Eksploatacja i Niezawodnosc – Maintenance and Reliability

Volume 25 (2023), Issue 1

journal homepage: http://www.ein.org.pl

Article citation info:
Wu J, Cui J, Shu Y, Wang Y, Chen R, Wang L. Multi-level health degree analysis of vehicle transmission system based on PSO-BP neural network data fusion. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2023: 25(1) http://doi.org/10.17531/ein.2023.1.4

Indexed by: Web of Science Group

Multi-level health degree analysis of vehicle transmission system based on PSO-BP neural network data fusion

Jianpeng Wu[a], Jiahao Cui[a], Yuechao Shu[a], Yuxin Wang[a], Ruihan Chen[a], Liyong Wang[a*]

[a] Beijing Information Science and Technology University, China

Highlights

- Accurate prediction vehicle transmission system health degree,
- Mechanical module has the greatest impact on the system health,
- Use PSO-BP neural network integrates 20 types characteristic indicators,
- Considered three modules influence on system health.

Abstract

In order to realize the evaluation of the vehicle transmission system health degree, a prediction model by multi-level data fusion method is established in this paper. The prediction model applies PSO(Particle Swarm Optimization)-BP(Back Propagation) neural network algorithm, calculates the whole machine health degree and each module respective weights from the test data. On this basis, it analyzes the error between the model calculated health degree and theoretical health degree. Then the research verifies the validity and prediction model accuracy. The health degree which is obtained by the single module feature parameters fusion, and the vehicle transmission system health degree is investigated, which is less effective compared to the three-level fusions. After that, by analyzing the vehicle transmission system multi-parameter feature weights, it is found that the mechanical module accounted for the largest damage rate, and the three modules influenced the vehicle transmission system health degree in the order of mechanical module, hydraulic module, and electric control module. The study has played a guiding role in the health management of complex equipment.

Keywords

Vehicle transmission system, Data fusion, PSO-BP algorithm, Health degree

1. Introduction

Vehicle transmission system is a complex system, integrating machine, electricity and hydraulic module. Its service performance degradation is a complicated gradual process of multi-physical field, multi-module variables and multi-level performance parameters. It is difficult to achieve accurate assessment and comprehensive characterization by a single vibration signal or physical parameter. The load conditions in the transmission system components are complex. The load domain is wide, the transient shock load is large, the load changes frequently. Moreover the dynamic load presents stronger random asymmetric alternating characteristics, which is more likely to induce accidents such as broken shafts, teeth of gears, shafts and bearings. Therefore, it is difficult to conduct online real-time evaluation of performance degradation based on limited on-board signals. The research on the vehicle transmission system health degree is a current hot topic, and scholars have done a lot of works. Chen [2] describes the nonlinear dynamics caused by vibration and impact in order to achieve structural health monitoring and damage detection. Suh [23] proposed a data-driven health segmentation method based on convolutional neural network, which can monitor the wear condition of bearings earlier and more effectively. For the mechanical systems health prediction and management, Huh [5] proposed a data-driven fault diagnosis method which applies critical information map identifying the difference between the signal spectrograms of normal and abnormal status. Morais [16] monitors the the force in the mechanical system, which is more likely to be realized in the monitoring of rotating parts. Bachar [1] summarized the application of optic Fiber Bragg Grating (FBG) strain sensors for gear diagnostics, developed a new diagnosis method based on FBG strain sensor.

Lei [13] uses deep learning to train deep neural networks, using mechanical frequency domain signals to achieve adaptive extraction of fault features, and accurately identifies health conditions for different fault types at different multi-stage gear transmission systems fault locations under multiple operating conditions and a large sample number. It is also a good method to use autoencoder to automatically learn features and complete

(*) Corresponding author.
E-mail addresses: J. Wu (ORCID: 0000-0002-6360-2047), 15811319103@163.com, J. Cui (ORCID: 0000-0002-8459-6192) 2370408276@qq.com, Y. Shu, 18148004285@163.com, Y. Wang, happyllwyx@163.com, R.Chen, 1491867381@qq.com, L. Wang, wly_bistu@126.com

health prediction by deep neural network [7, 24]. Pang [18] proposes a data-driven neural network, using Neuber criterion and Manson coffin equation to estimate the fatigue life of rotors, which provide a feasible online health monitoring method for steam turbine rotors. Seventekidis [22] studies structural health detection by combining finite element simulation and deep learning methods Jiang [8]proposes a novel framework to fulfill the task of prognostics and health management with a smart sensors, consisting of embedded sensing elements, wireless communication modules and micro-controllers. Kumar [12] proposed a classification model for bearing degradation evaluation based on machine learning classification matrix, which improved the accuracy of the classification model. Yan [25] proposed a health index extraction method, which is better characterize the degree of degradation compared to relying solely on spectral oil data.

In the study of hydraulic system, Kim [10] proposes a method for fault diagnosis of gear box based on embedded convolutional neural network in the hydraulic module health degree evaluation. Prakash [19] develops an artificial intelligence model, which uses deep neural network to predict the working behavior of the cooling circuit in the hydraulic system. And he proposes four different models and compared their performance. Rodrigues [21] proposed to estimate the aircraft hydraulic system health based on the each component health in the system, linking the health factors of each component. Kelley[9] realized the prediction of hydraulic system health based on distributed sensors and neural network nonlinear autoregressive exogenous model. Also other scholars introduce information fusion in the health diagnosis research, and achieved excellent achievements [6]. Helwig [4] uses a multi-channel non dispersive (NDIR) system working in the mid infrared range to detect the liquid state in the hydraulic system. Yong [26]analyzes the hydraulic oil characteristics, carries out the hydraulic module circuit analysis，calculates the friction calorific value. Meng [15] uses the competitive learning and unsupervised clustering advantages by self-organizing neural network to study the health clustering and safety recognition of the system. Macaluso [14] introduces a method of prediction and health management for fly-by-wire Electro-Hydraulic Servo Actuators without adding new sensors. Krishnan [11] developed health monitoring and prognosis of Permanent magnet synchronous motor by creating intelligent digital twin in MATLAB/Simulink. Guo [3] proposes an importance density choice scheme grounded on the Minimum Hellinger Distance principle to obtains accurate remaining useful life prediction for the electrohydraulic servo actuator. Zhang [27]，based on the phase current, proposes a fusion method of Mix Logical Dynamic model and Elastic Net Regression model for Electro-Mechanical Actuator Health Indicator extraction. Qi[20] proposes the progressive fault diagnosis method for overall diagnosis of whole the electro-hydrostatic actuator system, which can be divided into four levels for health detection and fault diagnosis of the overall the electro-hydrostatic actuator system.

