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Research on Cyclic Time Domain Extrapolation of Diesel Engine Crankshaft Load Spectrum Based on SVR Model

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Abstract. The load spectrum is primarily used to provide a dynamic raw input of a basic load change to the component for simulation calculations or fatigue tests of fatigue life. In the load spectrum compilation of engine crankshaft, in order to preserve the influence of load sequence effect on fatigue damage during extrapolation and improve the accuracy of time domain extrapolation, this paper proposes a cyclic time domain extrapolation method based on SVR model. The research results show that the machine learning model has good learning ability and generalization ability, and the time domain extrapolation method can better realize the expansion of the measured samples of the crankshaft.

1. Introduction
The load spectrum is primarily used to provide a dynamic raw input of a basic load change to the component for simulation calculations or fatigue tests of fatigue life [1, 2]. The real vehicle test is the most direct source of the crankshaft load spectrum. However, due to limitations in test conditions and time and economic cost constraints, long-term load measurements cannot be achieved. This requires extrapolation of the measured load to further expand the sample size.

With the advent of the era of big data, more and more data with high complexity, strong nonlinearity and multiple sets of dimensions need to be analyzed and processed [3]. From the large number of measured data of engine parameters, it is found that the inherent data relationship of “high gold content” is the basis for analyzing complex data, and the regression prediction analysis of data is an important content for guiding the intrinsic relationship of data to guide practical application. Support vector machine is an effective machine learning method in data mining technology. It is a new tool that relies on optimization methods and spatial transformation to solve machine learning problems (“dimensional disaster” and over-learning, etc.). The cyclic machine learning model is built based on the support vector machine method, and then the time domain extrapolation of the measured load data of the crankshaft is realized.
2. SVR Model Based on Minimal Structural Risk

In essence, machine learning is an approximation of the real model of the problem being studied. Usually an approximate model is assumed, and then the approximate model is gradually approached to the real model according to appropriate principles.

However, it is certain that the real model is unknown and uncertain, so how to measure the degree to which the approximate model approximates the real model is a problem that needs to be considered. The degree of this approximation is defined as risk, which is the starting point of the principle of minimum structural risk.

2.1. Minimal structural risk

Based on the hypothesis of the approximate model, due to the unknown and uncertainty of the real model, the magnitude of the real risk is also unknown and uncertain. In order to achieve the measurement of the real risk, we can start from the known variables to achieve the real risk. The approximation, for example, assumes a classifier model that can implement the sample partitioning function, and constructs a variable that classifies the accuracy of the results. Define this variable as an empirical risk.

On the basis of empirical risk, in order to enable the approximation model to have better generalization and generalization ability, it should be further considered how much the degree of confidence can be accepted in the overall level to accept the approximate model on unknown samples. The degree of confidence is a confidence risk. Therefore, the real risk should include the above two parts. It is necessary to consider the empirical risk to make the model have higher precision for the description of the sample, and also consider the confidence risk to make the model have a good generalization effect, that is, the empirical risk and the confidence risk are simultaneously Minimize and minimize structural risk.

2.2. SVR Model

The SVM algorithm is a machine learning algorithm that takes into account both empirical risk and confidence risk while minimizing [4, 5].

1) For linearly separable cases. That is, the two classification problem. Assume that the training sample set is \((x_1, y_1), \ldots, (x_n, y_n)\), \(x_i, y_i \in \mathbb{R}\). Its optimal classification hyperplane is a straight line \(\omega \cdot x + b = 0\). Then the original question can be expressed as follows:

\[
\begin{align*}
\min & \frac{||\omega||^2}{2} \\
\text{s.t} & \quad y_i(\omega \cdot x_i + b) \geq 1, i = 1, 2, \ldots, l
\end{align*}
\] (1)

Equation (1) is a minimal problem with an inequality constraint. Because for the equality constraint, you can use the Lagrangian method to solve the derivative and extremum points. For the purpose of simplification, the original problem is transformed into the form of the dual problem, that is, the minimization is converted into a maximum, and the inequality constraint is transformed into an equality constraint to be solved, as shown in the equation (2):

\[
\begin{align*}
\max & \quad Q(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \\
\text{s.t} & \quad \sum_{i=1}^{l} \alpha_i y_i = 0, \quad \alpha_i \geq 0
\end{align*}
\] (2)

The original problem is to find an optimal condition that satisfies equation (1); and then it can be transformed into the form of its dual problem, that is, converted into a set of \(\alpha\) values, corresponding to \(L\) samples, with \(L\) alpha values, ie each A sample corresponds to an alpha value, and the goal is to find such a set of \(\alpha\), which can make equation (2) satisfy the constraint at the same time. Suppose now that such and \(\alpha\) has been found. For a new sample, if it needs to predict its category, it can be solved by the expression of the objective equation (3): let \(x\) and each sample of the training set cycle. The inner product is multiplied, then multiplied by a label \(y\), multiplied by the alpha value, plus a threshold \(b\), and finally
the sign function $\text{sgn}$ is used to determine whether it is 1 or -1, and then classified. This is a basic method and principle for using SVM for two classifications.

