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Performance Optimization of Hydrogen Fueled Engines Based on Genetic Information Fusion Algorithm

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According to the research status of hydrogen fuel engine and the theory of information fusion algorithm, this paper proposes a hydrogen engine optimization model based on information fusion algorithm. Firstly, the genetic neural network information fusion model is constructed, and then the economic and dynamic characteristics of the hydrogen engine are optimized on the MATLAB experimental platform by using the model. Finally, the experimental results are analyzed and reasonable suggestions are put forward. Experimental results show that the method is feasible and accurate.

1. The core status and characteristics of hydrogen engine

In recent years, with the rapid development of industrial society, it brings us not only rich in material life, but also the lack of oil resources and the negative impact of serious air pollution. Therefore, the search for clean alternative energy has become the common goal of all walks of life. Hydrogen, as the secondary energy source, has attracted worldwide attention because of its clean, efficient and pollution-free advantages. Pavlos and Tsujimura (2017) believed that Hydrogen's energy density is one of the highest among the commonly used fuels for internal combustion engines. At present, there are two kinds of hydrogen energy applications in automobiles: hydrogen fuel cell and hydrogen internal combustion engine. Due to the high cost and low reliability of hydrogen fuel cells, both in economics and technology, it is difficult to develop rapidly in the short term. In contrast, hydrogen engines, which are intermediate transition products, can be obtained with minor modifications to the currently used petroleum fuel engines. Sun et al., (2014) believed that hydrogen is probably the unique versatile fuel which provides permanent solutions to fuel depletion and global environmental problems. Therefore, at this stage, hydrogen fuel engine has great room for development.
(Sebastian,2014) believed that the engine efficiency is mainly affected by the compression ratio and the air-fuel ratio, hydrogen engine having higher efficiency because of its lean operation.Bharath and Echekki (2012) investigated the ability of fuel injection strategies based on multiple-pulse direct injection (DI) as well as combinations of port fuel injection (PFI) and direct injection to prepare an ideal in-cylinder hydrogen–air mixture and control the auto ignition process.Ali et al., (2017) elaborated a multi-agent system modeling approach and pair it with Design of Experiments for objective evaluation of the IF-SoS design space. Mnks et al., (2016) showed that using the exergy-based optimal control strategy leads to an average of 6.7% fuel saving and 8.3% exergy saving compared to commonly used FLT based combustion control.
The physical and chemical properties of hydrogen are different from those of gasoline. The characteristics of hydrogen are high flammability, wide ignition limits, good diffusivity and high octane number, etc. However, the current problem is that in the hydrogen-gasoline dual-fuel engine, the abnormal combustion phenomenon is more likely to occur due to uneven mixing or improper operation parameters, such as excess air coefficient and ignition advance angle, resulting in engine power decline, economic and dynamic deterioration. In order to effectively avoid the abnormal combustion phenomenon and improve the output characteristics of the engine, this paper will use Genetic-Neural network information fusion algorithm to optimize the engine performance. The experimental data of excess air coefficient and ignition advance angle were fused to find out the relationship between the two factors and the output power and the effective thermal efficiency and to find the optimal excess air coefficient and ignition advance angle values.

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2. The introduction of information fusion model

The concept of information fusion was first produced in the United States, its research originated in the US military system construction needs. Information fusion, in essence, is similar to human beings and animals in understanding external things. Uwe et al., (2016) proposed an innovative distributed architecture encompassing intelligent sensor nodes, self-configuring real-time communication networks, and a suitable sensor and information fusion system for condition monitoring. The development of multiple information fusion technology provides a new way to solve the uncertain problem of complex system, this is determined by the unique multidimensional information processing of information fusion. It has been widely used in target recognition, medical diagnosis and other fields, however, the application of this technique to diagnosis optimization is only started in recent years. The research work in this field is still in its infancy, and has not yet formed a complete information fusion fault diagnosis system and theoretical framework. This paper attempts to use the Genetic algorithm - Neural network information fusion model for experiment.

