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Considering the Life Prediction of Construction Machinery Workshop

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Abstract: Traditionally, the replacement of products in construction machinery workshop is based on empirical cycles, although this strategy is simple, it cannot give full play to the full life of the products, resulting in underutilization, reduction of part accuracy, and increase of surface roughness. In order to solve the shortcomings of the existing research on life prediction of construction machinery workshop, this paper briefly discusses the selection of workshop construction machinery product samples and equipment parameter settings for the proposed life prediction model of construction machinery workshop based on the discussion of gated cyclic unit neural network and hydraulic motor life prediction criteria. And the design of the prediction model is discussed, and finally the prediction model is compared with the other two models for experimental analysis. The experimental data show that the prediction effect of the gated cyclic unit neural network is better than the other two models, and its prediction results are closer to the real life value. Its prediction accuracy reaches up to 94.8%. Therefore, it is verified that the gated recurrent unit neural network can make accurate prediction of the life time of the construction machinery workshop.

1. Introduction

Once the engineering machinery and equipment in the workshop fails, it will cause certain economic losses or even more serious consequences. Therefore, it is of great theoretical significance and practical value to carry out the life prediction of engineering machinery and equipment in workshops.

Nowadays, more and more scholars have conducted a lot of research on the life prediction of construction machinery shop through various technologies and system tools, and have also obtained certain research results through practical research. Aiming at the shortcomings of traditional machine tool life prediction methods such as low accuracy of life prediction and few sample base attributes, Ma M proposed a machine tool life prediction model combined with machine tool attributes. The machine tool life prediction model uses KL dispersion distribution theory, uses the mode superposition method to analyze the machine tool life, calculates the theoretical life of the machine tool, and then carries on the simulation, obtains the predicted value of the machine tool life. The original parts data are enhanced to complete the life prediction model based on deep learning. The machine tool life was quantitatively analyzed. The experiment of predicting the life of machine tool with training dataset proves the effectiveness of this model [1]. Adel W M proposed the additional hardening effect. The validity and adaptability of the new model are verified by the multiaxial fatigue test data. The accuracy of life prediction and the range of material application are satisfactory. A multiaxial fatigue life model based on critical plane method is proposed. By introducing a non-proportional additional damage coefficient, the joint effects of loading path and additional hardening can be considered. Through the multi-axial fatigue test data of eight materials and nine loads, the prediction accuracy of the model is compared with that of the KBM model and FS model, and the life prediction accuracy and material applicability of the model are verified. The new model has clear physical meaning and is convenient for practical engineering application [2]. According to the prediction analysis of the life of rubber at different temperatures, Rai concluded that the aging due to the influence of temperature has a great impact on the residual life of rubber. According to the rubber tensile information at different temperatures, the strain energy was set as the rubber aging parameter, and the residual life prediction model was established. The test results of the model are tested and the predicted results are compared with the real results. The results show that the average relative error of this model is less than 18.89%[3]. Although the existing research on the life prediction of construction machinery is very rich, the research on the life prediction of workshop construction machinery fused with gated circulating unit nerve still has some limitations.

This paper presents the mathematical model of the gated recurrent unit neural network, which is used to take into account the life prediction technology of construction machinery workshop, and explains how to translate the formula into reality in the actual prediction process. The gated recurrent unit neural network does not simply propagate the data forward and backward, but can handle two-way time series data. In addition, the results of the remaining life prediction of the three models were analyzed by experimenting with hydraulic motors in the workshop. It can be seen that GRUNN has better prediction capability than PCA-SVR and DCNN, and the correct prediction rate data are sufficient for the gated recurrent unit neural network method to have some advantages over some traditional methods.

2. Considering the Life Prediction of Construction Machinery Workshop

2.1. Gated Cycle Unit Neural Network

Gated recurrent unit neural network, GRU does not need to separate the neural unit to adjust the information, update the door current state information by the degree of influence of the previous moment of information; reset the door to determine the degree of information input to the implicit layer of the previous moment to the current moment is forgotten [4].

