function can be obtained as follows.

$$f(x)=\sum_{i=1}^{n}(a_i^*-a_i)K(x_i,x_j)+b \tag{5}$$

In this paper, an SVR-based prediction model is established by loading the LIBSVM toolbox in Matlab. Specific steps for the algorithm of the SVR-based prediction model are as follows [8]:

1) Select monitoring data of conventional state characteristic parameters of ship power-system equipment as a sample set. Then, divide the set into a training set and a prediction set according to the time sequence.

2) Preprocess the data. Normalize data in both the training and prediction sets, mapping the data to [0, 1]. Specifically, the normalization function is given by

$$x'=\frac{x-x_{\min}}{x_{\max}-x_{\min}} \tag{6}$$

where x' is a normalized sample datum; $x_{\min}$ and $x_{\max}$ are the minimum and maximum of the data set, respectively.

3) Determine the kernel function. The selection of a kernel function must satisfy the Mercer's condition (any positive semi-definite function can be used as a kernel function). In this paper, a Gaussian radial basis function (RBF) is selected:

$$K(x_i,x_j)=\exp\{-\|x_i-x_j\|^2/(2\sigma^2)\} \tag{7}$$

where σ is kernel width.

4) Select and optimize the hyper-parameters C (the penalty coefficient) and g (the value of σ in the kernel function) in SVR.

5) Train the training set with the optimized hyper-parameters C and g.

6) Verify the SVR-based prediction model with the test sample set.

1.3 Optimization of hyper-parameters by SA

From Section 1.2, the core of the SVR model is to select the penalty coefficient C and the kernel-function parameter g. In this paper, an SA algorithm is used to optimize the hyper-parameters C and g of ε-SVR. Metropolis criterion is the key to the convergence of the SA algorithm to a global optimal solution. Specifically,

$$p=\begin{cases}1, & \text{if } S(x_{\text{new}})<S(x_{\text{old}})\\ \exp\left(-\dfrac{S(x_{\text{new}})-S(x_{\text{old}})}{T}\right), & \text{if } S(x_{\text{new}})>S(x_{\text{old}})\end{cases} \tag{8}$$

where p is the probability of accepting a new solution; x_{new} is a new state; $S(x_{\text{new}})$ is the energy of a new solution; x_{old} is the current state; $S(x_{\text{old}})$ is the energy of the current solution; T is the current temperature.

In updating the optimal solution to the objective function by iteration, if the energy of a new solution is lower than that of the current solution, the new solution is accepted directly. Otherwise, the new solution is not directly rejected. Instead, the solution inferior to the current one is accepted with a certain probability. Thus, the algorithm can jump out of the local optimal solution and finally obtain a global optimal one [9]. As shown in Fig. 1, it is assumed that with an initial solution at Point A in the figure, the algorithm converges to a local optimal solution Point B along the iterative direction. However, instead of terminating here, the program accepts a solution (Point C) inferior to Point B with a certain probability according to the Metropolis criterion. Thus, it jumps out of the local optimal solution and finally converges to the global optimal solution at Point D.

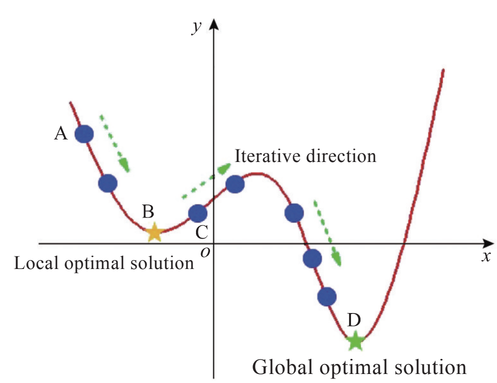


Fig. 1 Optimization diagram of SA algorithm

Specific steps for implementing the SA algorithm are as follows:

1) Initialization. Select an initial temperature T_0 high enough, and let $T=T_0$. Then, randomly select an initial solution S_1 as the starting point of algorithm iteration. Besides, set the maximum number L of iterations at each temperature and the end temperature T_{end}.