Mattia et al., (2017) used the genetic algorithm to choose the most appropriate energy structure for the considered system to collapse a fine multigroup library into a few-groups one, usable for transient transport calculations. Georgios et al., (2017) used a genetic algorithm to minimize a weighted cost function between matching the substation data and the individual mean daily demands and showed the effectiveness of substation monitoring in LV network modelling. The Neural network fusion algorithm has the function of self-learning and associative storage, and has high nonlinear control ability, but it is easy to fall into local extreme and the convergence speed is slow. In order to compensate for these deficiencies, we use Genetic algorithms to optimize. Genetic algorithm is a robust algorithm for efficient probabilistic search of a coded parameter space using randomization techniques. Using Genetic algorithm to optimize the learning rules and network weights of neural networks, the learning rate and computing speed can be improved. The Genetic algorithm is used to adjust the structure of the neural network, and its structure is dynamic to make it more intelligent. At the same time, the problem of local optimal convergence is avoided to a great extent.

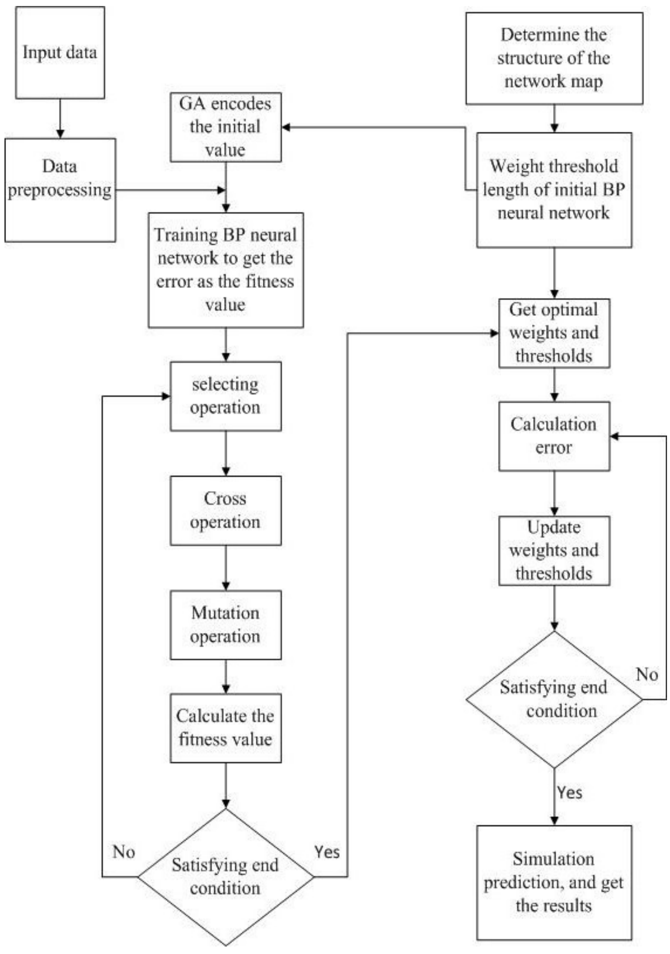

Figure 1: Algorithm flow

3. Experimental methods and operational procedures

The test was carried out on a hydrogen engine which was refitted from a single cylinder gasoline engine, the specific parameters shown in Table 1, When the rotational speed is 3,000 r/min, the effects of excess air coefficient and ignition advance angle on the output power and the effective thermal efficiency are tested experimentally.The excess air coefficient is ϕ_a,the ignition advance angle is θ,the output power is P_e, the effective thermal efficiency is η_{et}.