The GRU is calculated as:

$$f_x = \partial(Q_i u_x + G_i k_{x-1} + c_i) \tag{1}$$

$$s_x = \partial(Q_s u_x + G_s k_{x-1} + c_s) \tag{2}$$

$$k_x^{'} = \tanh(Q_k u_x + i_x G_k k_{x-1} + c_k) \tag{3}$$

In Eqs. (1)-(3): u_x denotes the current prediction x sample input; k_{x-1} denotes the previous prediction hidden layer sample output; i_x and s_x are the reset gate and update gate, respectively; $k_x^{'}$ is the pending activation state of the current prediction sample; $Q_* \in I^{l\times m}$ and $G_* \in I^{l\times l}$ correspond to the weight matrix of the current input layer sample and the previous prediction hidden layer sample output, respectively [5]. $c_* \in I^{l\times l}$ denotes the bias term; ∂ and tanh are the activation functions. The network is composed of forward and backward propagating GRUs, and the bidirectional structure can increase the model capacity and flexibility, making the bidirectional recurrent neural network can handle bidirectional time series data [6].

2.2. Construction Machinery Workshop Life Prediction

Traditional life prediction methods mainly include the following three categories.

(1) The use of stress product life prediction: this method is mainly based on the differences in the method of applying stress, so as to be able to distinguish between different methods of life prediction, and thus be able to choose various methods of life prediction for different products [7].

(2) Using the life expectancy method in probabilistic statistical analysis: it refers to the use of a large number of tests to derive the failure criterion of the product, and then according to the principles of statistical analysis [8]. Appropriate statistical models are selected to "fit" the failed product, so that the failure characteristics of the product life and its expected value of life [9].

(3) The use of new information technology life prediction: is through the computer to simulate human thinking, even the ability to learn, the ability to deduce and other complex processes to the product life prediction [10].

2.3. Hydraulic Motor Life Prediction Criteria

According to JB/T10829-2008, when the nominal displacement of piston motor is greater than 25mL/r, the volumetric efficiency should be more than 94%, and the nominal displacement of the test motor is 27.4mL/r, so its volumetric efficiency is greater than 94% [11]. For the same motor, when the volumetric efficiency is lower than a certain value, the motor is judged to have failed. For the motor, the volumetric efficiency is relative, and the volumetric efficiency of the motor will change at different speeds [12]. By considering all factors, the motor is considered to have failed when the volumetric efficiency of the motor in the test condition is 4% lower than the initial value [13].

3. Investigation and Study of Life Prediction Taking into Account the Workshop of Construction Machinery

3.1. Workshop Construction Machinery Product Sample Selection

This experiment selects the workshop construction machinery products hydraulic motor, according to the different internal structure of the product, can be divided into vane type, piston type hydraulic motor and so on [14]. The mechanical products selected for this life prediction test must meet the requirements of the actual working conditions, that is, to maintain normal operation under the experimental working conditions [15]. Combined with the actual working conditions, the relevant parameters of the product are shown in Table 1.

Table 1. Sample parameters

Project	Hydraulic motor	Model	Xsm25
Rated speed(r/min)	1200	Rated pressure(MPa)	15
Displacement(mL/r)	24.7	Rated torque(N.M)	320

3.2 Equipment Parameters Setting

The test bench used in this experiment is mainly used for the life testing of hydraulic pumps and hydraulic motors, which can predict the failure of hydraulic components of different specifications [16]. The maximum loading pressure and rotational speed of the test bench are much higher than the rated pressure and rated rotational speed of the test motor, which fully meet the test requirements, and the pressure and rotational speed tend to be stable during the operation of the motor, and the accuracy of the measurement data obtained is high [17]. During the test, the test stand was used to calculate the volumetric efficiency of the motor by recording the inlet and outlet pressure, flow rate, motor speed, and leakage volume, and to save the data [18]. The equipment parameters are shown in Table 2:

Table 2. Equipment parameters

Project	Range	Response rate	Precision
Pressure transducer transducer	0-450bar	400HZ	0.35%
Speed sensor	0-400/min	≤10ms	0.25%
Torque transducer	0-2600r/min	≤10ms	0.25%
Temperature sensor	0-270 ℃	≤10ms	±1 ℃

4. Application study of Life Prediction Taking into Account the Construction Machinery Workshop

4.1. Establishment of Life Prediction Model for Construction Machinery Workshop

In order to extract the failure characteristic information related to the remaining life of the hydraulic motor in the construction machinery workshop, and to overcome the shortcomings of the machine learning method relying on manual experience and to improve the prediction efficiency and accuracy of the model, the prediction flow chart of the product is shown in Figure 1.

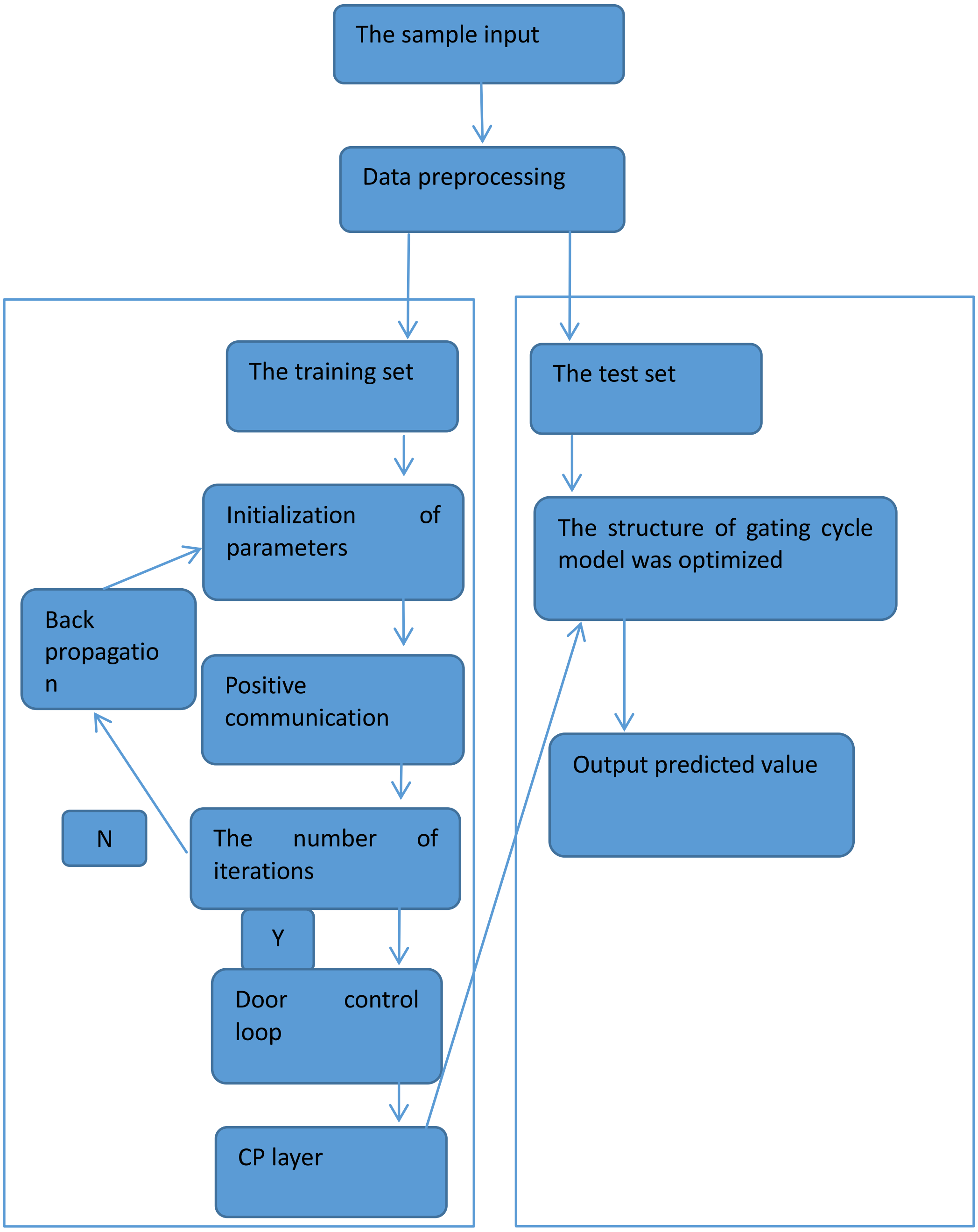

Figure 1. Flow chart of remaining life prediction of hydraulic motor

The detailed steps of life prediction based on gated recurrent unit neural network are as follows:

(1) Build a hydraulic motor acquisition system to collect hydraulic motor failure information.

(2) Pre-process the collected sample data (pre-processing includes data normalization), and divide it into two kinds of training set and test set, the training set is used for the training of hydraulic motor remaining life prediction, and the test set tests the performance of the model.

(3) Establish the 1DCNN model and set the initialization parameters. According to the sample input form and requirements, a network model of suitable depth is established, and suitable hyperparameters (learning rate, batch size, number of iterations, etc.) are determined, and an

inverted pyramid design is used in setting the number of neurons in the convolutional layer.

(4) 1DCNN training. The samples are input to the network, and the inter-data features are learned by forward propagation, and these features are passed forward through different layers, and the last layer is passed through the actual output, and the loss and the error between the output and the expected output are calculated, and the number of iterations required to be satisfied or not is used as the basis for judgment. For those that do not meet the requirements use the gradient descent algorithm to back-propagate the error to the previous layer to fine-tune the parameters, then forward propagation, otherwise, and so on and so forth until the number of iterations is reached.