In previous research, the vehicle transmission system health degree study is relatively lacking, mostly most studies only consider the single module health evaluation. Regarding the issue above, in order to obtain the vehicle transmission system health, in this paper, a prediction model by multi-level data fusion method is established. The model uses PSO-BP neural network to calculate the system health degree and the proportion of each module parameter. Then, the weight of 20 types characteristic parameters is analyzed, and the key factors affecting the system health are analyzed. This model can provide a basis for equipment condition-based maintenance.

2. Multi-level performance parameter

The health degree evaluation of the vehicle transmission systems is directly influenced by three modules: the mechanical module, the electric control module, and the hydraulic module. The performance evaluation is based on the characteristic parameters extracted from the data collected by sensors. The mechanical module characteristic parameters sources include vibration sensors, speed and torque sensors, vehicle dynamics models, throttle opening and other data. The electronic control module characteristic parameters sources include temperature sensors, controller return signals and other data. The hydraulic module characteristic parameters sources include oil temperature, oil pressure sensor and other data. Moreover, each module evaluation is influenced by the performance evaluation in many aspects. Based on the target attribute fusion evaluation application requirements, a hierarchical composite fusion processing structure is used. Thus, a three-level progressive evaluation system is established, including module, performance, and parameter level, as shown in Figure 1.

(1) Module level. The vehicle transmission system health degree is derived from the fusion evaluation of the three modules health degree, while the module-level evaluation is each component performance comprehensive score under this module.

(2) Performance level. The module-level health degree evaluation is derived from each performance characterizing individual module fusion evaluation. The specific performance characterizing the service capability of the three modules, mechanical, electrical and hydraulic, together constitute the parameter module performance level. The performance level is a comprehensive access to each evaluation aspect such as durability performance, component work quality, transfer efficiency and stability of typical components. Through the analysis and inference of these properties, the module-level health degree can be inferred. For example, mechanical module health degree includes: mechanical durability, shift quality, and power transfer quality. Electronic control module health degree includes: sensor work quality, sensor work capability, and controller operation status. Hydraulic module health degree includes: hydraulic module oil supply capability, pump motor power transfer capability, oil pressure stability, and oil temperature stability. The performance level health evaluation is based on the overall evaluation of the characteristic parameters corresponding types.

(3) Parameter level. The performance level health degree evaluation is derived from the evaluation decision of the corresponding single parameter or the multiple parameters fusion evaluation, and the parameters characterizing each performance together constitute the parameter level. The parameter level is to cover each module performance evaluation degradation characteristics, and the corresponding performance level health is obtained by considering the parameter evaluation together. For example, in the mechanical module performance evaluation, the mechanical durability evaluation is determined by the damage rate. And the shift quality is derived from the fusion evaluation of shift time, shock wave and slip work. The power transfer quality is derived from the fusion evaluation of output shaft speed, output shaft torque, minimum relative steering radius and transmission efficiency for specific working conditions. In the electronic control module performance

evaluation: the sensor working quality is derived from the signal fluctuation amplitude and signal fluctuation frequency, and the sensor working capability is derived from the signal pole duration evaluation. The controller operation status is derived from the heartbeat, control signal response time, control signal frequency and amplitude fusion evaluation. In the hydraulic module performance evaluation: hydraulic module oil supply capacity is derived from the fusion evaluation of oil pump volumetric efficiency and lubrication flow rate. The pump motor power transmission capacity is derived from the fusion evaluation of pump motor speed, pump motor volumetric efficiency and pump motor torque. The oil pressure stability is derived from the fusion evaluation of shift process oil pressure similarity, specific working condition oil pressure similarity and oil pressure characteristic parameter group. The oil temperature stability is derived from the specific working condition oil temperature similarity. The experimental data in this study is directly obtained by real vehicle acquisition, and the parameter layer data is used as model input.

(4) Data level. The parameter level health degree evaluation is derived from the features extracted by the sensors or the analysis though the real vehicle data acquisition or the features obtained from the simulation model, and all the extracted sensors together constitute the data level.

