Research on Performance Degradation Modeling for Machine Gun's Barrel Based on FOAGRNN

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Abstract. A method to establish performance degradation model for barrel based on general regression neural network with fruit fly optimization algorithm (FOAGRNN) was proposed. It took the muzzle velocity reduction as performance degradation feature with the increase in the number of shooting ammunition quantity under various working conditions, based on the performance degradation experimental data of barrel. The forecasting results were basically consistent with experimental results, which proved the feasibility of the method.

1. Introduction

The performance degradation discipline of machine gun's barrel under various working conditions and to establish performance degradation model are important to correct use the weapons, which has received extensive attention.

Many scholars have carried out much research into the forecasting method of the performance of machine gun's barrel. Chen guo-li[1] proposes a method of calculating bore erosion and wear figures using its nonlinear approximation and generalization abilities based on BP neural network and predict the barrel life based on maximum erosion and wear figures. Zhang jun[2] and Shan yong-hai[3] studied the relationship between the machine gun's shooting ammunition quantity before the life and environment factors, and then established accelerated life model for machine guns based on LS-SVM. However, the prediction of performance degradation of machine gun's barrel under various working conditions is rarely studied. Generalized regression neural network (GRNN) has been proven to be effective in dealing with the non-linear problems, but it is very regretfully finds that the GRNN have rarely been applied to the Performance degradation forecasting of machine gun's barrel.

The generalized regression neural network (GRNN) proposed by the scholar Specht[4] in 1991 was a kind of supervised learning neural network. The GRNN has strong non-linear mapping ability, high error tolerance and robustness. Since the smoothing parameter of the GRNN obviously affects the prediction performance of neural network, the fruit fly optimization algorithm is used to automatically select the parameter of GRNN, and then forecast the performance degradation of barrel by the optimal neural network model[5].

In this paper, forecasting results are verified by the actual test data, which validated the effectiveness of establishing performance degradation model for barrel based on general regression neural network with fruit fly optimization algorithm (FOAGRNN).

2. Performance degradation modeling for machine gun's barrel

2.1 Performance degradation test of machine gun's barrel

Through the theoretical research on the mechanism of barrel life end and the statistical analysis on a large number of experiment data, it is shown that test ambient temperature and shooting interval seriously affected the performance degradation of machine gun's barrel. Thus, it took the test ambient temperature and shooting interval as the experiment factor, and took the muzzle velocity reduction as performance degradation feature with the increase in the number of shooting ammunition quantity to establish the performance degradation model of machine gun's barrel.

In this study, experiment method of performance degradation is employed under type II censored constant stress. The ambient temperature of the experiment selected 22, -25, -45 and 50, and the shooting interval selected 0.5min, 1min, 2min and 3min, and 7 machine gun's barrels were used. Based on the experiment with different ambient temperature and shooting interval, the muzzle velocities with corresponding shooting ammunition quantity are obtained, as shown in Table 1 and Table 2. Due to the muzzle velocity values are random, in order to facilitate comparative analysis, velocity values were normalized to non-dimensional velocity.

Table 1 Relationship between muzzle velocity and shooting ammunition quantity under various working conditions（Training samples）

	T/℃	T_s/min	N/round	v_0/m·s^{-1}	v_0^*
1	22	0.5	0	806.4	1
			612	825.3	1.023
			1073	819	1.016
			1605	803.9	0.997
			2265	755.3	0.937
2	22	3	0	804.5	1
			674	825.8	1.026
			1435	813.5	1.011
			2280	779.4	0.969
			3240	713.1	0.886
3	50	2	0	806.7	1
			554	815.1	1.01
			1135	831	1.03
			1802	808.2	1.002
			2487	775.3	0.961
4	-45	2	0	811.8	1
			559	824.1	1.015
			1400	832	1.025
			2235	822.6	1.013
			3210	805.1	0.992

T is test ambient temperature, T_s is shooting interval, N is shooting ammunition quantity, v_0 is muzzle velocity, v_0^* is non-dimensional muzzle velocity

2.2 Performance degradation modeling for barrel based on generalized regression neural network

The generalized regression neural network (GRNN) is a type of radial basis function (RBF) network, which is a kind of supervised learning neural network. The GRNN has excellent performances on approximation and learning speed. The GRNN is fast learning and convergence to the optimal regression surface which gathers most sample data. When the number of sample data is small, the GRNN still has a good forecasting result.