2) Randomly generate a new solution S_2 with regard to the current temperature T and the number k of iterations (where $k=1, 2, ..., L$).

3) Calculate the increment $\Delta f=f(S_2)-f(S_1)$, where $f(S_1)$ and $f(S_2)$ are evaluation functions of S_1 and S_2,

respectively.

4) If $\Delta f < 0$, accept S_2 as the new current solution, and let $S_1 = S_2$. If the probability p=exp($-\Delta f/T$) is greater than a random number rand(0, 1) between 0 and 1, replace S_1 with S_2 as the new current solution, and namely, let S_1=S_2. Otherwise, retain the current solution S_1.

5) Cooling. Set a cooling rate q, as well as temperatures T_k and T_{k+1} of the k^{th} and $(k+1)^{\text{th}}$ iterations. Specifically, $T_{k+1} = q \times T_k$. If $T_{k+1} < T_{\text{end}}$, stop the iteration to output the current solution as the global optimal solution, and then terminate the algorithm. Otherwise, return to step 2) to repeat steps 2)−5).

Fig. 2 shows the flow chart of the algorithm. The SA algorithm is irrelevant to the selected initial value. According to the Metropolis criterion, the algorithm can accept a deteriorated solution with a certain probability during the search, thus jumping out of a local optimal solution. In addition, this algorithm has asymptotic convergence and a relatively clear structure [10]. Therefore, parameter optimization of the ε-SVR based prediction model by using the SA algorithm can effectively improve the prediction accuracy of the model.

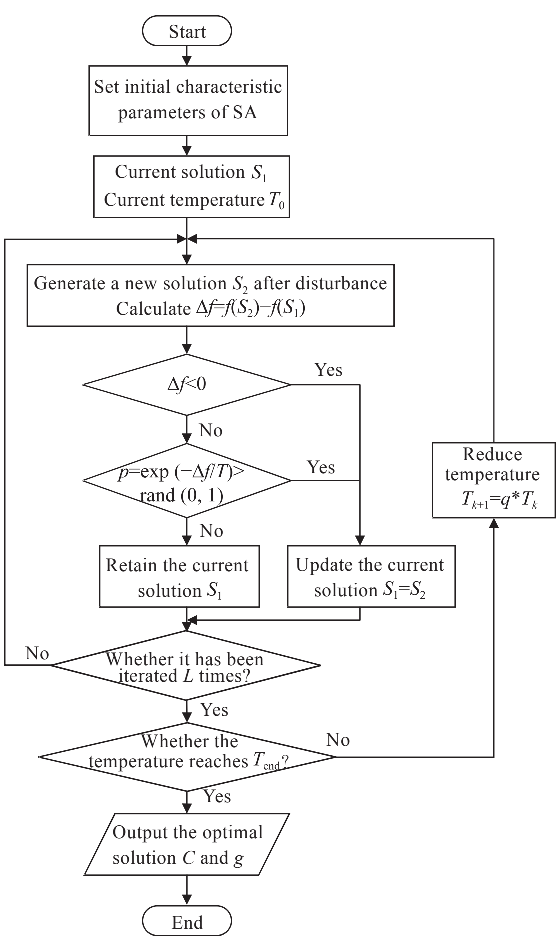


Fig. 2 Flow chart of the SA algorithm

1.4 Normal transformation of residuals

According to the residuals between real and predicted data calculated by the SA-SVR based model, evaluation errors of operation states of intelligent-ship power-system equipment can be obtained, which are shown in some unknown distributions. Therefore, it is necessary to normalize residuals, so that adaptive thresholds can be calculated on the premise that residuals conform to the hypothesis of normal distribution [11]. In this paper, Johnson distribution is used for normal transformation of the modeling residual variable X. Thus, three families S_{B}, S_{L}, and S_{U} of distribution (subscripts B, L, and U denote bounded, lognormal, and unbounded distributions, respectively) are established, as listed in Table 1. In Table 1, h is standard normal distribution; γ, η and δ, λ are position and scale parameters of a Johnson curve, respectively.