$$
\begin{align*}
f(x) &= \text{sgn}\left(\sum_{i=1}^{l} \alpha_i^* y_i (x \cdot x_i) + b\right) \\
\omega^* &= \sum_{i=1}^{l} \alpha_i^* x_i y_i, \quad b^* = -\frac{1}{2}\omega^* \cdot (x_r + x_s)
\end{align*}
$$

(3)

2) For nonlinear problems. Extending the SVM to a certain degree of compatibility, fault tolerance is not a strictly linear separable problem, that is, dealing with linear indivisible problems. For the linear indivisible problem, a penalty factor $C$ is introduced, and $C$ is used to control the tolerance limit of sample classification credibility. If $C$ is large, it indicates that we attach great importance to this item, that is, we do not want it to be classified incorrectly. Think about it when you are face-to-face; if $C$ is small, you don't think it's that important. That is, by adjusting the size of $C$, the tolerance for abnormal samples is adjusted, as shown in equation (4):

$$
\begin{align*}
&\min \frac{1}{2}||\omega||^2 + C \sum_{i=1}^{l} \xi_i \\
&\text{s.t. } y_i(\omega \cdot x_i + b) \geq 1 - \xi_i \quad i = 1, 2, \ldots, l, \quad \xi_i > 0
\end{align*}
$$

(4)

The conversion to a dual problem is shown in equation (5):

$$
\begin{align*}
&\max Q(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \\
&\text{s.t. } \sum_{i=1}^{l} \alpha_i y_i = 0 \\
&\quad 0 \leq \alpha_i \leq C
\end{align*}
$$

(5)

If we can't find a linearly separable classification plane between samples in low-dimensional space to separate all the samples, then mapping to a high-dimensional space makes it easy to achieve linear separability. This is achieved by using a kernel function. Its main function is to map samples (non-linear) in low-dimensional space to high-dimensional space, and strive to achieve linear separability. At the same time, when optimizing the target of the original problem, each time we need to perform inner product operations on the loop between the training set samples. After the dimension is increased, the amount of inner product in the high-dimensional space will become very large. The dimension of the kernel function that can be used to calculate the inner product is still in the low-dimensional space, but the output of the kernel function is still in the high-dimensional space. Similar to the form of a neural network, a kernel function is equivalent to a hidden layer of neurons, passing through the input layer, to the hidden layer, multiplying the $\alpha_i y_i$ connection weight, and finally to the output layer. As shown in Figure 1. It is generally believed that the Radial Basis Function (RBF) has a high computational accuracy.

![Figure 1. Principle of SVM kernel function](image-url)
3) SVM regression problem. SVM is used to solve the regression problem to form Support Vector Regression (SVR). On the basis of SVM used to solve the classification problem, SVR defines the solution of the regression problem as the optimal classification hyperplane that no longer looks for the sample, but further finds an optimal fitting surface so that the sample set data points and the distance of the face is the smallest [6]. Assume that $\epsilon$ is the distance from the sample point to the fitted surface and $\xi$ is the introduced insensitive coefficient. There are many ways to solve the $\alpha$. One sample per alpha. Convert equation (6) to a dual problem and get the fitting form.

$$
\begin{align*}
\min & \frac{1}{2}||\omega||^2 + C \sum_{i=1}^{l}(\xi_i + \xi_i^*) \\
\text{s.t.} & \quad y_i - \omega \cdot \Phi(x_i) - b \leq \epsilon + \xi_i \\
& \quad -y_i + \omega \cdot \Phi(x_i) + b \leq \epsilon + \xi_i^* \\
& \quad \xi_i \geq 0, \quad \xi_i^* \geq 0
\end{align*}
$$

(6)

3. Cyclic Prediction Based on SVR Model

Using the machine learning method, the time-domain extrapolation of the load-time history data of the crankshaft is mainly based on the machine learning method, which can describe the complex features such as the nonlinearity of the load data, but directly focus on the internal structure of the data and Features, establish a continuous improvement of the regression calculation learning model, through the parameter optimization to achieve generalization of data prediction, that is, to achieve time domain extrapolation of load data. This extrapolation method can preserve the order of load action as much as possible in the process of extrapolating the measured load data, so as to preserve the load sequence effect as much as possible in the study of further fatigue simulation calculations. The effect of cumulative effects.

3.1. Cyclic Prediction

In order to continuously reflect the load data of the latest test into the model in the modeling process, the learning process of “modeling-prediction-correction” is repeated repeatedly to achieve the purpose of improving the generalization prediction accuracy of the machine learning model. A modeling method using rolling time window is proposed.

