Research Article

An Approach for Performance Assessment of Tracked Vehicle Transmission Based on the Median-Rank Weight and the Least-Square Support Vector Machine

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1. Introduction

Tracked vehicle transmission is a complex system integrated with different mechanical-electro-hydraulic components. To ensure the lifetime and timely maintenance of the tracked vehicle transmission, reliability evaluation and condition assessment should be performed [1]. Meanwhile, to guarantee the normal operation of transmission, the assessment of the vehicle transmission performance is necessary [2, 3] and performance improvement will be achieved finally. With the help of the rotating parts, such as gears, shafts, and bearings, tracked vehicle transmission could realize different functions, such as straight driving, steering, and braking [4]. In the process of vehicle power transmission, power loss is inevitable. Since the efficiency of transmission is related directly to the power loss in vehicle systems, it is worth a lot researching the overall power losses inside the transmission [5–7], in order to modify the transmission performance [8]. For example, lubricating oil is employed for lubrication and heat dissipation, which leads to the loss of power, namely, the churning loss. The churning loss is affected by many factors, such as oil level, oil viscosity, speed of the rotating parts, external load, etc [9]. During efficiency tests of tracked vehicle transmission, the test conditions include quantitative factors such as gear position and its typical test speed, loading level, as well as uncertainties such as temperature and the fluid level inside the tank [10–12].

To satisfy the requirements of combat, the vehicle transmission must have a variety of working modes with multiple corresponding gear positions, of which the straight driving mode accounts for the largest proportion, hence the straight driving mode is selected as the main research object. To make a comprehensive and accurate assessment of the vehicle transmission efficiency performance in a straight drive mode, test data from multiple operating conditions need to be considered. Li et al. applied a Markov model to evaluate the quality performance of a flexible manufacturing system [13]. Wang et al. proposed a hierarchical fuzzy comprehensive evaluation algorithm to assess the running state of the 6 kV power vacuum switch cabinet for the improvement of operational safety and reliability of the power supply system [14]. However, if the performance of
Each working condition is assessed separately and then obtain the weighted summation on the basis of the analytic hierarchy process, the inherent correlation between the no-load condition and the specified loading condition cannot be reflected. In addition, if there are too many working conditions to test, the timeliness of the assessment will delay and human and financial resources will be wasted, so the number of working conditions and the assessment method related to the transmission efficiency performance need to be studied. In order to solve the problem of missing or singular values in the test data when assessing the performance of transmission efficiency of individual vehicle transmission, smooth processing of no-load power loss and loading transmission efficiency in the test data should be required with artificial intelligence [15, 16]. In this regard, LSSVM is a good choice for its high accuracy with small size of training samples [17, 18]. Vong et al. employed LSSVM and Bayesian inference for the prediction of automotive engine power and torque [19]. Ghiassi et al. adopted LSSVM with a new combinational kernel function for structural damage detection [20].

As mentioned above, a normalized comprehensive performance assessment indicator based on median rank weighting is proposed for tracked vehicle transmissions in the straight driving mode, which achieves the information fusion of two different dimensions that are no-load power loss and transmission efficiency, respectively. The median rank weighting is calculated with nonparametric statistics, which can avoid the errors caused by the wrong assumption of probability distribution and make the assessment results more generalized [21, 22]. LSSVM is used to realize the prediction of a single transmission under multiple operating conditions, and then realize the calculation of the performance assessment indicator with the dynamic number of speed measurements. Further, the number of speed measurements could be obtained with the smooth performance assessment indicator, which ultimately saves the time of the performance assessment process and avoids waste in the testing process.

The organization of this paper is as follows. The experimental design of tracked vehicle transmission and the performance assessment indicator construction based on the experimental results are proposed in Section 2. The theoretical background of LSSVM is briefly presented for the prediction of median rank of no-load power loss and the median rank of transmission efficiency of the single testing sample with various working conditions in Section 3. The vehicle transmission performance assessment process is introduced in Section 4. Experiment datasets are employed to verify the proposed method in Section 5, and in Section 6, the conclusions are finally drawn.

2. Experimental Design of Tracked Vehicle Transmission

2.1. Working Principle of Tracked Vehicle Transmission. Tracked vehicle transmission is a complex system with integration of electromechanical-hydraulic components, as shown in Figure 1, which consists of more than 20 components, such as front drive assembly, hydraulic torque converter (HTC), planetary variable speed mechanism, and hydraulic manipulation system. The working principle is as follows: the power is input from the forward transmission and separated into two paths. The power flow in the main path goes through HTC to the planetary transmission mechanism, and then passes through the main shaft to both sides of the power integrations; in the auxiliary path the power flow is driven by the forward transmission to the coupling pump motor and then transmitted by the zero shaft to the sun wheels in power integrations. When driving straightly, the power is going through the main path and the coupling pump motor does not work.

