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Acoustic Performance of Exhaust Muffler Based Genetic Algorithms and Artificial Neural Network

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Abstrak

Tingkat kebisingan merupakan salah satu indikator penting sebagai tolok ukur kualitas dan kinerja suatu mesin diesel. Kebisingan saluran buang pada mesin diesel dapat diperhitungkan sebagai bagian penting dari peredam suara saluran buang yang terpasang dan merupakan sebuah cara yang efektif untuk mengatur kebisingan gas buang. Paper ini menggunakan program uji ortogonal untuk menentukan parameter struktur peredam dengan masukan tingkat suara yang dihasilkan serta bahan bakar diesel. This article using orthogonal test program for the muffler structure parameters as input to the sound pressure level and diesel fuel each output artificial neural network (BP network) learning sample. Matlab artificial neural network toolbox to complete the training of the network, and better noise performance and fuel consumption rate performance muffler internal structure parameters combination was obtained through genetic algorithm gifted collaborative validation of artificial neural networks and genetic algorithms to optimize application exhaust muffler design is entirely feasible.

Keywords*: acoustic performance, genetic algorithm, neural network, noise*

Abstract

The noise level was one of the important indicators as a measure of the quality and performance of the diesel engine.Exhaust noise in diesel engines machine accounted for an important proportion of installed performance exhaust muffler and it was an effective way to control exhaust noise. This article using orthogonal test program for the muffler structure parameters as input to the sound pressure level and diesel fuel each output artificial neural network (BP network) learning sample. Matlab artificial neural network toolbox to complete the training of the network, and better noise performance and fuel consumption rate performance muffler internal structure parameters combination was obtained through genetic algorithm gifted collaborative validation of artificial neural networks and genetic algorithms to optimize application exhaust muffler design is entirely feasible.

Keywords*: acoustic performance, genetic algorithm, neural network, noise*

1. Introduction

Exhaust noise in the diesel engine machine noise, which occupies an important proportion, install the good performance of exhaust muffler is the effective way to control exhaust noise.According to the diesel engine exhaust has the characteristics of high temperature, high pressure, and considering the service life of the muffler, most of the diesel engine is used resistance muffler, so design noise reduction effect is good, good dynamic performance of the diesel engine exhaust resistance muffler is of great significance. In the past decade, intent on increasing acoustical performance, the assessment of a new acoustical element was introduced and discussed by Sullivan and Crocker in 1978 [1]. Based on the couple equations derived by Sullivan and Crocker, a series of theories and numerical techniques in decoupling the acoustical problems were proposed [2]-[5].The shape optimization of a one-chamber muffler equipped with a perforated tube and plug/non-plug tubes has been discussed with neural network. Bai et al.[6]studies exhaust muffler optimization design based on the neural network, it put artificial neural network into the exhaust muffler design. While

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cheng feng [7] studies design of diesel engine exhaust muffler based on BP network by means of orthogonal planning and digital signal processing, the learning –samples of artificial neural networks were ontained. Zhang studies software development of optimal design of exhaust mufler based on genetic algorithm [8] .

Genetic algorithm based on neural network collaborative optimization can be divided into two aspects, on the one hand, the genetic algorithm in the application of neural network, genetic algorithm is used to optimize the structure of the neural networks, including optimizing network structure, optimize the weight coefficient and at the same time, optimize structure and parameters of the three aspects, on the other hand neural network in the application of genetic algorithm is mainly use neural network instead of genetic algorithm in the fitness calculation.

In engineering practice, since the various researchers in the different experimental methods, experimental conditions, data processing method, the expression of the mathematical model equation obtained is also different, mostly cumbersome difficult to apply. Therefore, to a complex process, it is very difficult to establish the mechanism of the mathematical model and then optimize, and sometimes even the specific expression can not be drawn, need only feasible objective function value genetic algorithm combined with powerful approximation ability of artificial neural network can effectively solve this problem.The combination of genetic algorithms and neural networks in automatic control, structural optimization, computer science and other aspects has made a wide range of applications, and is indeed feasible.