Table 1 Johnson distribution system

Family of distribution	Normal transformation	Parameter condition	X condition
S_{B}	$h=\gamma+\eta\cdot\ln\left(\dfrac{X-\delta}{\lambda+\delta-X}\right)$	$\eta,\lambda>0,-\infty<\gamma<\infty,$ $-\infty<\delta<\infty$	$\delta<X<\delta+\lambda$
S_{L}	$h=\gamma+\eta\cdot\ln(X-\delta)$	$\eta>0,-\infty<\gamma<\infty,$ $-\infty<\delta<\infty$	$X>\delta$
S_{U}	$h=\gamma+\eta\cdot\sinh^{-1}\left(\dfrac{X-\delta}{\lambda}\right)$	$\eta,\lambda>0,-\infty<\gamma<\infty,$ $-\infty<\delta<\infty$	$-\infty<X<\infty$

With the functions in Table 1, the modeling residual variable X can be transformed into standard normal distribution h. The specific steps are as follows:

1) Select a random positive number z according to the method proposed by Slifker et al. [12].

2) According to the probability density formula $\Phi(\zeta)=\int_{-\infty}^{\zeta}\dfrac{1}{\sqrt{2\pi}}\mathrm{e}^{-u^2/2}\mathrm{d}u$ of a standard normal distribution, calculate probability density $\Phi(\zeta_J)$ of four symmetric and equidistant standard normal deviations $\zeta_J=\{-3z,-z,z,3z\}$, where J=1, 2, 3, 4, and u is a random variable.

3) On the basis of the relation $i_J = s*\Phi(\zeta_J)+0.5$, calculate the i_J^{th} observed value of the samples, where s is the total number of samples.

4) Fit the sample data linearly to obtain the fitting function $g(i)$. Then, calculate the quantiles $X_{i_J}=g(i_J)$ of the sample. The quantiles are set as follows: $X_{-3z}=X_{i_1}$ $X_{-z}=X_{i_2}$ $X_z=X_{i_3}$, and $X_{3z}=X_{i_4}$

5) Let $m=X_{3z}-X_z$ $n=X_{-z}-X_{-3z}$, and $p=X_z-X_{-z}$. Then, set the quantile ratio as $QR=mn/p^2$.

6) Distinguish the three families in the Johnson distribution system by using the quantile ratio QR. Distinguishing criteria are as follows: In the case of

$QR < 1$, select S_B distribution; in the case of $QR = 1$, select S_L distribution; in the case of $QR > 1$, select S_U distribution.

7) After the selection of distribution forms, calculate specific parameters of the three transformed types with the following formulas.

(1) For S_B distribution:

$$\eta = z\left\{\operatorname{arcosh}\left[\frac{1}{2}\left[\left(1+\frac{p}{m}\right)\left(1+\frac{p}{n}\right)\right]^{\frac{1}{2}}\right]\right\}^{-1}$$

$$\gamma = \eta \operatorname{arsinh}\left\{\left(\frac{p}{n}-\frac{p}{m}\right)\left[\left(1+\frac{p}{m}\right)\left(1+\frac{p}{n}\right)-4\right]^{\frac{1}{2}}\left[2\left(\frac{p^2}{mn}-1\right)\right]^{-1}\right\}$$

$$\lambda = p\left\{\left[\left(1+\frac{p}{n}\right)\left(1+\frac{p}{m}\right)-2\right]^2-4\right\}^{\frac{1}{2}}\left(\frac{p^2}{mn}-1\right)^{-1}$$

$$\delta = \frac{X_z+X_{-z}}{2}-\frac{\lambda}{2}+p\left(\frac{p}{n}-\frac{p}{m}\right)\left[2\left(\frac{p^2}{mn}-1\right)\right]^{-1} \tag{9}$$