Suppose the sample size of a training set is $N_i$, the rolling time window size is j, and the test set is set to the load data in $(N_i+1 \sim N_{i+j})$. The machine learning model is established and the sample period is found. The optimal parameters, and then the model generalized prediction is $(Y_{i+1} \sim Y_{i+j})$, and the performance measurement parameters are mean-square error (MSE) and square correlation. The coefficient ($r^2$) is used as a measure reflecting the degree of difference between the estimated amount and the estimated amount. Next, the samples of the training set are sequentially adjusted to $N_{i+m}$, the rolling window is still j, and the test set is set to load data in $(N_{i+j+1} \sim N_{i+j+2})$. Further optimization of the parameters of the machine learning model during the sample period, and then using the model generalization prediction to obtain the prediction set $(Y_{i+j+1} \sim Y_{i+j+2})$, also using MSE for generalization performance. Quantification is provided to provide reference and improvement direction for the model to learn the prediction process of the load data in the next test set sample $(N_{i+j+3} \sim N_{i+j+4})$;

Assuming that the sample size of the original data is $N$, the prediction learning process is analogized until the learning model of all samples is achieved. Let $y_{t+j}$ and $\hat{y}_{t+j}$ represent the real crank load sample values forwarded to the j step at time t and the corresponding predicted values, respectively.

$$
\hat{y}_{t+j} = E(y_{t+j}|y_0, y_{t-1}, \cdots, y_t)
$$

(7)

Equation (7) indicates that the forward crankshaft load prediction value at step j based on time t is the expected value of the forward real load value of all the information before the given time t.
3.2. Analysis of Variables
The research object is a 6-cylinder V-type supercharged diesel engine with a rated speed of 2200r/min and a nominal power of 360kW. In order to grasp the operating conditions and excitation response of the engine after loading, sensors are arranged at the electronic control unit, the flywheel disc, the accelerator pedal mechanism, the wheels, and the like. In the data acquisition test, the vehicle continuously travels on the gravel and undulating road surface. During the driving process, the vehicle fully simulates various mission conditions such as emergency stop, rapid turn, and rapid acceleration/deceleration in the battlefield environment, and uses the CAN bus to sample at 10 Hz. Frequency, collecting seven parameters such as engine speed, rack displacement, exhaust temperature, inlet water temperature, oil pressure, vehicle speed and gear position; further, based on engine bench performance test, establish MAP mapping, and fit corresponding engine torque parameters A total of eight parameters of the sample data.

![Correlation coefficient graph of each parameter variable](image)

In order to measure the engine load parameters of the above test field, in order to gather the variables with similar correlation modes, the rows and columns of the correlation coefficient matrix are reordered by principal component analysis, and the correlation coefficient matrix is performed by the correlation graph method. Visual representation, as shown in Figure 2. The pie chart filled with clockwise in the upper triangle of the figure represents the correlation coefficient of the binary variable; the color depth in the lower triangle indicates the correlation of the variables.

It can be seen that there is a significant correlation between the variables. For sample sets with more complex variable data, further simplified dimensionality reduction is required. Principal Component Analysis (PCA) can achieve dimensionality reduction of data, and can find redundant environmental variables from related variables, thus extracting principal component variables that can retain the original dataset information as much as possible. The relevant variables are transformed into a small set of unrelated variables. Through analysis, when the number of principal components of the explanatory variable is 4, the cumulative variance contribution rate reaches 97.89%, and the integrity of the contained information is better.

3.3. Results of Forecast Extrapolation
The load time history of the equivalent bending moment force measured by the engine crankshaft is shown in the Figure 3.
The load time history of the equivalent bending moment force is shown in Figure 3. The SVR predictive extrapolation model based on the incremental learning rolling time window is established. The learning effect of the model on the training set is shown in Figure 4. The prediction effect of the test set is shown in Figure 5.
Figure 5. Predictive extrapolation results versus test set

It can be seen that for the equivalent moment force parameter, the extrapolated predicted value of the model is close to the true value. By calculation, the evaluation index: MSE = 0.00288051; R² = 0.985606; the test set prediction result: MSE = 0.00124057; R² = 0.999379.

4. Conclusion
In this paper, the SVR predictive extrapolation model based on the incremental learning rolling time window can optimally analyze the measured data of the engine crankshaft torque and equivalent bending moment force to achieve machine-based learning. The load spectrum of the method is extrapolated in time domain. The method can expand the sample size of the original measured data based on the extrapolation of the load spectrum time domain, and provide a basic dynamic input of the load change to the component in further design development or fatigue life calculation simulation.

References
[1] SKORUPA M. Load Interaction Effects During Fatiguecrack Growth under Variable Amplitude Loading—a Literature Review. Part I: Empirical Trends [J]. Fatigue & Fracture of Engineering Materials & Structures, 1998, 21 (8): 987-1006.
[2] POTTER J M, WATANABE R T. Development of Fatigue Loading Spectra [M]. PA:ASTM International, 1989.
[3] HEULER P, KL TSCHKE H. Generation and Use of Standardised Load Spectra and Load-Time Histories [J]. International Journal of Fatigue, 2005, 27 (8): 974-990.
[4] Steve G. Support vector machines for classification and regression [J]. Southampton University, 2006, 16 (4): 325-329.
[5] Baailay V L. On domain knowledge and feature selection using a support vector machines [J]. Pattern Recognition Letters, 2004, 20 (5): 475-484.
[6] Smola A J, Scholkopf B. A tutorial on support vector regression [J]. Statistics and Computing, 2004, 14 (3): 199-222.