For engine exhaust muffler, the muffler structure, different structural parameters for its noise reduction effect is significantly different. Diesel engine and muffler work process is very complex, theoretical calculations and the actual design of the internal structure of the muffler, and has been the subject of studies.

In engine exhaust muffler structure parameter optimization is the noise of the target value, less noise, this structure is better, but the noise as the structural parameters of how far function has yet traditional mathematical expression, this paper using the neural value of the output of the network after the network training as a fitness function in the genetic algorithm.

2. The Test Program Arrangements

2.1. Factor in the choice

Different parameters of the internal structure of the exhaust muffler, the muffler of the exhaust noise is different. In [9] using the method of orthogonal experiment investigated the intake and exhaust perforated pipe perforation aperture, intubation diameter insertion depth of two indicators of the noise value and the engine fuel consumption rate of the exhaust port at drawn to the inner diameter of the inner cannula and the exhaust aperture of the perforated tube within a certain range, the better the smaller the muffling effect, the inner cannula little effect on the conclusions of the depth and the intake aperture of the perforated tube muffler. Text [10] BP network to further investigation into the exhaust flow of perforated pipe interface meter, intubation length, the bulkhead position 4 factors of the two indicators. The papers on the basis of the text [11], in the same four factors to increase the number of horizontal and examine the goals of the test are: exhaust port at the noise value and the rate of fuel consumption.

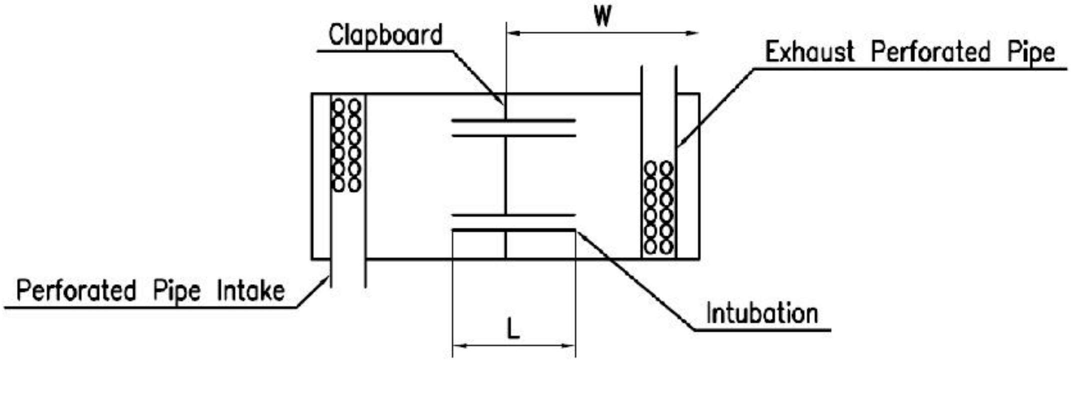

Figure 1. Structural diagram of the muffler

2.2. Experimental Design

According to determining the object of study and research goals, four factors must have more than one level, to obtain a sufficient information amount in order to reduce the number of trials for the multi-level combination of four factors using orthogonal test method, this paper selects five levels to each factor, according to the required data in the network during training as well as the actual experiment, 50 set of experiments were arranged, using the orthogonal table.

Table 1. Orthogonal table

Level	Factor			
	A	B	C	D
	Intake perforated pipe perforation Rows	Intubation length	Bulkhead position	Exhaust perforated pipe perforation Rows
1	7	60	155	15
2	8	70	95	13
3	9	80	75	10
4	10	50	135	18
5	11	40	115	20

2.3. The test apparatus and test method

The test device including 178F diesel engine, power detector, measuring fuel consumption with the balance and stopwatch, B & K2230 sound level meter. According to the "tube mouth method" to determine muffler insertion loss, according to GB4760-84 “muffler measurement method" of the provisions of the diesel engine exhaust pipe leads to the laboratory, install the muffler at the end of the exhaust pipe, the measurement point located in the muffler row The air inlet axis angle of 45°, 1 m away from the exhaust port center. Test chamber according to GB1105-74 "bench test method for an internal combustion engine", the diesel engine, the measurement of the diesel engine to adjust to a certain condition, and stable in this state, the measured noise value and the fuel consumption amount.