(2) For S_L distribution:

$$\eta = \frac{2z}{\ln(m/p)},\quad \gamma = \eta \ln\left[\frac{m/p-1}{p(m/p)^{\frac{1}{2}}}\right]$$

$$\delta = \frac{X_z-X_{-z}}{2}-\frac{p}{2}\left(\frac{m/p+1}{m/p-1}\right) \tag{10}$$

(3) For S_U distribution:

$$\eta = 2z\left\{\operatorname{arcosh}\left[\frac{1}{2}\left(\frac{m}{p}+\frac{n}{p}\right)\right]\right\}^{-1}$$

$$\gamma = \eta \operatorname{arsinh}\left\{\left(\frac{n}{p}-\frac{m}{p}\right)\left[2\left(\frac{mn}{p^2}-1\right)^{\frac{1}{2}}\right]^{-1}\right\}$$

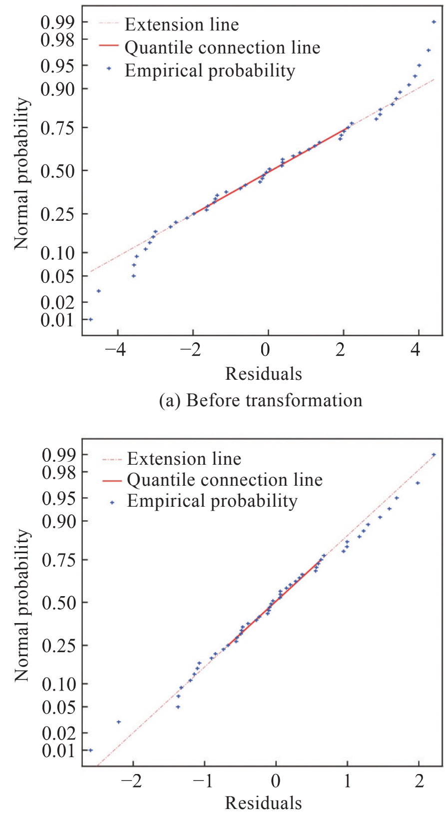
$$\lambda = 2p\left(\frac{mn}{p}-1\right)^{\frac{1}{2}}\left[\left(\frac{m}{p}+\frac{n}{p}-2\right)\left(\frac{m}{p}+\frac{n}{p}+2\right)\right]^{\frac{1}{2}}$$

$$\delta = \frac{X_z+X_{-z}}{2}+p\left(\frac{n}{p}-\frac{m}{p}\right)\left[2\left(\frac{m}{p}+\frac{n}{p}-2\right)\right]^{-1} \tag{11}$$

8) According to the selected distribution forms, calculate h after normal transformation by using Table 1.

After the normal transformation of residuals, a KS-test (Kolmogorov-Smirnov test) can be carried out in Matlab. The output verification result of 0 indicates that the data after the transformation conform to standard normal distribution. Fig. 3 and Fig. 4 show normal probability plots and frequency distribution histograms of residuals before and after normal transformation, respectively.

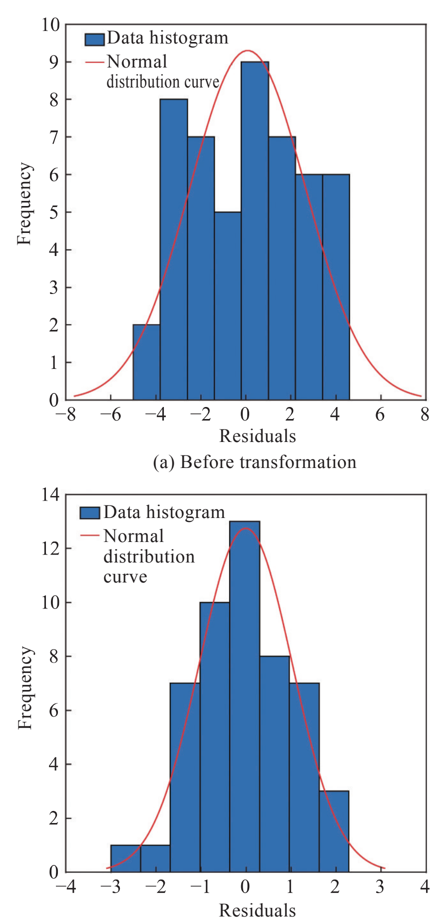
In Fig. 3, the empirical probability of each residual is plotted with a blue "+" mark. A red solid reference line is used to connect the first and third quartiles of the data, and a red dotted reference line is used to extend the solid line to both ends of the data. If all the sample points are near the red reference line, it is assumed that the samples obey a normal distribution. If the samples do not obey a normal distribution, the "+" marks will form a curve. From