Table 1: Experimental hydrogen engine parameters

Cylinder diameter (mm)	Piston stroke (mm)	Combustion chamber shape	Compression ratio
84	90	Hemisphere	8.5

Genetic algorithm - Neural network information fusion model is used to train the experimental data in MATLAB simulation experiment platform. The concrete flow is shown in Figure 1.
The fusion model has three modules: BP neural network structure determination, Genetic algorithm optimization and neural network prediction. This experiment has two input parameters: excess air coefficient and ignition advance angle, and an output parameter: the output power or effective thermal efficiency .So the Neural network structure is chosen as 2 - 5 - 1, with 15 weights and 6 thresholds, and the individual encoding length of Genetic algorithm is 21.The first 72 groups of experimental data are regarded as training data, and the rest are regarded as test data. The absolute value of the prediction error of the training data is considered as the fitness value of the individual, and the smaller the individual fitness value, the better the individual. The detailed steps are as follows:
Step 1: Population initialization. Using real encoding method for individual encoding, and each individual is a real number composed of the weights and thresholds of the neural networks.
Step 2: Construct the fitness function, and find the individual fitness value. According to the individual, the initial weight and threshold of the neural network are obtained, using the training data to train the neural network, and then predict the output of the system. The absolute value of the error between the predicted output and the expected output is taken as the individual fitness value F, the calculation formula is as follows:

$$F = k(\sum_{i=1}^{n} abs(y_i - o_i)) \tag{1}$$

In the formula: n is the output node number of the network; y_i is the expected output of the I node of the neural network; O_i is the predicted output of the I node; k is the coefficient.

Step 3: Selection operation. Select the individuals with good fitness to form a new species group. The methods of selecting operations are roulette and tournament, we choose the latter. Roulette method is based on the proportion of fitness selection strategy. The selection strategy of each individual I is p_i:
Among them, F_i is the individual fitness value, because the fitness value is smaller, the better, so the fitness value is reciprocal before the individual is selected, k is the coefficient, and N is the number of individuals.

$$f_i = k / F_i \tag{2}$$

$$p_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \tag{3}$$

Step 4: Cross operation. Select two individuals from the population, and the two individuals are crossed by a certain probability to obtain new individuals. Because the real coding method is adopted when encoding the individual, the real crossover method is adopted in the crossover operation. The intersection of the k-th chromosome α_k and the l-th chromosome a_l at the j site is as follows:

$$\begin{aligned} a_{kj} &= a_{kj}(1-b) + a_{lj}b \\ a_{lj} &= a_{lj}(1-b) + a_{kj}b \end{aligned} \tag{4}$$

In the formula, b is a random number between [0, 1].
Step 5: Mutation operation. The j-th gene a_{ij} of the i-th individual is selected to perform the mutation operation. Methods as below:

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) * f(g) & r > 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) * f(g) & r \le 0.5 \end{cases} \tag{5}$$

In the formula, α_{max} is the upper bound of the gene α_{ij}, and α_{min} is the lower bound of the gene α_{ij}; $f(g)=r_2(1-g/G_{max})^2$, r_2 is a random number, g is the current number of iterations, G_{max} is the maximum number of evolution, and r is the random number between [0,1].

Step 6: Determine whether the evolution is finished. If not, then return to step 2. If it is, the optimal individual obtained by the genetic algorithm is assigned to the neural network to predict the output.

4. The analysis of experimental results

4.1 Dynamic fusion results of hydrogen engines

The test results show the changes of the output power when the engine speed is 3,000 r/min, the excess air coefficient increases from 0.8 to 2.5, and the ignition advance angle increases from 0 degrees to 42 degrees. When the training frequency reaches 96, the mean square error is 0.00027563, the value has to meet the requirements, which is shown in Figure 2. As shown in Figure 3, the fitness of genetic algorithm is 1.02, this value is low. As shown in Figure 4, when the excess air coefficient increases from 0.8 to 0.95, the output power increases significantly, and when ϕ_a increases from 0.95 to 1, P_e increases slowly, and when ϕ_a=1, the output power reaches the maximum value of 6.485 Kate-winslet.