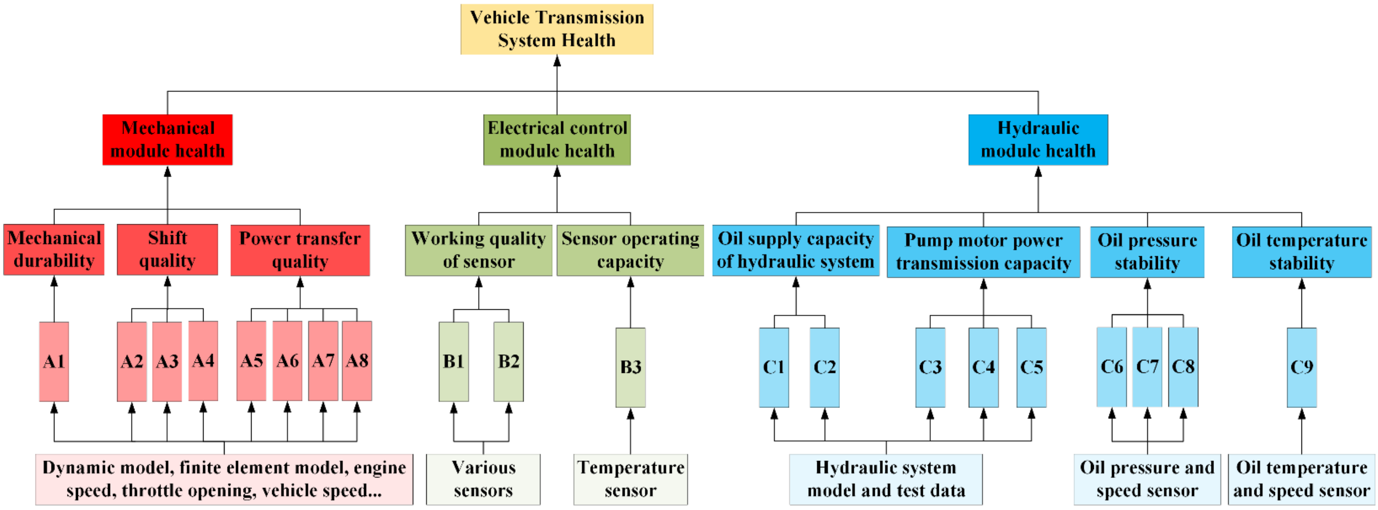


Fig.1. Comprehensive transmission device performance parameter level.

3. Multi-level data fusion method

BP neural network is a kind of back-propagation neural network, which is relatively mature in data prediction and scene application. It is widely used in load prediction and sudden fault identification in the mechanical transmission process. When initializing the training network weights and thresholds, the connect weight V and the threshold W are selected from the random value in the [-0.999,0.999] interval. Calculate the output after the input parameters. The input layer output vector in the network is consistent with the input mode vector. Calculate the input and output of each neuron in the hidden layer according to formula (1) and formula (2).

$$s_j^p = \sum_{i=1}^{n} x_i^p w_{ij} - \theta_j \tag{1}$$

$$b_j^p = f(s_j^p) \tag{2}$$

where $j = 1,2, \dots q$; p represents the neurons number of in the input layer.

Then we adjust the error of each neuron in the output layer, according to the given expected output, feed-forward loop training, verify the error value, and reach the given error range:

$$d_t^k = (y_t^k - c_t^k) f'(l_t^k) \tag{3}$$

where $t = 1,2, \dots, q$; k represents the neurons number in the output layer.

In PSO optimization algorithm, each optimization problem solution is a particle in the d-dimensional search space. All particles are regarded as virtual points without mass and volume in d-dimensional space. Each particle also has speed and position to determine their search direction and distance. PSO is initialized as a group of random solutions, and then the optimal solution is found through iteration. Update the particle velocity and position using the following formula:

$$V_i^d = wv_i^d + c_1 r_1 (p_i^d - x_i^d) + c_2 r_2 (p_g^d - x_i^d) \tag{4}$$

$$x_i^d = x_i^d + av_i^d \tag{5}$$

where $i = 1,2,\dots,m$; $d = 1,2,\dots,D$; c_1 and c_2 are non-negative constant learning factors; r_1 and r_2 are random numbers within [0,1]. W is a non negative inertia factor; a is the weight.

As shown in Figure 2, the twice data fusion model is constructed in turn as shown in Figure 2, including parameter level feature fusion model and module level health degree fusion model. The first data fusion model is responsible for fusing the feature parameters under each module level and outputting each submodule health degree. The second data fusion model is responsible for fusing the three submodules health degree, and finally outputting the vehicle transmission system health degree after model training. The PSO-BP model training part is one step of the vehicle transmission system multi-level data fusion process.

(1) Initialization. The various parameters involved in the PSO algorithm are selected, such as the maximum iterations number T_{max} in the algorithm, the learning training factors c_1, c_2, and the particle velocity search interval [$V_{\min}$, $V_{\max}$]. The search points positions and their velocities are randomly initialized, each particle initial position is set in advance, and the global extremes are found from the individual extremes and the positions are recorded.

(2) Solving the fitness. The fitness value is calculated by the initially formulated fitness function. If the calculated result is better than the current individual extreme value, the individual optimal position is updated to the calculated particle position. It is necessary to find the optimal value among all the individual extremes of the particles currently provided. After that, if it is better than the current global extremes, the global extremes are updated to that optimal value and the global optimal position is

updated to the individual optimal particle position.

(3) Update the particle position and velocity. If $V_i<V_{min}$, update V_i to V_{min}, $V_i>V_{max}$, update V_i to V_{max}, and vice versa, update the acceleration factor to continue the search until the condition is satisfied.

(4) End of optimization search. If the iterations number is greater than the iterations T_{max}, or the global optimal position satisfies the minimum bound, the global optimal position is the final optimal value and the optimal solution is output, otherwise, return to (2) and continue iteration.

(5) Calculate the error, using the expected output form the network and the actual output, and calculate the error function partial derivative $\delta_0(k)a$ for each neuron in the output level.

(6) Judging the output. Assume that the search space is an N-dimensional space and this population consists of n particles. This population $X=(x_1,x_2,...x_n)$, where the position of the k-th particle is denoted by $X_k=(x_{k1},x_{k2},...x_{kD})$, the velocity is denoted by $v_k=(v_{k1},v_{k2},...,v_{kD})$, and the particle individual extremum is denoted by $P_k=(p_{k1},p_{k2}, ...,p_{kD})$, and the overall global extremes are represented by $P_g=(p_{g1},p_{g2},...,p_{gD})$.PSO algorithm parameters mainly include: population size m, inertia weight w, acceleration constants c_1 and c_2, maximum velocity V_{max}, and iterations maximum number G_{max}. The algorithm parameters design is determined according to the specific problem, usually inertia weight $w = 1$, acceleration constant $c_1 = c_1 = 2$. The inertia weight keeps the particles moving inertially, so that they have the tendency to expand the search space and have the ability to explore new regions. The acceleration constants c_1 and c_2 represent the weights of the statistical acceleration terms that push each particle to P_i and P_g positions. A low value allows the particle to hover outside the target region before being pulled back, while a high value results in an abrupt dash toward or over the target region.

