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Runtime Prediction of Armored Vehicle Engine Based on Neural Network

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Abstract. To a great extent, engine's runtime of armored vehicle reflects its technical state. By estimating engine's runtime, the remaining service life can be forecasted. In this paper, the virtues of neural network prediction are introduced. Aiming at a certain armored vehicle engine, the BP neural network regression prediction model is constructed based on four typical state parameters including cylinder compression pressures, acceleration time, deceleration time and supply fuel advance angle. The model is trained and validated by samples data. The prediction results indicate that the model is effective and feasible. At last, two prediction problems that need to be studied hard are proposed.

Keywords: BP neural network, prediction, armored vehicle engine

1. Introduction

Engine is the heart of armored vehicle. With time going on and abrasion of the parts increasing, engine's technical state will gradually become inferior, resulting in either economy and power performance descending or faults. The engine is considered to be up to its limit of service life when its technical state reaches to a certain ultimate condition. Then the decision that the engine will be retired or overhauled should be made. Engine's runtime is its operation hours (For armored vehicle, it is motor hours). By estimating the runtime, the remaining service life can be forecasted. Therefore, studying prediction technique to estimate engine's runtime and scientifically is the base to make maintenance strategy.

2. Theory of Neural Network Prediction

2.1. Virtues of Neural Network Prediction

The prediction capability of neural network is mainly based on its all-right character of function approximation. Namely it can express any nonlinear relation. In this way, it provides new thought to solve complex problems of nonlinear relation prediction. Neural network is nonlinear, so it has a very good ability to catch nonlinear data and it is a good supplement for the linear regression prediction model and linear time series prediction model. For most prediction objects (especially for objects including nonlinear relation), large numbers of prediction experimentations have proved that the neural network prediction method can reach to a higher precision.

Now the neural network kinds which are applied to prediction aspect mainly include BP network and RBF network. Moreover, BP network is most frequently adopted. As a kind of nonlinear prediction method and duel to its own data-driven characteristic, BP neural network model is used for prediction problems broadly in all sorts of domains on condition that the inner mechanism of object doesn't need to be detected [3].

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2.2. Regression Prediction Model of BP Neural Network

BP neural network model can be used for causal prediction like regression prediction method. Actually, many problems should be noticed in the regression prediction, for example, abnormal data and multicollinearity. These problems can affect the accuracy of regression prediction. On the contrary, BP neural network prediction can overcome the problems. For nonlinear regression problems, BP neural network can gain a good prediction result.

This paper takes single hidden layer BP neural network model as an example to introduce the causal prediction. The input layer, hidden layer and output layer of single hidden layer BP neural network model are shown in the figure 1.

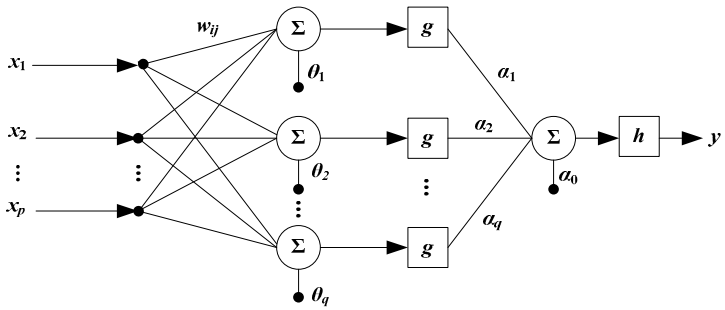

Fig. 1: Single hidden layer BP neural network regression model

In this neural network structure, the input layer has p nodes which correspond to the p explanatory variables x_1, x_2, $\cdots$, x_p in the causal sequence. The output layer has q nodes. Parameter ω_{ij} (j =1, 2,$\cdots$, p , i =1, 2,$\cdots$, q) is the weight between the *j*th input layer node and the *i*th hidden layer node. Parameter θ_i （ i =1, 2,$\cdots$, q ） is the bias of the *i*th hidden layer node. Parameter α_i （ i =1, 2,$\cdots$, q ） is the weight between the hidden layer nodes and output layer node.

The activation function of the hidden layer is usually logistic sigmoid function. The output layer has only one node which represents the prediction value y . The activation function between the hidden layer and output layer is usually linear function.