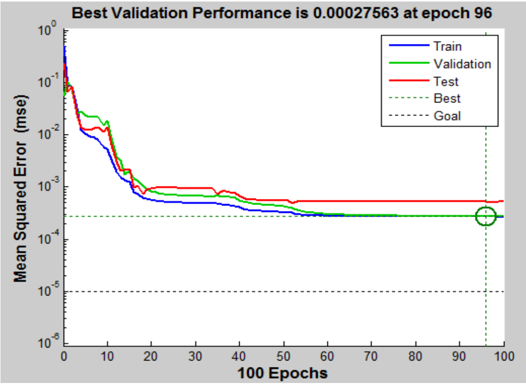

Figure 2: Mean square error of the system

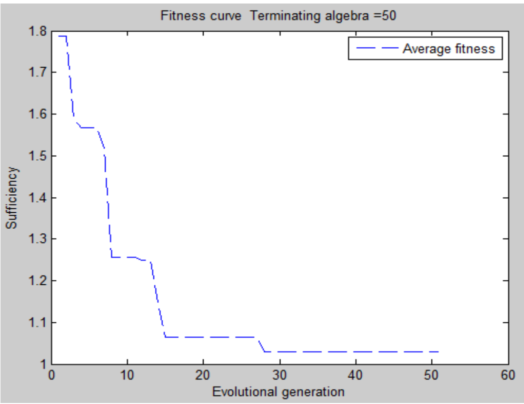

Figure 3: Fitness of genetic algorithm

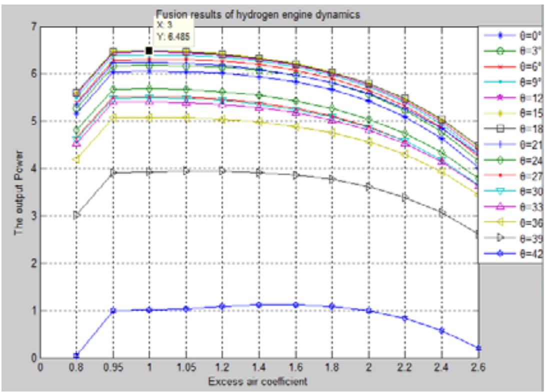

Figure 4: Output power variation diagram

This is because, at ϕ_a=0.95-1.05, the minimum duration of combustion is the shortest and the average rate of flame propagation is the highest, in addition, the coefficient of variation of the amount of the actual substance after the combustion of the mixture increases as well as the increase in the amount of fuel evaporation, so that the intake temperature decreases, the charge coefficient increases, the maximum combustion pressure, the maximum combustion temperature, the pressure rise rate and the power reach the maximum value. From ϕ_a=1 to ϕ_c=1.4, the output power decreased slowly, when ϕ_c>1.6, the output power drops rapidly. It can also be seen from the diagram that the curve of the ignition advance angle is 42 degrees at the bottom is slightly different from the other curves, but the overall trend is basically the same, which shows that the experimental results have universal significance.

It can be seen from Figure 4 that when the ignition advance angle increases from 0 to 15 degrees, the output power increases continuously, but the recruitment is less and less. At θ=15 degrees, the output power reaches the maximum value, from θ=18 degrees to θ=21 degrees, P_c decreases slowly, when the θ=36-42 degrees, the power drops rapidly. The ignition advance angle has a great influence on the combustion process of the engine. If the ignition is too early, the compression negative power will increase, the pressure rise rate and the maximum combustion pressure will increase, and it is easy to produce deflagration and other abnormal combustion phenomena; if the ignition is too late, the expansion ratio decreases, and the heat transfer surface area increases during combustion, and the maximum combustion pressure drops. Therefore, there is an optimum ignition advance angle in each condition, and the optimum ignition advance angle is 15 degrees in this experimental environment. The factors affecting the optimum ignition advance angle are speed, load, etc. The optimum ignition advance angle has a positive correlation with the speed, and has a negative correlation with the load.