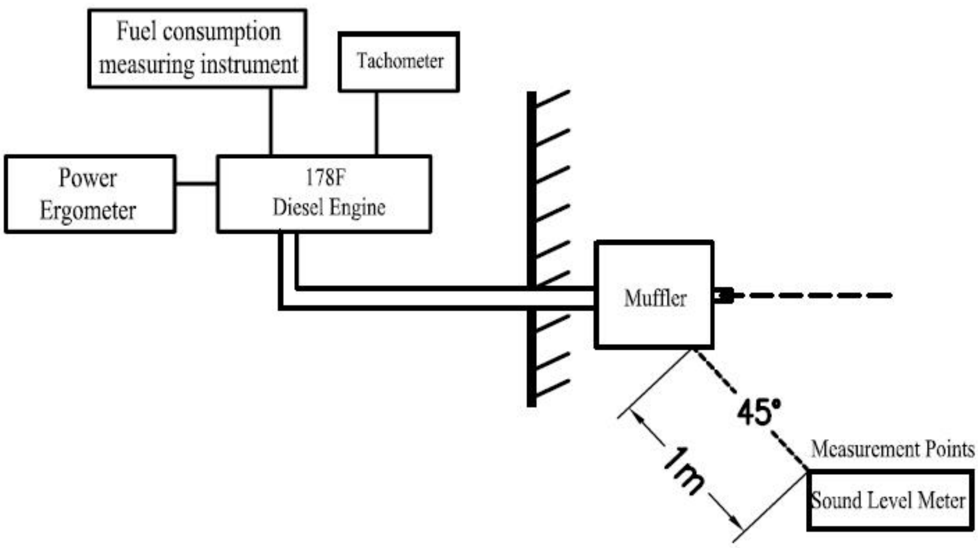

Figure 2. Test device sketch

Of the test in accordance with the orthogonal table arrangements were made to install a different muffler 50 experiments. Output frequency in the power of the engine group 2 kw, costume to 3000 rpm, respectively measured by the noise of the exhaust gas at the outlet of this 50 group of experiments, A the SPL value and the time required of 20 g diesel fuel, while recording the engine, Appendix table experimental data for measuring the mean value, wherein the fuel consumption rate is a combination of the output power and the fuel consumption of 20 seconds and calculated. Before determining of the learning sample, some strange data may be excluded artificially. Generally if the muffler noise increase the fuel consumption will increase.

2.4. The diesel exhausts muffler aerodynamic performance evaluation

The evaluation of the performance of the diesel exhausts muffler performance and aerodynamic performance evaluation. In addition, the product design should take into account the size of diesel engines machine installation also as an evaluation of the structural performance, maintenance requirements, life.

Examine exhaust muffler for internal combustion engine performance, general power loss than to evaluate. The muffler of the power loss ratio, is after the internal combustion engine in the calibration conditions, the muffler is not used, power and use muffler device power difference and not a percentage of the muffler when the power of, i.e., measuring muffler power loss than when should be carried out in accordance with the relevant provisions of the internal combustion engine bench test. In addition, it should be noted that before and after the change the exhaust muffler is mounted as far as possible to maintain the environmental conditions of the test, the state of the machine is relatively stable, so as to avoid the error. Exhaust muffler can also be used to evaluate the dynamic performance of the pressure loss. The pressure loss is due to the friction of the the muffler internal combustion surface and the airflow, the piping elbow, the piercing element, the pipe sections mutations result in the loss of mechanical properties, generally indicated with the full pressure of the inlet and outlet of the muffler to the pressure loss. If the pressure loss increase then the power of the internal combustion engine muffler increase.

The muffler noise elimination performance reflected in the size of the amount of noise elimination, the insertion loss method to evaluate that:

$$L_{IL} = L_{p前} - L_{phou}(dB) \quad (1)$$

Where L_{pfront} —before the installation of muffler in the same point of the sound pressure level

L_{pafter} —after the installation of muffler in the same point of the sound pressure level

3. BP artificial neural network design and training

BP algorithm basic idea is: For comparison, if an input sample weights threshold and excitation function computing obtain an output, then it desired sample output deviation from the output start inverting spread the error, weights, threshold adjustment, making the network output gradually and hopes [12].