(5) The fully connected layer of the gated recurrent neural network model (removing the softmax layer) is followed by an ELM classifier instead of the softmax layer for model training.

(6) Obtain the optimal gated recurrent neural network prediction model structure, input the test set into the optimal prediction model, and obtain the hydraulic motor remaining life prediction results.

4.2. Application of Life Prediction Model Considering Construction Machinery Workshop

In order to further verify the effectiveness of the gated recurrent unit neural network (GRUNN) prediction model established in this paper, 70% of the samples were still selected as the training set and 30% as the test set, and different models were designed for comparison, including machine learning PCA-SVR and also deep learning DCNN. in order to verify the effectiveness and accuracy of (GRUNN) scientifically and fairly, the three models of The same structure is used with the same parameters as the (GRUNN) model, and the loss function of the neural network is HM-MSE-Score function. The specific correctness of the prediction results are shown in Table 3.

Table 3. Prediction results accuracy data

Sample	GRUNN	PCA-SVR	DCNN
100	92.3%	78.6%	89.1%
200	93.4%	76.1%	88.3%
300	94.8%	77.5%	87.8%
400	93.9%	75.8%	86.5%
500	94.7%	77.8%	84.6%

Figure 2 gives a visual comparison of the predictions of different models on the test set, GRUNN is closer to the real remaining life of hydraulic motor than PCA-SVR and DCNN with the increase of sample data, while the prediction value of PCA-SVR is basically larger than the actual value, i.e., the remaining life prediction lags behind, which is easy to cause the hydraulic motor to reach the life and still continue processing, and finally cause the processed products cannot meet the requirements and scrap, increasing the production cost This will increase the production cost and waste production resources. The overall data show that the model established in this paper can not only converge to the real value faster, but also be closer to the real value.