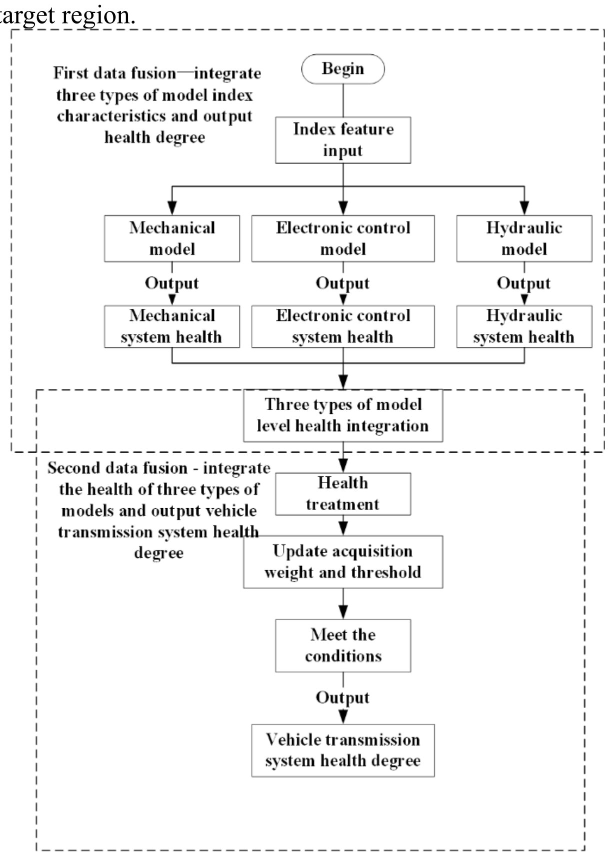


Fig.2. Multi-level data fusion training steps.

V_{max} determines the region resolution between the current position and the best position, i.e., the solution interval accuracy. It has to be designed appropriately.

If it is too large, the particle is likely to fly over the good position if it is too small, the particle cannot search enough outside the local good region and easily fall into the local optimum.

If $c_1= c_2=0$, the particle will keep flying at the current speed until it reaches the boundary. It can only search a finite region, so it is difficult to find a good solution.

If $w = 0$, the velocity depends only on the particle's current best position P_i and its historical best position P_g, and the velocity itself has no memorability. Suppose a particle is located in the global best position, and it will remain stationary. While other particles fly to the weighted center of its own best position P_i and the global best position P_g. Under this condition, the particle population will shrink to the current global best position, i.e., converge to the local optimum, which is more like a local algorithm. After adding the first part, the particles have the tendency to expand the search space, i.e., the first part has global search capability. This also allows w to adjust the balance of global and local search algorithm capabilities for different search problems. If $c_1=0$, particle has no "cognitive" capability, but only "social" reference. The ability to reach a new search space is achieved by the particle interaction. It converges faster than the standard version, but for complex problems. It is more likely to fall into local extrema than the standard version.

If $c_2=0$, particle does not have "social" information sharing between particles. Since the information interaction between individuals is lack, a population which size m is equivalent to single m particles run. Therefore, the chance to obtain a solution is very small.

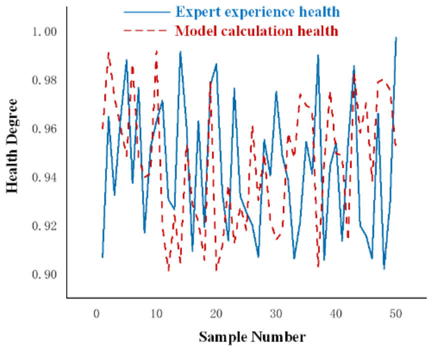
The inertia weight w also relaxes the requirement for V_{max}, since both serve to maintain a balance between global and local search capabilities. In this way, when V_{max} increases, balanced search can be achieved by decreasing w. And the decrease in w can lead to a corresponding decrease in the required iterations number. For global search, it is usually better to have a high exploration capability in the early stage to get the appropriate seeds, and a high exploitation capability in the later stage to speed up the convergence rate. Therefore, w can be set to decrease with time or the iterations number.

4. Results and health degree analysis

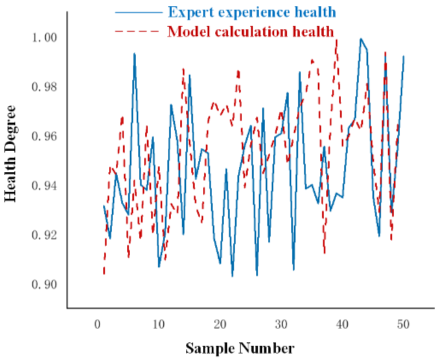
The three modules parameter characteristics are used as the first level fusion model input parameters, including 20 types characteristic parameters such as damage rate, speed, torque, oil pressure, and oil temperature, respectively. The submodule health degree from expert empirical is used as the fusion model output parameter. Then the three types target module models calculated first level health degree is used as the second level fusion model input parameter, and the vehicle transmission system is the second level fusion model output. The whole multi-level data fusion network model consists 200 feature training sets. The source of the data is vehicle data. The on-board sensor data is transmitted by CAN, mainly including oil pressure, temperature, speed, mileage and controller status information, totaling 69 types. The data are collected in real time at a sampling rate of 20Hz. Among them, the shift time is set from the change of the handle gear value to the transmission ratio reaches the target gear and the difference between the transmission ratios is less than 10% for 10 consecutive data points, which is the end time of the shift.