(a) Before transformation

(b) After transformation

Fig. 3 Normal probability plot



(a) Before transformation

(b) After transformation

Fig. 4 Frequency distribution histogram

Fig. 3, before the normal transformation of residuals, the "+" marks in the normal probability plot are not distributed along the red reference line, forming a curve. By contrast, after the normal transformation, the blue "+" marks are close to the red reference line. From Fig. 4, the frequency distribution histogram of residuals after normal transformation is close to the red normal-distribution curve, which verifies the feasibility of normal transformation with the method in this paper.

1.5 Realization of adaptive thresholds

After the normal transformation of residuals, thresholds can be calculated according to the formulas in Table 1. Specific steps are as follows.

1) Determine the threshold interval $-v \leqslant h \leqslant v$ of the standard normal distribution h according to the Pauta criterion, where v is the maximum threshold.

2) According to the selected distribution forms, calculate thresholds of X by using the following formulas.

(1) For S_B distribution:

$$\frac{e^{\left(\frac{-v-\gamma}{\eta}\right)}(\lambda+\delta)+\delta}{e^{\left(\frac{-v-\gamma}{\eta}\right)}+1} \leqslant X \leqslant \frac{e^{\left(\frac{v-\gamma}{\eta}\right)}(\lambda+\delta)+\delta}{e^{\left(\frac{v-\gamma}{\eta}\right)}+1} \tag{12}$$

(2) For S_L distribution:

$$e^{\left(\frac{-v-\gamma}{\eta}\right)}+\delta \leqslant X \leqslant e^{\left(\frac{v-\gamma}{\eta}\right)}+\delta \tag{13}$$

(3) For S_U distribution:

$$\lambda \sinh\left(\frac{-v-\gamma}{\eta}\right)+\delta \leqslant X \leqslant \lambda \sinh\left(\frac{v-\gamma}{\eta}\right)+\delta \tag{14}$$

3) Thresholds of operation parameters of intelligent-ship power-system equipment are obtained by substituting $X = X_{\text{test}} - X_{\text{SVM}}$ into step 2), where X_{test} and X_{SVM} are test and predicted data, respectively.

(1) For S_B distribution:

$$\frac{e^{\left(\frac{-v-\gamma}{\eta}\right)}(\lambda+\delta)+\delta}{e^{\left(\frac{-v-\gamma}{\eta}\right)}+1} + X_{\text{SVM}} \leqslant X_{\text{test}} \leqslant \frac{e^{\left(\frac{v-\gamma}{\eta}\right)}(\lambda+\delta)+\delta}{e^{\left(\frac{v-\gamma}{\eta}\right)}+1} + X_{\text{SVM}} \tag{15}$$

(2) For S_L distribution:

$$e^{\left(\frac{-v-\gamma}{\eta}\right)}+\delta+X_{\text{SVM}} \leqslant X_{\text{test}} \leqslant e^{\left(\frac{v-\gamma}{\eta}\right)}+\delta+X_{\text{SVM}} \tag{16}$$

(3) For S_U distribution:

$$\begin{aligned} &\lambda \sinh\left(\frac{-v-\gamma}{\eta}\right)+\delta+X_{\text{SVM}} \leqslant \\ &X_{\text{test}} \leqslant \lambda \sinh\left(\frac{v-\gamma}{\eta}\right)+\delta+X_{\text{SVM}} \end{aligned} \tag{17}$$