2.2. Working Condition Analysis and Experimental Design. According to armored vehicle integrated transmission bench test method GJB 5210-2003 (in Chinese), there are 6 straight forward gears (F1–F6) and two reverse gears (R1 and R2) under the no-load condition as well as the specified loading condition. The test scheme of power loss test under the no-load condition is shown in Table 1, and the same test scheme is set for the specified loading condition. There are 75 test samples for each speed in each gear under different loading conditions, and the statistical values under each condition are shown in Figures 2 and 3. It can be seen from Figure 2 that the no-load power becomes larger with the increase of speed in different straight driving gears, among which the change is most obvious in the F6 gear. It can be seen from Figure 3 that the transmission efficiency increases with increasing speed in F1, F2, R1, and R2, while it decreases with increasing speed in F3–F6. This is because the vehicle transfer unit is in a hydro-mechanical operation mode in F1, F2, R1, and R2, while it is in a purely mechanical operation mode in F3–F6. Therefore, assessment of the performance of vehicle transmission in terms of no-load power loss or transmission efficiency alone can lead to one-sided results.

2.3. Construction of the Performance Assessment Indicator. Suppose the number of testing speeds at all gear positions is N, and the number of the testing sample is j at corresponding speed. The median rank is defined as follows:

\[
Q_i = \frac{i - 0.3}{j + 0.4},
\]

in which \(i\) represents the \(i\)th location in the \(j\) samples which ordered from small to big.

When the current testing speed number is \(n\), \(1 \leq n \leq N\), the weight of each sample concerning no-load power loss is calculated as

\[
w_k = \frac{1/ \alpha_k}{\sum_{k=1}^{n} 1/ \alpha_k},
\]

in which \(\alpha_k\) represents the median rank of testing sample with no-load power loss, and \(\sum_{k=1}^{n} \alpha_k = 1, 1 \leq k \leq n\), is satisfied.
Finally, the performance assessment indicator is constructed as

\[ PQ = \sum_{p=1}^{n} w_p Q_p, \quad p \leq n \leq N, \quad (3) \]

in which \( Q_p \) represents the median rank of the testing sample with transmission efficiency, and it could be calculated with equation (1).

The threshold to judge the transmission performance is defined as follows:

\[ PQ \geq 0.75 \longrightarrow \text{outstanding}, \]
\[ 0.5 \leq PQ < 0.75 \longrightarrow \text{good}, \]
\[ 0.3 \leq PQ < 0.5 \longrightarrow \text{medium}, \]
\[ PQ < 0.3 \longrightarrow \text{bad}. \quad (4) \]

Consequently, the performance state could be identified with four stages: outstanding, good, medium, and bad. According to the performance state, some improvements could be performed on the tracked vehicle transmission.

3. Data Prediction with Interval Based on LSSVM

LSSVM is a modification of the support vector machine, which replaces the inequality constraint in traditional SVM with an equation constraint. The loss function of the error squared sum is employed as the empirical loss of the training set; thus, the quadratic programming problem could be transformed into a linear system of the equations problem and the speed and the convergence accuracy of solving the problem are improved. Suppose that a training set of \( n \) samples \((x_1, y_1), \ldots, (x_n, y_n)\), \( x, y \in \mathbb{R}^m \) are given, the input space is mapped to a high-dimensional feature space by a nonlinear function. In the feature space, the following optimal linear regression function is constructed as follows:

\[ f(x) = w^T \phi(x) + b, \quad (5) \]

in which \( w \in \mathbb{R}^k \) is the weight vector, and \( b \in \mathbb{R} \) is a constant. In this way, the nonlinear fitting problem is transformed into
a linear fitting problem in a high-dimensional feature space. According to the principle of structural risk minimization, the regression problem can be expressed as a constrained optimization problem by considering the function complexity and fitting error:

$$\min J(w, e) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*),$$

(6)

with the constraints

$$\begin{align*}
y_i - wx_i - b &= \varepsilon + \xi_i, \\
w x_i + b - y_i &= \varepsilon + \xi_i^*, \quad i = 1, 2, \ldots, n, \\
\xi_i, \xi_i^* &\geq 0,
\end{align*}$$

(7)

where $\xi_i, \xi_i^*$ are the relaxation variables, and $\varepsilon$ is the insensitivity parameter of the loss function. Using $\varepsilon_i^2/2$ instead of $\xi_i + \xi_i^*$, the corresponding Lagrange function is established as

$$L(w, b, e; a) = J(w, e) - \sum_{k=1}^{n} a_k \{ w^T \varphi(x_k) + b + e_k - y_k \},$$