According to the data parameters types collected by the integrated drive, the multi-level data fusion model input nodes established based on the data fusion method are determined as 20. The intermediate hidden levels number is finally determined as 5, and the nodes in each level number is taken as 32, 64, 128, 256, 512, respectively. the model is trained according to the selected training set, and during the training process, the training set is used to learn each. The implicit levels weights and biases, where the weights and biases in the multilevel data fusion network are randomly initialized and it is subject to the normal distribution with zero as its average and one as its variance.

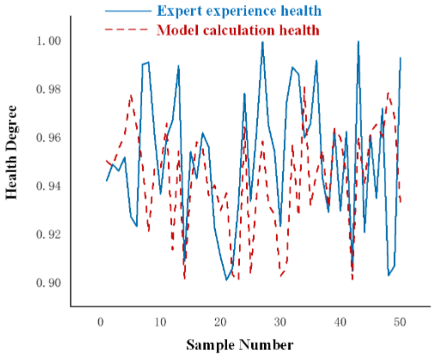
The original data are compared with prediction results of the overall the vehicle transmission system health degree. Figure 3 shows 50 sets of characteristic control samples selected randomly. It can be seen that the health degree percentages of each submodule and the overall vehicle transmission system are above 90%, indicating that the vehicle transmission system is in good condition, and it can ensure the vehicle transmission system works smoothly.



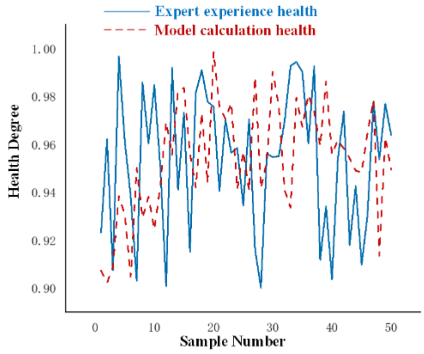
(a) Mechanical module level health degree.



(b) Electronic control module health degree.



(c) Hydraulic module health degree.



(d) Vehicle transmission module health degree

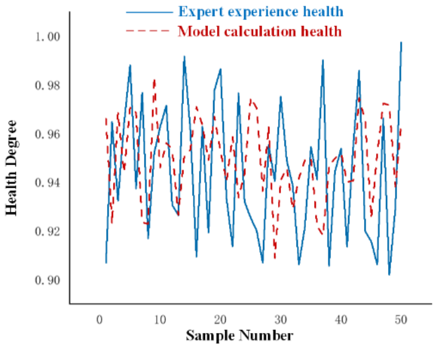
Fig.3. Health degree comparison between original data and prediction results.

The accuracy of the constructed model is judged by comparing the relative error between the original data health degree real value and predicted value. One training sample feature set is used as the research object, as shown in Table 1. The mechanical module health degree prediction error is 3.7%, and the electric control module health degree prediction error is 1.3%, the hydraulic module health degree prediction error is 1.74%, the vehicle transmission system health degree prediction error is 1.73%. The average relative error of the four types prediction values is 2.6% in absolute value, which indicates that the constructed multi-level data fusion model has a good fusion effect.

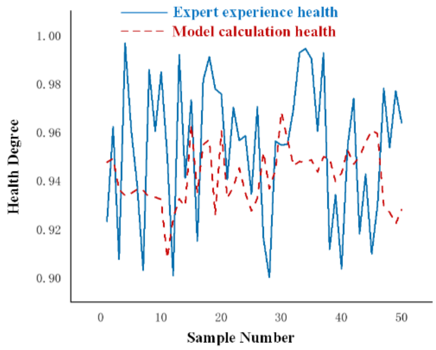
Table.1 Four types health degree real value, predicted value and relative error.

Characteristic health degree	Mechanical module	Electronic control module	Hydraulic module	Integrated drive
True health degree	0.985	0.963	0.958	0.972
Predicted health degree	0.948	0.976	0.941	0.955
relative error	0.0375	0.0134	0.0177	0.0174

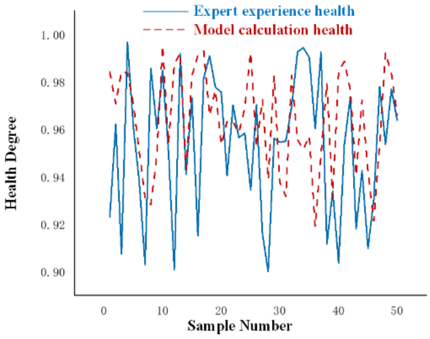
The one type module characteristic parameters fusion effect on the health degree of the respective module and vehicle transmission system is considered singly. (a) Eight types mechanical module characteristic parameters are used as input the fusion model parameters, and two types health degree of the mechanical module and the integrated drive are used as output the fusion model parameters. (b) Three types electric control module characteristic parameters are used as input the fusion model parameters, and two types the electric control module health degree and the integrated drive are used as output the fusion model parameters. (c) Nine types hydraulic module characteristic parameters as the input the fusion model parameters, and the two types the hydraulic module health degree and the vehicle transmission system as the output the fusion model parameters. As shown in Figure 4 below, the same 50 sets samples are selected for validation, and the fusion effect is poorer when considering a single class module compared to three classes modules. In particular, in the electric control module level, the multi-level data fusion model used does not achieve the desired effect for fusing samples with only three types of input parameters. Therefore, it is high reference value to consider fusing three types of modules for the vehicle transmission system health degree valuation.



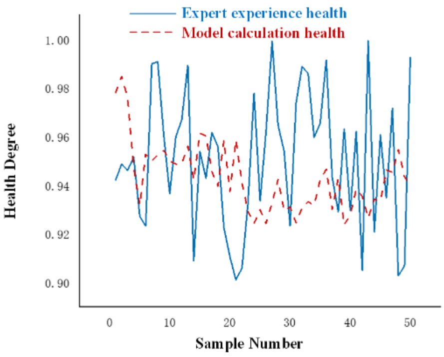
(a) Single mechanical module level health degree.