From the network relation in the figure 1, the function between output value y and input value x_1, x_2, $\cdots$, x_p is as follows.

$$y = h\left(\alpha_0 + \sum_{i=1}^{q} \alpha_i g\left(\theta_i + \sum_{j=1}^{p} \omega_{ij} x_j\right)\right) \tag{1}$$

The function (1) can also be written as follows.

$$y = f(x_1, x_2, \cdots, x_p, w) \tag{2}$$

If a stochastic disturbance value is joined in the function (2), then it becomes as follows.

$$y = f(x_1, x_2, \cdots, x_p, w) + \varepsilon \tag{3}$$

From the function (3), it is can be shown that this neural network model actually corresponds to a multiple linear regression model.

3. Runtime Prediction of Armored Vehicle Engine

Engine service life is its operation hours before it reaches to the limit technique state which is in the wear failure period. In the process of using the engine, operation and maintenance personnel pay more attention to current work state and how long it can work normally. Engine record notebook has registered its motor hours, but it can't reflect the true technique state. And it is not scientific and accurate to predict the remaining service life by motor hours. Consequently, combining with technique state parameters, the neural network model is used to predict engine runtime.

3.1. Parameters and Samples

Many parameters value data have been gained and collected in the former engine experiment of armored vehicle [4]. Some parameters, like Cylinder compression pressures $\hat{p}_{\max}$ 、 acceleration time $\hat{t}_i$ 、 deceleration time $\hat{t}_d$ 、 supply fuel advance angle $\hat{\theta}_{fd}$, can well reflect engine's technique state. Aiming at a certain type of armored vehicle, the above four typical parameters values were sampled from the existing data, as shown in the Table 1. The acceleration time is concerned with average fuel flux during acceleration time. Therefore, in the table 1, acceleration time $\hat{t}_i$ is an optimized value which is the result of acceleration time by average fuel flux. Based on these data, engine runtime can be estimated by the BP network regression model.

Table 1 Samples data

Vehicle number	Runtime t (h)	$\hat{p}_{\max}$ (MPa)	$\hat{t}_i$ (s•mL)	$\hat{t}_d$ (s)	$\hat{\theta}_{fd}$ (ºCA)	Data class
211	11	2.8950	3.5005	1.3978	34.950	Training data
405	59	2.8647	3.9012	1.5891	33.9000	
314	103	2.8228	4.3359	1.7882	32.8462	
411	140	2.8090	4.4293	1.8461	32.1142	
607	190	2.7847	4.6562	1.9169	31.1671	
604	250	2.7736	4.8549	1.9369	31.0942	
209	300	2.7521	5.0254	1.9458	30.3144	
601	350	2.7330	5.1509	1.9546	29.0114	
505	390	2.7132	5.2515	1.9420	28.9751	
404	450	2.6739	5.3802	1.9999	27.5521	
305	507	2.6527	5.5346	2.0902	26.4883	
217	550	2.6429	5.7113	2.1404	25.8854	
402	38	2.8744	3.7249	1.5134	33.9796	Testing data
215	187	2.7958	4.5435	1.8843	31.1880	
304	320	2.7439	5.1032	1.9499	29.5521	
118	497	2.6647	5.4532	2.0542	26.6285	

3.2. Data Pretreatment

In order to eliminate dimensions and reduce the negative impact on neural network's performance for unbalanced value, the samples are pretreated and normalized to reduce the variable's value into rage [0, 1]. There are several different methods to normalize data. In this paper, a method based on linear transformation is adopted to normalize data. That is formula (4) as follows [5].

$$x' = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} \tag{4}$$

where， x' —the outcome of data processing;

x —samples data of the four typical parameters;

$x_{\max}$ —the maximum value of variable x ;

$x_{\min}$ —the minimum value of variable x .

The service life of the kind of engine is about 550 hours. The runtime value data of the training data in table 1 can be normalized by the formula (5) as follows.

$$t' = t/550 \tag{5}$$

where, t'—the outcome of data processing

t—samples data of the runtime;

The normalize data are shown in the table 2.