The theoretical basis of the GRNN if non-linear regression analysis, and the GRNN can be represent as

$$E\left[\boldsymbol{Y}\middle|\boldsymbol{X}\right]=\frac{\int_{-\infty}^{\infty}\boldsymbol{Y}f(\boldsymbol{X},\boldsymbol{Y})d\boldsymbol{X}}{\int_{-\infty}^{\infty}f(\boldsymbol{X},\boldsymbol{Y})d\boldsymbol{X}} \tag{1}$$

where $\boldsymbol{X}=[x_1,x_2,\cdots,x_r]^{\mathrm{T}}$, $\boldsymbol{Y}=[y_1,y_2,\cdots,y_k]^{\mathrm{T}}$, $\boldsymbol{X}$ is a r-dimension input vector, $\boldsymbol{Y}$ is a k-dimension output vector and it is the predicted value of the GRNN model, $f(\boldsymbol{X},\boldsymbol{Y})$ is the joint probability density function of $\boldsymbol{X}$ and $\boldsymbol{Y}$, $E\left[\boldsymbol{Y}\middle|\boldsymbol{X}\right]$ is the expected value of the output vector $\boldsymbol{Y}$, given the input vector $\boldsymbol{X}$.

The GRNN consists of four layers: input layer, pattern layer, summation layer, and output layer, just as shown in Fig. 1.

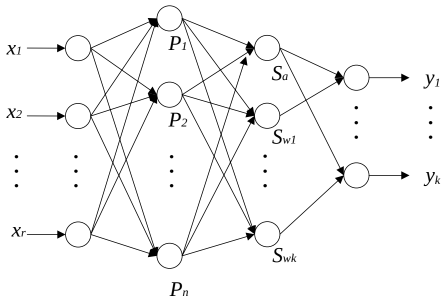

Fig.1 Schematic diagram of the GRNN architecture

(1) Input layer

The neurons of input layer receive information from input vector, and the number of neurons equals to the dimension of input vector. Then, the input neurons transfer the input data to the pattern layer.

(2) Pattern layer

The number of pattern neurons in the pattern layer equals to the number of the sample data. Each neuron computes the pattern Gaussian function expressed by

$$p_i = \exp[-\frac{(\boldsymbol{X}-\boldsymbol{X}_i)^T(\boldsymbol{X}-\boldsymbol{X}_i)}{2\sigma^2}] \quad i=1,2,\cdots,n \tag{2}$$

where $\boldsymbol{X}$ is the input presented to the network and $\boldsymbol{X}_i$ is each of the training vector, σ denotes the smoothing parameter.

(3) Summation layer

The summation layer has two summations S_a and S_w. S_a computes the arithmetic sum of the pattern neuron outputs. S_w computes the weighted sum of the pattern neuron outputs, and the connection weight y_{ij} from *i*th neuron in pattern layer to *j*th neuron in summation layer is the *j*th element in output vector $\boldsymbol{Y}_i$ of training sample data. The transfer functions can be represented as

$$S_a = \sum_{i=1}^{n} p_i \tag{3}$$

$$S_{wj} = \sum_{i=1}^{n} y_{ij} p_i \qquad j=1,2,\cdots,k \tag{4}$$

(4) Output layer

The number of neurons in output layer equals to the dimension k of the output vector. The jth element of prediction result $\hat{\boldsymbol{Y}}$ is the output of the *j*th neuron in output layer, represented as

$$y_j = \frac{S_{wj}}{S_a} \qquad j=1,2,\cdots,k \tag{5}$$

In this study, $\boldsymbol{X}$ is a 3-dimension vector consists of test ambient temperature, shooting interval and shooting ammunition quantity, $\boldsymbol{Y}$ is the, n is the number of training sample data. (2)~ (5) are used to calculate the forecasting result of the muzzle velocity reduction.

2.3 Model Parameter Optimization based on fruit fly optimization algorithm

Since the training of the generalized regression neural network (GRNN) do not need iteration, and the number of hidden neurons and the interconnected weights between layers are uniquely determined by the training samples, the value of smoothing parameter directly affects the prediction performance of neural network. Therefore, the process of training neural network is looking for optimal smoothing parameter σ.

Many researchers selected σ by priori knowledge or experience, which may be un-efficient for forecasting. In order to improve the prediction accuracy of the model, the fruit fly optimization algorithm (FOA) is used to automatically determine the smoothing parameter value of the GRNN model.

Fruit fly optimization algorithm (FOA) proposed by the scholar Pan[6] is a novel evolutionary computation and optimization method for finding behavior of the fruit fly. The fruit fly itself is superior to other species in sensing and perception, especially in osphresis and vision. The osphresis organs of fruit flies can find all kinds of scents floating in the air. When the fruit fly gets close to the food location, it can also use its sensitive vision to find food and fly towards that direction.