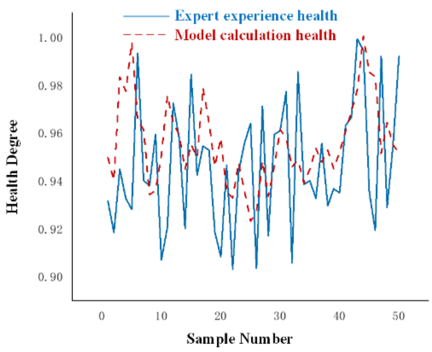
(d) Vehicle transmission system health degree.



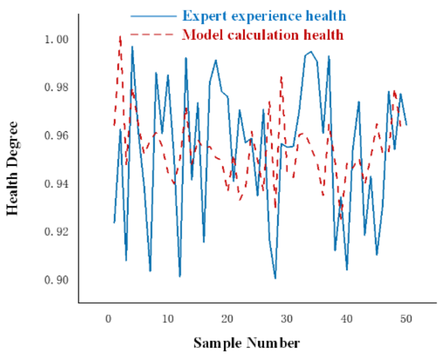
(b) Vehicle transmission system health degree.



(e) Single hydraulic module health degree.



(c) Single electronic control module health degree.



(f) Vehicle transmission system health degree.

Fig.4. Module level and comprehensive transmission device health degree integration comparison diagram.

5. Multi-parameter weight analysis

The vehicle transmission system is a complex system integrating electromechanics and hydraulics, and its service environment contains a variety of complex operating conditions, while the interaction between system components, modules and submodules is highly coupled, and its service performance degradation is a complex gradual process of multi-physical fields, multi-module variables and multi-level performance parameters, which is difficult to be accurately evaluated and comprehensively characterized by a single vibration signal or physical parameters. A multi-level parameter system could ensure an effective and accurate assessment of the complex systems degradation degree. In this system, the vehicle transmission system health degree is used as the target level data. The comprehensive the vehicle transmission system health degree consists of three modules health degree. The single module health degree can be characterized by multiple system performance. Each characterized performance can be evaluated by multiple feature parameters, and different feature parameters come from different physical models, real vehicle data, bench sensor data, etc. Among them, the parameter level calculation plays a key role in the system construction. Different parameters have different influence on system health degree, and this section conducts multi-parameter feature weighting analysis, in order to analyze the different influence factors on system health degree during the transmission system working and analyze the key factors affecting system health degree.

The 20 types parameter feature weights of the multilevel fusion model results are extracted and each parameter weights in the fusion process are analyzed. As shown in Figure 5, it can be seen that the mechanical module weights are higher than the other two modules. The mechanical module damage rate accounts for the largest weight of the 20 parameter feature weights, with a value of 0.095. Therefore, the mechanical module meta-components performance is the main factor affecting the vehicle transmission system health degree

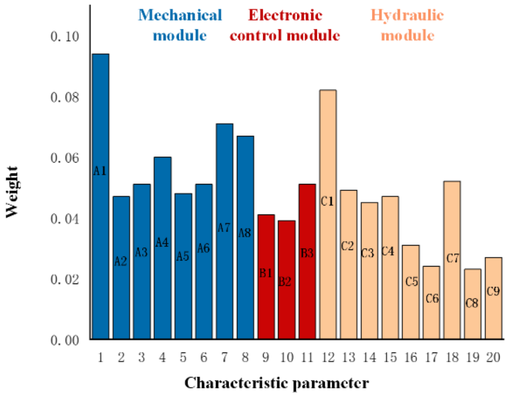
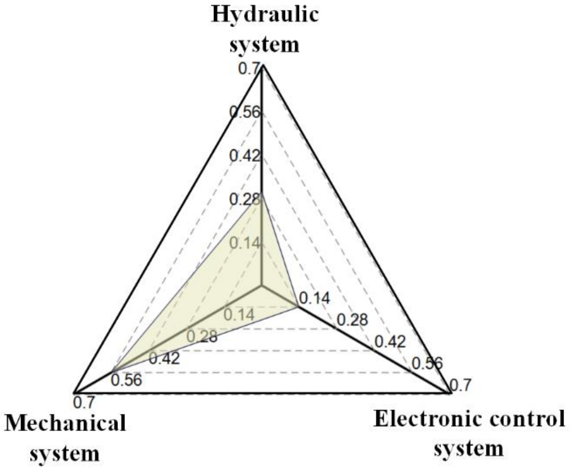
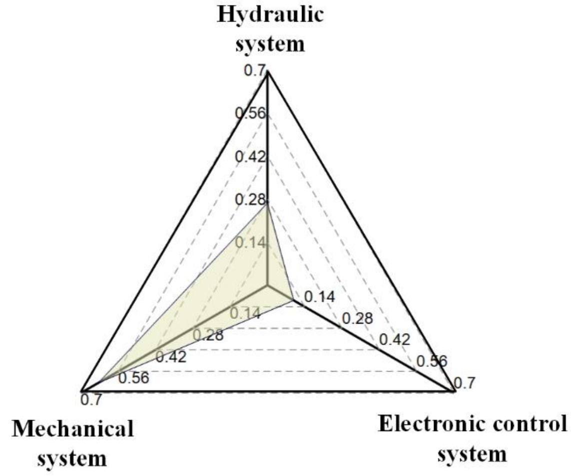


Fig.5. 20 feature weight distribution histogram.