With the above flow chart of threshold calculation, a sliding time window is introduced to realize adaptive thresholds. First, suppose that there is a window containing s modeling residuals, and normalize these residuals. Then, calculate the thresholds according to the above method, and take their average as the threshold at this time. Finally, without changing the total number of data in the window, slide the window backward frame by frame, and repeat the above calculation to obtain the threshold at each moment in turn. Thus, the self-adaptation of thresholds is realized. As window size will directly affect accuracy of thresholds and sensitivity to abnormal data, it is necessary to adjust the window size according to actual working conditions [3,13].

After the prediction model is established according to historical data of state monitoring, training and prediction samples of the model can be updated continuously with real-time state-monitoring measurements based on the simulated queue tail interpolation. Moreover, the calculation of the current model can be repeated. As the RBF-based ε-SVR prediction model has taken into account effects of degradation and different working conditions during its establishment, adaptive thresholds can be calculated in real-time without the necessity of model updating.

Fig. 5 shows the flow chart of establishing the adaptive-threshold model for power-system equipment of an intelligent ship.

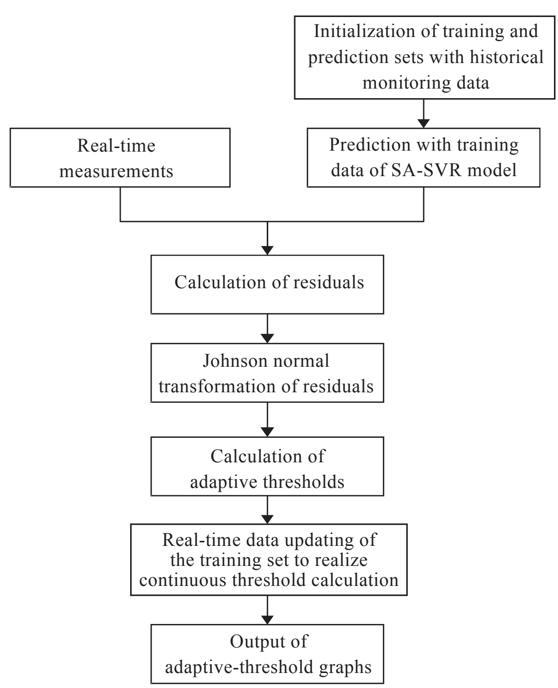


Fig. 5 Flow chart of the dynamic adaptive threshold model

2 Verification of adaptive threshold model

2.1 Method verification

In this paper, the method was verified by using state characteristic parameters of power-system equipment of a ship in normal operation. During parameter selection, an over-large sliding-window size, that is, excessive data in a window, will weaken the influence of a single group of data on calculation results and then reduce sensitivity of the model. As a result, parameter changes reflected by thresholds will be delayed accordingly. On the other hand, a too-small sliding-window size will amplify the influence of random errors. This may make the model excessively sensitive, thus reducing the accuracy of evaluation results. With comprehensive consideration, the window size in this paper was set to 50 to balance the requirements on timeliness of evaluation results and sensitivity of the model. Fig. 6 shows the calculated adaptive thresholds.