The specific steps of FOA are as follows:

Step 1: Initialize the population size $sizepop$, maximum iteration number $maxgen$ and the initial fruit fly swarm location(U_axis, V_axis). Set $gen = 0$.

Step 2: Given the random flight direction $Random$ and the distance h for finding food of an individual fruit fly.

$$U_i = U\_axis + 2h \times (Random - 0.5) \quad (6)$$

$$V_i = V\_axis + 2h \times (Random - 0.5) \quad (7)$$

where $Random$ is a random value between 0 to 1.

Step 3: Estimate the distance from individual fruit fly to the origin ($Dist_i$), and then the smell concentration judgment value (S_i) can be calculated, and this value is the reciprocal of distance.

$$Dist_i = \sqrt{U_i^2 + V_i^2} \quad (8)$$

$$S_i = 1 / Dist_i \quad (9)$$

Step 4: Input S_i as σ into the GRNN for performance degradation forecasting for machine gun's barrel. According to the forecasting result, calculate the deviation between the forecasting value and the actual value (RMSE) as the smell concentration $Smell_i$.

$$Smell_i = \text{Function}(S_i)\text{=RSME} \quad (10)$$

Step 5: Find out the individual fruit fly with the best smell concentration (the minimum value of RMSE) among the fruit fly swarm. And judge if the smell concentration is superior to the previous iterative smell concentration. Keep the best smell concentration value and coordinate (U_axis, V_axis).

$$[bestSmell \ bestIndex] = \max(Smell_i) \quad (11)$$

$$U\_axis = U(bestIndex) \quad (12)$$

$$V\_axis = V(bestIndex) \quad (13)$$

$$Smellbest = bestSmell \quad (14)$$

Step 6: When gen reaches the max iterative number, the stop criterion satisfies and go to step 7. Otherwise, the fruit fly use vision to fly to that location, $gen = gen + 1$, and repeat the implementation of step2 ~step5 to iterative optimization

Step 7: Input the optimal smoothing parameter σ into the GRNN model and output the forecasting result of test sample data.

3. Examples computation and analysis

The simulation experiments based on the data in table 1 and table 2 ran in the MATLAB 2010a environment. 20 sample data of 4 groups in table 1 used as training data and 3 groups of data in table 2 used as test data. Test ambient temperature, shooting interval and shooting ammunition quantity are input factors, non-dimensional muzzle velocity v_0^* is output factor.

In this study, 20 training samples divided into 2 groups are inputted to the FOAGRNN model for cross training, and supposed the maximum iteration number $maxgen = 50$, population size $sizepop = 30$, the random flight direction and the distance section[-1,1]. Initial smoothing parameter σ generated randomly by the algorithm. The smell concentration $Smell_i$ is employed the root-mean-square error (RMSE) which measures the deviation between the forecasting value and the actual value. The convergence can be seen in generation 14, the RSME and optimal smoothing parameter value are 0.0284 and 53.4. Fig.2 shows the iterative RMSE trend of the FOAGRNN searching of optimization parameter, and the fruit fly swarm flying route for optimization parameter is shown in Fig.3

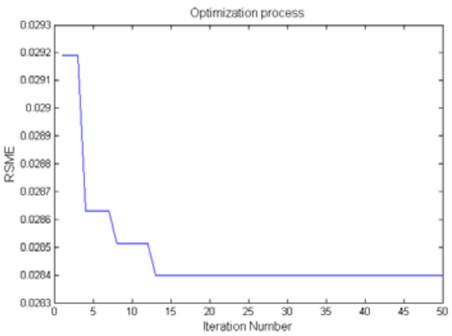

Fig.2 The convergence curve of the RSME

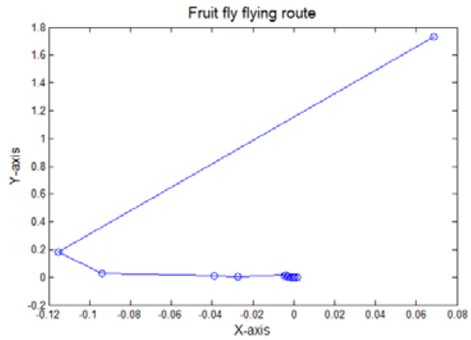

Fig.3The fruit fly swarm flying route for optimization parameter

Table 2 and Fig. 4~Fig.6 give the performance degradation forecasting results of 3 groups of test data with the FOAGRNN. Table 2 also lists the relative errors of the forecasting results.