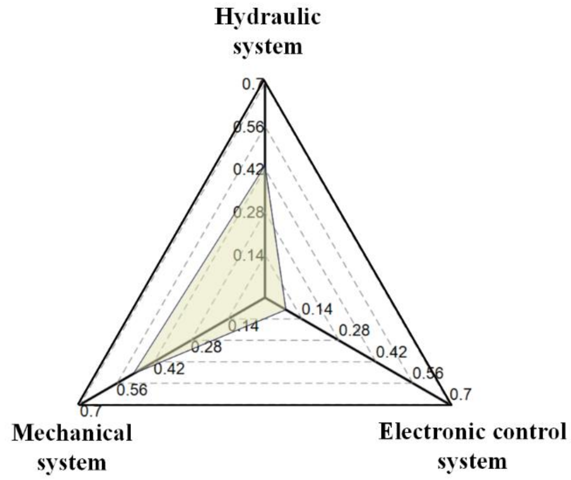
The weight assignment problem in three types modules is analyzed with different parameter feature data samples, as shown in Figure 6, which is a radar plot of three types modules health degree the weight assignment form four data samples, respectively. Through the radar diagram visual expression effect, observing the weights size which is obtained from the four types data feature samples fusion results. The weight of the mechanical module fluctuates around 0.56, the weight of the hydraulic module fluctuates around 0.3, and the weight of the electronic control module fluctuates around 0.14. The proportion of mechanical module weight accounts for more than a half. It can be seen that the order of influencing the vehicle transmission system health degree is mechanical module, hydraulic module, and electric control module in order. By comparing the predicted data in reference [17] with the fault tree, it can be seen that the failure of the automobile transmission system is mainly caused by mechanical components. The two conclusions are similar.



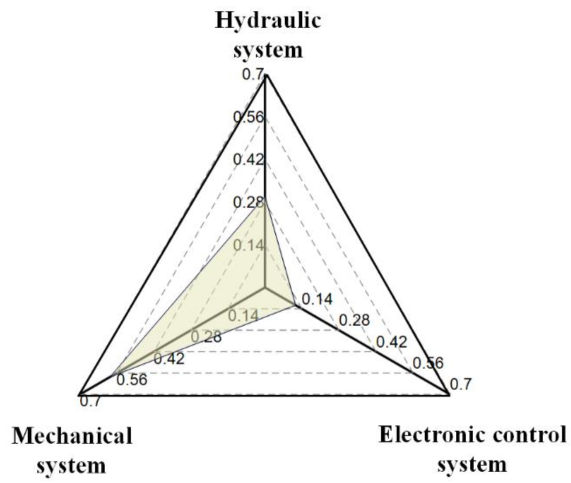
(a) Three types module weight distribution radar chart for data 1.



(b) Three types module weight distribution radar chart for data 2.



(c) Three types module weight distribution radar chart for data.



(d) Three types module weight distribution radar chart for data 4

Fig.6. Three types modules weight distribution radar diagram.

Based on the multi-level data fusion model with limited real measurement data, the health degree fusion results maximum deviation from the expert experience health degree does not exceed 5%, and the constructed multi-level data fusion model has a high fusion efficiency. The three types module-level parameter characteristics fusion has good fusion effect and practical significance for the vehicle transmission system health degree comprehensive evaluation. In contrast, the single module-level characteristic parameter fusion effect on the overall the vehicle transmission system health degree is poor, and the module-level health degree deviation from the vehicle transmission system health degree is large. The vehicle transmission system health degree influence order is mechanical module, hydraulic module and electric control module. The mechanical module components performance is the main factor affecting the overall the vehicle transmission system health degree.

6. Conclusion

In order to explore the vehicle transmission system health degree, we establish a multi-level data fusion model which uses PSO-BP neural network. The model can accurately predict the system health. Based on the limited measured data, the vehicle transmission system health degree is obtained by the single module feature parameters fusion, and three module feature parameters fusion are compared. Then the 20 types multi-level fusion model results parameter characteristic weights are extracted for analysis. The following conclusions are obtained.

(1) The predicted values average absolute relative error of the four types multi-level data fusion algorithm is 2.6%, indicating that the constructed multi-level data fusion model has a good fusion effect.

(2) The single module-level characteristic parameter fusion, which is difficult to acquire the vehicle transmission system health degree, and it is a large deviation between the module-level health degree and the vehicle transmission system health degree.

(3) Mechanical module has the greatest impact on the vehicle transmission system health degree, followed by hydraulic module and electronic control module. Moreover, the damage rate in mechanical module accounts for the largest weight of the 20 parameter characteristics, and the mechanical module components performance is the main factor affecting the overall the vehicle transmission system health degree.

By predicting the vehicle transmission system health degree, this model can help maintenance personnel better control the operation status of equipment and promote the efficient and safe operation in equipment throughout its life cycle.