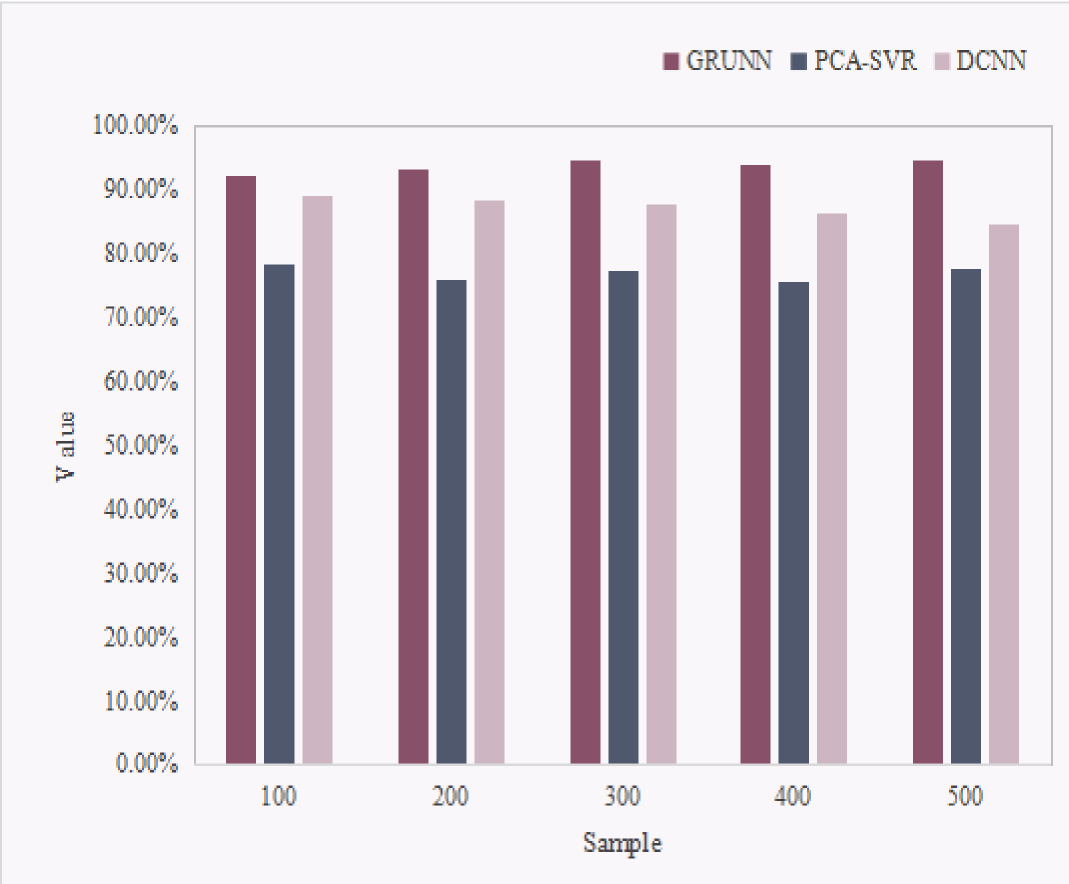

Figure 2. Comparison of prediction accuracy

5. Conclusion

In order to solve the problem of the remaining fatigue life prediction accuracy in the workshop construction machinery, this paper uses the gated recurrent neural network to improve the prediction accuracy, based on the consideration of the workshop construction machinery products hydraulic motor, the import and export pressure, flow rate, motor speed and leakage of hydraulic motor equipment was recorded and analyzed, and the results of the calculation of the remaining life of hydraulic components based on the gated recurrent neural network on The gated recurrent neural network approach is used to optimize the hydraulic components of the hydraulic motor, which provides a certain reference for the design and manufacture of construction machinery workshop. Due to the limitation of the conditions, the damage needs to be further improved in the future research.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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