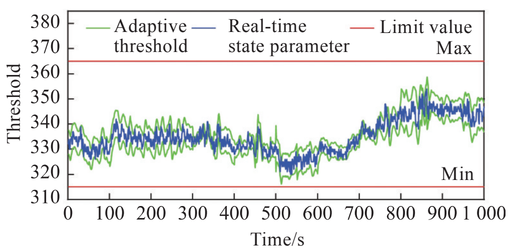


Fig. 6 Verification of dynamic adaptive threshold model

In Fig. 6, the red solid lines refer to traditional fixed-threshold lines of intelligent-ship power-system equipment; the blue solid line refers to a real-time state-parameter curve; the green solid lines refer to adaptive-threshold curves. According to Fig. 6, the adaptive thresholds are more consistent with the real-time state parameters of the ship power-system equipment than the traditional fixed thresholds. With a more compact bandwidth of thresholds, threshold sensitivity can be improved. In terms of monitoring alarm, the defect of failing to give an alarm in the case of equipment anomalies caused by over-high fixed thresholds can be overcome. This is conducive to optimizing maintenance and management of ship power-system equipment. Moreover, with improved accuracy, adaptive thresholds can reflect the actual operation of ship power-system equipment more accurately. Thus, a more reasonable and effective reference basis can be provided for state evaluation and auxiliary decision-making of intelligent ship power-system equipment.

2.2 Verification of abnormal data

Operation states of the main propulsion diesel engine can be described by a single parameter, that is, "exhaust temperature". Abnormal exhaust temperatures of the main propulsion diesel engine of a ship were used as verification data to verify the established adaptive-threshold model. Specifically, the real-ship data were collected with a period of 1 s. Fig. 7 shows the results.

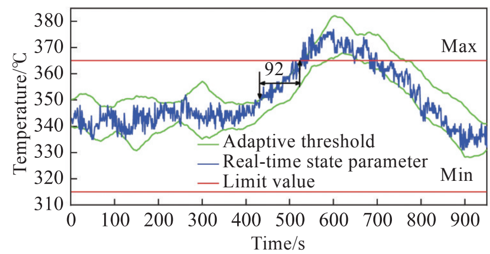


Fig. 7 Verification of abnormal data in the dynamic adaptive threshold model

From Fig. 7, compared with the traditional fixed-threshold method, in the case of abnormal rises in exhaust temperature of the main engine, the adaptive-threshold method can successfully detect the anomalies and give alarms 92 s in advance. Therefore, this method overcomes the disadvantage that the fixed-threshold method is insensitive to abnormal working conditions of power-system equipment, and improves the efficiency of an intelligent-ship monitoring alarm system. Thus, it can provide more accurate data for system state evaluation and auxiliary decision-making.

3 Conclusions

An adaptive-threshold model for conventional state characteristic parameters of intelligent-ship power-system equipment was presented in this paper. First, during the adaptive optimization of thresholds, an SA algorithm was used to optimize the SVR-based prediction model to predict state characteristic parameters. Then, residuals between predicted and actual data were calculated, and on this basis, adaptive thresholds were calculated in combination with the Johnson distribution system. According to the verification results based on real-ship operation data, as reference thresholds, adaptive thresholds have narrower bandwidth than traditional fixed thresholds do. Thus, the adaptive-threshold method is of better adaptability in the case of equipment anomalies and able to give earlier alarms, providing more decision-making time for ship managers. In addition, adaptive thresholds are more closely related to real-time monitoring data, and their changing trends can be used as a reference basis for state evaluation and life prediction of intelligent ships.

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智能船舶动力系统设备的自适应阈值方法

高泽宇，张鹏*，张博深，张跃文，孙培廷

大连海事大学 轮机工程学院，辽宁 大连 116026

摘　要：[目的] 针对智能船舶动力系统设备的状态监控报警不及时、阈值带宽过大、状态评估参数不准确等问题，提出自适应阈值的确定方法，用以对动力系统设备进行监控报警和状态评估。[方法] 首先，采用模拟退火算法优化回归支持向量机（SVR）预测模型，对动力系统设备的常规状态特征参数进行建模；然后，对建模残差进行正态转化，并结合滑动时间窗来构建自适应阈值模型；最后，选取某船舶主推进柴油机的排烟温度作为研究对象进行实例验证。[结果] 研究结果表明，相较于传统固定阈值，自适应阈值模型的带宽更为紧凑，具有良好的自适应性，能够提前识别动力系统设备的异常现象。[结论] 所提方法提高了监控报警系统的效率和阈值精度，可为早期故障诊断和系统状态评估提供更准确的依据。

关键词：智能船舶；自适应阈值；回归支持向量机；模拟退火；状态特征参数