BP algorithm is composed by the four processes: input mode by the input layer to the output layer through the intermediate layer "mode" process, the desired output of the network and the actual network between the output of the input of the error signal from the output layer through the intermediate layer to the forward propagating error back propagation process layer, layer-by-layer correction connection weights: Shun spread by "mode" network error back propagation repeated alternately "memory training" process; networks tend to converge the network global error tends to minimize the value of learning convergence process[13].

4. Results and Discussion

4.1. Genetic algorithm combined with neural network collaborative optimization of in muffler structure optimization design application

Genetic algorithm is a from specific prob genetic strategy, including the choice of population size, selection, crossover and mutation methods, as well as determine the crossover probability and mutation probability parameters lems restricted optimization algorithm. But must advance to design the fitness function expression, and fitness expression to determine the requirement of target function expression, but most of the optimization problem is difficult to determine a goal function expression, can use BP network function approximation and generalization ability to solve the problem.

The relationship between the input and output of a neural network model to fit, and then after the genetic algorithm to seek excellent, combined with genetic algorithm and neural network has been trained to construct an optimized procedure allows the system to the user's requirements as a target and search for the optimal value [14].

To insert loss minimum for target function, operating variable is put forward more than four variables, To solve the optimization problem can be described as follows:

$$\min\ L_{IL} = f(x1, x2, x3, x4) \tag{2}$$

In the hybrid algorithm the neural network weight vector and threshold value code into a string, constitute a real array, and production [-1, 1] between the groups random number (individual) as a genetic algorithm of the initial population. Assumed group scale for N, i.e., there are N chromosomes, In the genetic operation of each generation, each chromosome decode, calculate the right vector and threshold value[15-16], and find out each chromosome corresponding actual output value $y_k\ (k = 1,2,...,m; m$ is the neural network input and output sample logarithm), then The fitness of chromosomes for $i(i = 1,2,...,N)$ are:

$$f_i = 1/\exp(E_i) \tag{3}$$

While, $E_i = \sum_{k=1}^{n} (y_k - t_k)^2$, t_k is the goal of the neural network output. Adopt the index form to make the error sum of squares of individual fitness variation.

The operation of the hybrid algorithm procedure is as follows:

1. According to a given input and output training sample set, the design of the neural network input layer, hidden layer and output layer node number, Determine the topological structure of neural network.
2. Set the genetic algorithm population size N, set P_c, P_m and adaptive adjustment method, random generation [- 1, 1] between N chromosomes as the initial population.
3. The population of the chromosome decode and calculate the first I chromosomes error sum of squares E_i and fitness value f_i.
4. compute $f_{\max}$ and f_{avg} , And the fitness for f_{max} chromosomes corresponding neural network weights vector and threshold value recorded as B_1, judge $f_{\max}$ whether meet the accuracy requirement, and can satisfy the steering steps (8), or turn to step (5).
5. For genetic selection operation, and do adaptive adjustment to P_c and P_m, using improved genetic operator in genetic operation, form a new generation of group.
6. Put B1 value back propagation calculation, find out each layer neuron error signal, with BP algorithm to adjust formula of B1 weights adjustment after several times to get B2
7. Generation from the group and a new generation of group and B2 choose N good chromosome form the next generation of new groups, to step Shock (3)
8. To fitness for $f_{\max}$ chromosomes decode, get the neural network weight value vector and threshold, end algorithm. While scheme uniform crossover is 0010110010101101111000101101100100101010, scheme mutation is 0101111111100110011011101110011110100011

4.2. Concrete realization of the program

There are 3 layers in BP network layers and hidden layer nodes are 21, the initial learning rate is 0.02, adapting self-adaptive learning rate method, samples in addition to test No. 28 and 42 as training samples, and as confirmation sample test No. 10, 24, 30, 37, and 49 samples as test data of the neural network training.