(8)

in which $a_k \in R$ is the Lagrange multiplier. According to the Karush–Kuhn–Tucker condition, the partial derivative of $L$ with respect to the parameters $w, b, e_k, a_k$ is obtained as

$$\begin{align*}
\frac{\partial L}{\partial w} &= 0 \rightarrow w = \sum_{i=1}^{n} a_i \varphi(x_i), \\
\frac{\partial L}{\partial b} &= 0 \rightarrow b = \sum_{i=1}^{n} a_i, \\
\frac{\partial L}{\partial e_i} &= 0 \rightarrow a_i = C e_i, \\
\frac{\partial L}{\partial a_i} &= 0 \rightarrow w^T \varphi(x_i) + b + e_i - y_i = 0.
\end{align*}$$

Eliminating the variables $w, e$, the following equation is obtained as

$$\begin{bmatrix} 0 \\ I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix},$$

(10)

where the kernel function is $\Omega_{ij} = K(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_j)$, $i, j = 1, 2, \ldots, n$; $y$ is the output sample; $I$ is the unit matrix; and $\alpha = [a_1, a_2, \ldots, a_n]$.

To satisfy the Mercer condition, the Gaussian kernel function

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \quad \sigma > 0,$$

(11)

is employed in this paper, and $\sigma$ is the kernel function bandwidth. Finally, the expression for LSSVM regression estimation is obtained as

$$y(x) = \sum_{i=1}^{n} a_i K(x_i, x) + b,$$

(12)

in which

$$\begin{align*}
b &= \frac{I^T (\Omega + C^{-1} I)^{-1} y}{I^T (\Omega + C^{-1} I)^{-1} I}, \\
\alpha &= (\Omega + C^{-1} I)^{-1} (y - b I).
\end{align*}$$

(13)

LSSVM is used to fit the no-load power loss data and loading transmission efficiency data from the test data to solve the problem of missing or odd values in the individual vehicle transmission test data. The gear, speed, and no-load power loss under no-load condition are used as input parameters, and the quantile of each no-load power loss is used as the output parameter; the gear, speed, and transmission efficiency under 50% load condition are used as input parameters, and the quantile of each transmission efficiency is used as the output parameter to obtain the quantile of no-load power loss and transmission efficiency under continuous condition, and finally the confidence interval of the normalized performance assessment indicator is given. Interval evaluation of LSSVM prediction could refer to reference [23].

### 4. Vehicle Transmission Performance Assessment Process

For a comprehensive and accurate assessment of the transmission performance of an integrated drive, test data from multiple operating conditions need to be considered. However, the test data often have singularities and omissions, which require smoothing and gap-filling of the data. In addition, if there are too many test conditions, the timeliness of the evaluation will be affected, as well as the waste of human and material resources. For this reason, the fitting of test data, the size of the number of test conditions, and the method of transmission performance assessment need to be studied to give the normalized performance assessment indicator under transmission efficiency. The implementation scheme of the proposed method is shown in Figure 4 with the following steps:

1. To test the no-load power loss at each gear with its corresponding rotational speed, to arrange the test samples from small to large, to calculate the median rank of each sample, and to substitute the gear, the rotational speed, and the no-load power loss as input variables and the median rank as output variables into the model LSSVM-1 for training.

2. To test the transmission efficiency of each gear with its corresponding speed under specified loading conditions, to arrange the test samples from smallest...
(3) The working conditions of the samples to be tested are substituted into the model LSSVM-1 to obtain the median rank of the no-load power loss, while the median rank with its confidence interval concerning transmission efficiency are calculated with the model LSSVM-2, respectively. As the number of conditions increases, the median ranks of the no-load power loss and transmission efficiency are renormalized each time.

(4) The normalized median rank value of the no-load power loss is used as the weighting factor, and it is multiplied with the median rank of transmission efficiency under the same working condition. Then all of the products will be summed up to obtain the normalized performance assessment indicator with

Figure 4: Flowchart of performance assessment concerning vehicle transmission.

Figure 5: Fitting of training data about no-load power loss based on LSSVM (excluding the 28th sample).
the confidence interval concerning vehicle transmission under the straight driving mode.

(5) Finally, with the prespecified threshold, the performance assessment of vehicle transmission could be judged based on the normalized performance assessment indicator.

5. Transmission Performance Assessment of Vehicle Transmission

5.1. Evaluation of Model Fitting Accuracy. The code for vehicle performance assessment was written based on the LSSVM toolbox. When the median rank of the testing
Figure 8: Prediction of the transmission efficiency data concerning the testing sample: (a) the 28th sample, (b) the twelfth sample, (c) the fifth sample, and (d) the 34th sample.

Figure 9: Absolute errors concerning the median rank of the no-load power loss of every testing samples based on the LSSVM prediction.