Table 2 Normalized data

Vehicle number	t'	$\hat{p}'_{\max}$	$\hat{t}_i'$	$\hat{t}_d'$	$\hat{\theta}_{fd}'$	Data class
211	0.0200	1.0000	0	0	1.0000	Training data
405	0.1073	0.8798	0.1812	0.2576	0.8842	
314	0.1873	0.7136	0.3779	0.5257	0.7679	
411	0.2545	0.6589	0.4201	0.6037	0.6872	
607	0.3455	0.5625	0.5228	0.6990	0.5827	
604	0.4545	0.5184	0.6126	0.7260	0.5746	
209	0.5455	0.4332	0.6898	0.7379	0.4886	
601	0.6364	0.3574	0.7465	0.7498	0.3449	
505	0.7091	0.2789	0.7920	0.7328	0.3409	
404	0.8182	0.1230	0.8502	0.8108	0.1839	
305	0.9218	0.0389	0.9201	0.9324	0.0665	
217	1.0000	0	1.0000	1.0000	0	
402		0.9183	0.1015	0.1557	0.8929	Testing data
215		0.6065	0.4718	0.6551	0.5850	
304		0.4006	0.7249	0.7435	0.4045	
118		0.0865	0.8833	0.8839	0.0820	

3.3. Structure and Application of BP Network

In this paper BP neural network with three layers is applied to estimate runtime. The input layer represents the parameters samples, so there are 4 neurons in input layer. Making a contrast with different BP models by the Matlab software, when the hidden layer has 8 neurons, the results are much better. The output layer has 1 neuron which represents the prediction value. The activation functions of the hidden layer and output layer both are log sigmoid function, as formula (6). And the BP Network is trained by the Levenberg-Marquardt algorithm.

$$\log\mathrm{sig}(n) = 1/\left(1+e^{-n}\right) \tag{6}$$

The training error curve is shown in the figure 2.

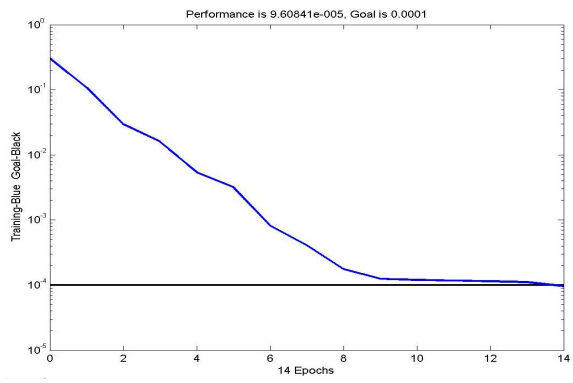

Fig. 2: Training error curve

Based on the testing data in table 2, the testing result values are gained in the table 3 by making simulations with the above trained BP neural network regression model. It is can be seen from table 3 that the testing values are close to the actual values. The error is little and acceptable. Therefore, it is feasible to estimate the runtime with this BP neural network model.

Table 3 Testing result

Vehicle number	402	215	304	118
Actual value(h)	38	171	320	487
Testing value(h)	35.9717	164.8093	328.8645	480.8535
Relative error	5.34%	3.62%	2.77%	1.26%

From table 3, we can see that the relative error becomes smaller and smaller with the runtime increasing. Because the engines are usually in a good condition, it doesn't need to estimate engine's runtime in its early period of service life. The estimation can be started from the middle period. In this way, we can get the more accurate results.

4. Conclusions

In this paper, we construct a BP neural networks regression model of armored vehicle engine to estimate its runtime. Furthermore, we can predict the remaining service life of the engines based its runtime. However, this model is not perfect and the result is not accurate enough. Several problems need to be studied deeply.

4.1. Try to Choose Accurate State Parameters and Acquire Perfect Original Data

The engine has too many parameters that can reflect its technique state. It is difficult to use all the parameters to construct prediction model. At the same time, the engine of armored vehicle is a complex machine and its testability is not satisfying. As a result, it is difficult to obtain the original state data. Nevertheless, the rational parameters and ideal original data can bring a precise prediction result. Undoubtedly, we should try our best to study how to choose accurate state parameters and acquire perfect original data.

4.2. Pursue Combination Prediction Studies

Armored vehicle engine is complex and includes many systems. It is difficult to get an ideal prediction result with a single method. Conversely, if several algorisms are combined to make prediction, not only can it acquire their virtues, but also can remedy respective shortcomings [6]. For example, combing neural network with fuzzy theory, it can bring qualitative information under the frame of neural network. This network is better than common neural network in the prediction domain. It is the inevitable trend to study combination prediction method.

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