Call Matlab in VC + + environment, specific procedures are as follows:

```
Where P1, P2, P3, P4 representative one after the variable is normalized
Where t1 represents a normalized noise value
engEvalString(ep, “val.P=[0.7 0.1; 0.7 0.9; 0.5 0.3; 0.34 0.9];”);
engEvalString(ep, “load 21jiedian.mat;”);
engEvalString(ep, “net.trainParam.show=50”;);
engEvalString(ep, “net.trainParam.min_grad=1e-15.;”);
engEvalString(ep, “net.trainParam.lr=0.02;”);
engEvalString(ep, “net.trainParam.lr_inc=1.05;”);
engEvalString(ep, “net.trainParam.lr_dec=0.7;”);
engEvalString(ep, “net.trainParam.epochs=300000;”);
engEvalString(ep, “net.trainParam.goal=1e-6;”);
engEvalString(ep, “[net.tr]=train(net,p,t,[],[],val);”);
engEvalString(ep,”a=slm (net,p);”);
engEvalString(ep,”t3=(a(1,:)=0.1)*(80.6-77.55)/0.8+77.5”);
```

Fitted results of the GA-BP network training maximum relative error does not exceed 0.8%, higher precision, network forecast results are as follows Table 2 and Table 3.

Table 2. Comparison of the actual value and GA-BP network prediction results

Test No.	Actual value (dB)	Forecast value(dB)	Error (%)
10	79.20	79.071	0.163
24	78.90	78.735	0.209
30	78.90	78.351	0.696
37	79.20	77.663	1.941
49	78.90	79.128	0.289

Table 3 The comparison of training results with different algorithms

Algorithm	Training time/s	Average error (%)
BP algorithm	247.05	2.7937
GA-BP algorithm	91.51	0.6596

As can be seen from the Table 2, the relative error of the test is very small, the degree of agreement is very good, and GA-BP network has some forecasting capability.

4.3. Result analysis

After the program is run, the results in the muffler structure parameter values are: intake perforated pipe perforation rows is 10.584, length of intubation is 57.600 cm, the clapboard position (from the exhaust port) is 112.120 cm, when exhaust perforated pipe perforation row number is 13.870, the noise value is the minimum and noise value is 76.00 dB, fuel consumption rate is 396.321 g/kw.h. And the noise value is 1.5 dB less than measured in the course of the experiment, the smallest noise value 77.50 dB, and the fuel consumption rate than the original 398.90 g/kw.h also decreased, to meet the test requirements. Theoretically proved that the collaborative optimization method of genetic algorithms and neural network on-feasible in muffler structure parameters optimization. Practical engineering applications, the perforated pipe perforated intake row number is 11, the length of intubation 57.60 cm and the bulkhead position (from the exhaust port) is 112.12 cm, exhaust the perforated pipes perforated rows is 14.

5. Conclusion

Genetic algorithms and neural network are key technologies for the 21st century computational intelligence techniques. Genetic algorithm has self-adaptation, global optimization and implicit parallelism, reflects a strong ability to solve the problem, the neural network is a massively parallel processor interconnection, which can solve optimization problem by highly interconnected neural elements, they complement each other, reinforce each other so as to get more powerful ability to solve practical problems.

1. Using Matlab neural network tools, 178F diesel exhaust muffler designed GA-BP network and learning sample were instructed through test to complete the training of the network. Through tested, training network on the structural parameters of the muffler forecast ability of GA-BP network optimization the exhaust muffler internal structure parameters is entirely feasible which specifies the ability of GA-BP network function model.
2. For the basic genetic algorithm, some limitations on genetic operators as well as the encoding method have analyzed, adapted adaptive value of its own changes, adaptive genetic algorithm to maintain the diversity of the population at the same time, to ensure the genetic algorithm better convergence.
3. call Matlab engine function to achieve Matlab and VC ++ mixed programming under VC ++ environment, making use of Matlab trained neural network to simulate the muffler internal parameters and noise value of digital modeling process to enable genetic algorithm optimization. Using trained GA-BP network output value as the value of the fitness function of genetic algorithm, genetic algorithm fitness function value is not necessarily when the waist have shown digital function model for other similar engineering problems a paths.

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