Figure 10: Absolute errors concerning the median rank of the transmission efficiency of every testing samples based on the LSSVM prediction.
sample was predicted, the remaining 74 samples with the no-load power loss data in Table 1 and the transmission efficiency data under 50% loading in Table 1 were substituted into the machine learning models LSSVM-1 and LSSVM-2 for training, respectively. The order numbers of each sample substituted into LSSVM for training at each speed in each gear for both operating conditions are as follows:

(1) F1-1600 → F1-1800 → F1-2000 → F1-2200→
(2) F2-1600 → F2-1800 → F2-2000 → F2-2200→
(3) F3-1600 → F3-1800 → F3-2000 → F3-2200→
(4) F4-1600 → F4-1800 → F4-2000 → F4-2200→
(5) F5-1600 → F5-1800 → F5-2000 → F5-2200→
(6) F6-1600 → F6-1800 → F6-2000 → F6-2200→
(7) R1-1600 → R1-1800 → R1-2000 → R1-2200→
(8) R2-1600 → R2-1800 → R2-2000 → R2-2200→

That is to say, each sample has 32 median rank numbers to represent its performance in both no-load power and transmission efficiency under 50% loading, respectively.

We arrange the 75 samples from small to large with labels from 1 to 75, and take the fifth sample, the twelfth sample, the 28th sample, and the 34th sample as examples for the illustration of the proposed approach according to the

![Graphs](image-url)

Figure 11: Performance assessment indicators and the assessment results of the testing samples: (a) outstanding, (b) good, (c) medium, and (d) bad.
flowchart of vehicle transmission performance assessment. In each test, the “leave one out” strategy is adopted for both LSSVM-1 and LSSVM-2 models, namely, 74 samples are used for training at each speed under every gear positions and the one remaining is used for testing. In the training process, the parameters of LSSVM are estimated based on cross-validation with the 10% sample size with two steps. First, coupled simulated annealing determines suitable parameters according to some criterion. Second, these parameters are given to a second optimization procedure to perform a fine-tuning step. The fitting results of the no-load power loss and transmission efficiency data under 50% loading are shown in Figures 5 and 6.

For the 28th testing sample, its corresponding no-load power loss data and the transmission efficiency data under 50% loading were substituted into the models LSSVM-1 and LSSVM-2 as input variables, respectively, to obtain the median rank of no-load power loss and transmission efficiency at each speed for each gear of the 28th sample, as shown in Figures 7(a) and 8(a), respectively. During the LSSVM prediction process, if there are negative values, they are treated as absolute values. The median ranks of the twelfth, the fifth, and the 34th samples are calculated sequentially and are shown in Figures 7(b)–7(d) and Figures 8(a)–8(d), respectively.

The absolute error was used to evaluate the fitting accuracy of the model with the following expressions.

$$\text{AE} = |y - \tilde{y}|,$$

where $y$ is the test median rank value, and $\tilde{y}$ is the fitted median rank value. The predicted absolute errors of the median rank of the no-load power loss and the median rank of transmission efficiency for each sample to be tested are shown in Figures 9 and 10. In Figure 9, the absolute error of the 28th test sample is larger at a certain operating point, but all other samples can meet the fitting accuracy requirements. In Figure 10, the absolute errors of each sample to be tested at each working point can be controlled within 0.08, which indicates that the prediction effect is good.

5.2. Vehicle Transmission Performance Assessment. According to the flowchart of vehicle transmission performance assessment, the corresponding normalized performance assessment indicator of transmission efficiency with its 95% confidence interval are obtained, the results are shown in Figure 11, respectively. According to the criterion of (4), four states of excellent, good, moderate, and poor can be distinguished. From Figures 7 and 8, it is shown that the median rank of no-load power loss is increased from the outstanding state to the bad state, while the median rank of transmission efficiency decreased.

In Figure 11(a), the normalized performance assessment indicator is slightly lower than the value calculated with the experimental data, but it can still be judged as “excellent” working condition. The normalized performance assessment indicator of the other three samples to be tested are basically consistent with the experimental values, which are good, moderate, and poor, respectively. It can be seen from Figure 11 that a stable normalized performance assessment indicator of transmission efficiency can be obtained when the number of speed measurement points is added dynamically within 10, thus laying the foundation for saving test time.

6. Conclusion

Through the median rank weighting method of no-load power loss and transmission efficiency with a 50% load, the normalized comprehensive performance assessment indicator of vehicle transmission is constructed based on LSSVM. The criterion of whether the comprehensive performance of vehicle transmission efficiency is qualified is given. The results show that the steady comprehensive performance assessment indicator of transmission efficiency could be obtained with a confidence interval of 95% in the first 10 speed measurement points.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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