References

1. Bachar L, Klein R, Tur M, Bortman J. Fault diagnosis of gear transmissions via optic Fiber Bragg Grating strain sensors. Mechanical Systems and Signal Processing 2022; (169-), https://doi.org/10.1016/j.ymssp.2021.108629.
2. Chen H, Kurt M, Lee Y S, et al. Experimental system identification of the dynamics of a vibro-impact beam with a view towards structural health monitoring and damage detection. Mechanical Systems and Signal Processing 2014; 46(1): 91-113, https://doi.org/10.1016/j.ymssp.2013.12.014.
3. Guo R, Sui J. Remaining Useful Life Prognostics for the Electrohydraulic Servo Actuator Using Hellinger Distance-Based Particle Filter. IEEE Transactions on Instrumentation and Measurement, 2020, 69(4):1148-1158. https://doi.org/10.1109/TIM.2019.2910919.
4. Helwig A, Muller G, Paul S. Health Monitoring of Aviation Hydraulic Fluids Using Opto-Chemical Sensor Technologies. Chemosensors 2021; 8(4),131, https://doi.org/10.3390/chemosensors8040131.
5. Huh J, Van H P, Han S, et al. A Data-Driven Approach for the Diagnosis of Mechanical Systems Using Trained Subtracted Signal Spectrograms. Sensors 2019; 19(5):1055, https://doi.org/10.3390/s19051055.
6. Jacobo V H, Ortiz A, Cerrud Y, et al. Hybrid expert system for the failure analysis of mechanical elements. Engineering Failure Analysis 2007; 14(8):1435-1443, https://doi.org/10.1016/j.engfailanal.2007.02.002.
7. Jia F, Lei Y, Lin J, et al. Deep neural networks: a promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. Mechanical System and Signal Processing 2016; 72/73: 303-315, https://doi.org/10.1016/j.ymssp.2015.10.025.
8. Jiang C, Wei Feng W. Prognostics and Health Management of Mechanical Systems. Advanced Materials Research 2013; 694–697:872–875, https://doi.org/10.4028/www.scientific.net/AMR.694-697.872.
9. Kelley J, Hagan M. New Fault Diagnosis Procedure and Demonstration on Hydraulic Servo-Motor for Single Faults. IEEE/ASME Transactions on Mechatronics 2020; 25(3): 1499-1509, https://doi.org/10.1109/TMECH.2020.2977857.
10. Kim Y, Na K, Youn B D. A health-adaptive time-scale representation (HTSR) embedded convolutional neural network for gearbox fault diagnostics. Mechanical Systems and Signal Processing 2022; 167:108575-, https://doi.org/10.1016/j.ymssp.2021.108575.
11. Krishnan M, Venkatesan S, Nagendran V, et al. Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin. IET Electric Power Applications 2019; 13(9):1328-1335, https://doi.org/10.1049/iet-epa.2018.5732.
12. Kumar S, Kumar P, Kumar G. Degradation assessment of bearing based on machine learning classification matrix. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2021(2); https://doi.org/10.17531/ein.2021.2.20.
13. Lei Y, Jia F, Lin J, Xing S, Ding S X, et al. An Intelligent Fault Diagnosis Method Using Unsupervised Feature Learning Towards Mechanical Big Data. IEEE Transactions on Industrial Electronics 2016; 63:3137-3147. https://doi.org/10.1109/TIE.2016.2519325.
14. Macaluso A, Jacazio G. Prognostic and Health Management System for Fly-by-wire Electro-hydraulic Servo Actuators for Detection and Tracking of Actuator Faults. Procedia Cirp 2017; 59:116-121. https://doi.org/10.1016/j.procir.2016.09.016.
15. Meng LH, Wang PZ, Liu ZG, et al. Safety Assessment for Electrical Motor Drive System Based on SOM Neural Network. Mathematical Problems in Engineering 2016; 2358142, https://doi.org/10.1155/2016/2358142.
16. Morais TS, Leao LD, Ap Cavalini A, Steffen V. Rotating machinery health evaluation by modal force identification. Inverse Problems in Science and Engineering 2019; 28(5): 659-715, https://doi.org/10.1080/17415977.2019.1644331.
17. Mu H, Yao Z, Yi X , et al. Reliability analysis for an EHCS of automatic transmission based on GO method// 2016 11th International Conference on Reliability, Maintainability and Safety (ICRMS). IEEE, 2016. https://doi.org/10.1109/ICRMS.2016.8050062
18. Pang T, Yu T, Song B. A Bayesian network model for fault diagnosis of a lock mechanism based on degradation data. Engineering Failure Analysis 2021; 122:105225, https://doi.org/10.1016/j.engfailanal.2021.105225.
19. Prakash J, Kankar PK. Health prediction of hydraulic cooling circuit using deep neural network with ensemble feature ranking technique. Measurement 2019; (151):107225, https://doi.org/10.1016/j.measurement.2019.107225.
20. Qi H T, Zhao D A, Liu D, et al. Double Redundancy Electro-Hydrostatic Actuator Fault Diagnosis Method Based on Progressive Fault Diagnosis Method. Actuators 2022; 11(9): 264, https://doi.org/10.3390/act11090264.
21. Rodrigues, Leonardo. Remaining Useful Life Prediction for Multiple-Component Systems Based on a System-Level Performance Indicator. IEEE/ASME Transactions on Mechatronics 2017; 23(1): 141-150, https://doi.org/10.1109/TMECH.2017.2713722.

22. Seventekidis P , Giagopoulos D. A combined finite element and hierarchical Deep learning approach for structural health monitoring: Test on a pin-joint composite truss structure. Mechanical Systems and Signal Processing 2021; 157(5):107735, https://doi.org/10.1016/j.ymssp.2021.107735.
23. Suh S, Jang J, Won S, et al. Supervised Health Stage Prediction Using Convolutional Neural Networks for Bearing Wear. Sensors 2020; 20(20): 5846, https://doi.org/10.3390/s20205846.
24. Sun W, Shao S, Zhao R, et al. A sparse auto- encoder-based deep neural network approach for induction motor faults classification. Measurement 2016; 89:171-178, https://doi.org/10.1016/j.measurement.2016.04.007.
25. Yan S, Ma B, Zheng C. Health index extracting methodology for degradation modelling and prognosis of mechanical transmissions. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2018; 21(1):137-144, https://doi.org/10.17531/ein.2019.1.15.
26. Yong B L, Lee G C, Park J W, et al. Failure Analysis of a Hydraulic Power System in the Wind Turbine. Engineering Failure Analysis 2019; 107:104218, https://doi.org/10.1016/j.engfailanal.2019.104218.
27. Zhang Y, Liu L, Peng Y, et al. Health indicator extraction with phase current for power electronics of electro-mechanical actuator. Measurement, 159:107787, https://doi.org/10.1016/j.measurement.2020.107787

Appendices

Table.2 Twenty characteristic indexes

Symbol	Meaning
A1	Damage rate
A2	Shift time
A3	Impact degree
A4	Sliding friction work
A5	Output shaft speed
A6	Output shaft torque
A7	Turning radius
A8	Transmission efficiency
B1	Signal fluctuation amplitude
B2	Signal fluctuation frequency
B3	Signal extreme value duration
C1	Oil pump volumetric efficiency
C2	Lubrication flow
C3	Pump motor speed
C4	Pump motor volumetric efficiency
C5	Pump motor torque
C6	Shift oil pressure similarity
C7	Oil pressure similarity under specific working conditions
C8	Oil pressure characteristic parameter group
C9	Oil temperature similarity