According to Fig. 4~Fig.6, it can be clearly seen that all of the 3 groups of forecasting results have the similar trends with actual value. From Table 2, the average relative deviation of 3 groups is 1.224%.

Table 2 Forecasting results and errors of test samples

	T/℃	T_s/min	N/round	v_0/m·s^{-1}	v_0^*	v_f	Error/%
			0	806.6	1.000	1.000	0.000
			632	829.7	1.029	1.023	-0.588
1	22	1	1059	823.9	1.021	1.018	-0.299
			1781	769.8	0.954	1.002	4.975
			2693	737.6	0.914	0.961	5.098
			0	811.5	1.000	1.000	0.000
			607	833.4	1.027	1.020	-0.658
2	22	2	1229	824.2	1.016	1.030	1.373
			1911	808.2	0.996	1.002	0.595
			2731	781.6	0.963	0.961	-0.216
			0	803.6	1.000	1.000	0.000
			537	816.3	1.016	1.015	-0.044
3	-25	2	1268	831	1.034	1.025	-0.848
			1951	826.1	1.028	1.002	-2.543
			2173	809.7	1.008	0.996	-1.131

T is test ambient temperature, T_s is shooting interval, N is shooting ammunition quantity, v_0 is muzzle velocity, v_0^* is, v_f is forecasting results of non-dimensional muzzle velocity.

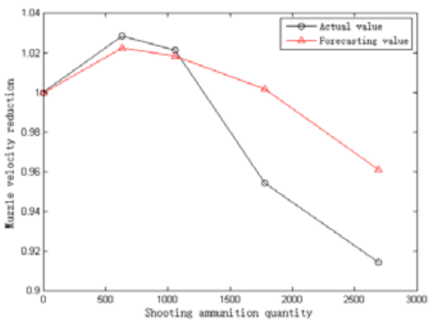

Fig.4 Forecasting results of the 1st group of test samples using FOAGRNN（Ambient temperature 22℃， shooting interval 1min）

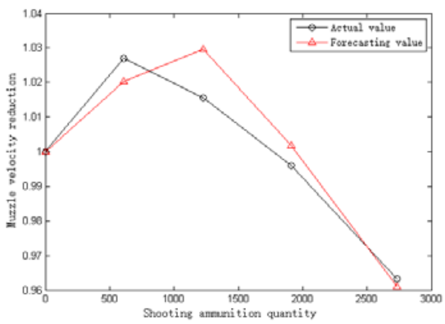

Fig.5 Forecasting results of the second group of test samples using FOAGRNN（Ambient temperature 22℃， shooting interval 2min）

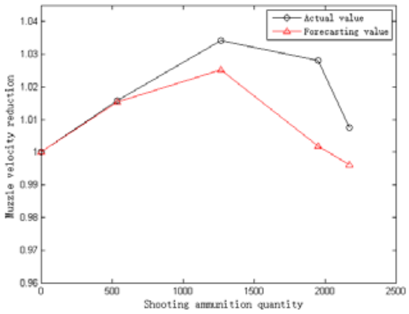

Fig.6 Forecasting results of the third group of test samples using FOAGRNN（Ambient temperature -25℃， shooting interval 2min）

Table 3 Forecasting results of barrel life using FOAGRNN

	T/℃	T_s/min	N_a	N_f	Error/%
1	22	1	2993	3227	7.82
2	22	2	3783	3773	-0.26
3	-25	2	3852	3782	-1.82

T is test ambient temperature, T_s is shooting interval, N_a is actual value of machine gun's barrel life, N_f is forecasting result of machine gun's barrel life.

The muzzle velocity reduction rate reached 15% is regarded as a standard to judge the life end of machine gun's barrel. When the non-dimensional muzzle velocity reached 0.85, the corresponding shooting ammunition quantity is the machine gun's barrel life. Table 3 gives the forecasting results of machine gun's barrel life of 3 groups of test samples with the FOAGRNN model.

It can be seen that the forecasting results of the performance degradation model based on the FOAGRNN are basically consistent with the actual value.

4.Conclusion

A method to establish performance degradation model for barrel based on general regression neural network with fruit fly optimization algorithm (FOAGRNN) was proposed.Based on the performance degradation experimental data, a performance degradation model of machine gun's barrel is built under various working conditions. The forecasting results were basically consistent with actual experimental value, which proved the feasibility of the method.

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