4.2 Economic fusion results of hydrogen engines

The economic index determined by this test is the effective thermal efficiency. The effective thermal efficiency is the ratio of the effective work of the actual cycle to the amount of heat consumed to obtain this effective work, that is,

$$\eta_{et} = \frac{W_e}{Q_1} \tag{6}$$

The results of economic fusion are shown in Figure 5, which can be seen from the diagram: when θ=0-24. This is degrees, ϕ_c=0.8-1.3, the effective thermal efficiency increases continuously. When θ =9 degrees, ϕ_c=1.3, the effective thermal efficiency reaches the maximum value of 20.32 %.This is because when the mixture in the cylinder is slightly diluted, the maximum combustion temperature decreases, the combustion product dissociation decreases, and the thermal efficiency reaches the highest. When ϕ_c=1.3-2.5, the effective thermal efficiency decreases rapidly. When θ=27-42 degrees, the effective thermal efficiency decreases first, then increases, and then decreases slowly with the increase of excess air coefficient, but the overall change is not large because when the ignition advance angle is too large, namely premature ignition, ϕ_c is smaller, that is, when the mixture is thicker, because of incomplete combustion, leading to thermal efficiency decline, when the excess air coefficient increases, the fuel can be completely burned, the maximum combustion temperature is decreased, and the thermal efficiency is improved. Therefore, when the mixture is thinner, the excess air coefficient is large, the ignition timing should be advanced, so as to ensure a higher economic efficiency.

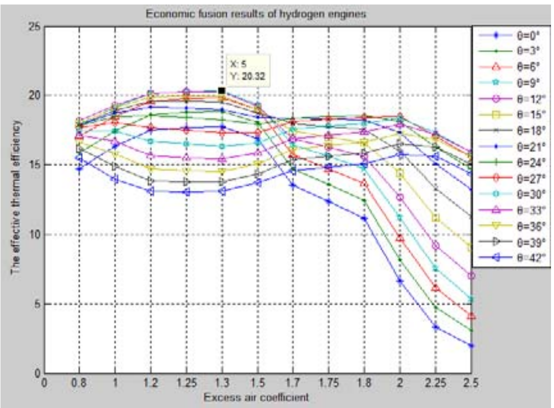

Figure 5: Effective thermal efficiency variation diagram

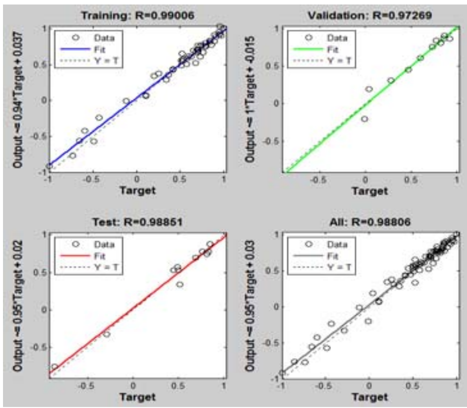

Figure 6: Regression curve

From the Figure 5, the ignition advance angle has a greater impact on the economy of the engine. According to statistics, if the ignition advance angle deviates from the optimum value of 5 degrees, the thermal efficiency decreases by 1 %, and deviates from 20 degrees, the thermal efficiency decreases by 16 %.Therefore, we should take measures to make the ignition advance angle in the best value, for example, the ignition advance angle electronic control device can be installed on the engine.

As shown in Figure 6, the fitting degree of the actual value and the predicted value reaches 0.98806, indicating that the experimental results are more accurate.

4.3 Comprehensive analysis of experimental results

When the rotational speed of hydrogen engine is 3000r/min, the power is the best at θ=15 degree, ϕ_c=1, and the economy is best at θ=9 degree and ϕ_c=1.3. The numerical difference between the two is not very large, we can take an optimal value interval, that is θ=9-15 degrees, ϕ_c=1-1.3, to take into account the economic and dynamic, so that the two are optimal.

5. Conclusions

In the 21st century, with the aim of seeking clean energy, the central position of hydrogen engines is unquestionable. Based on the existing problems of hydrogen engine, this paper proposes an optimization model and optimization method based on genetic information fusion algorithm. By optimizing the two operating parameters of excess air coefficient and ignition advance angle, the economic and dynamic performance of the hydrogen engine will be improved. Experiments show that the method adopted in this paper is reliable and practical.

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Reference

Dimitriou P., Tsujimura T., 2017, A review of hydrogen as a compression ignition engine fuel. International Journal of Hydrogen Energy, 42(38), 24470-24486.

Gowda B.D., Echekki T., 2012, Complex injection strategies for hydrogen-fueled HCCI engines. Fuel 97, 418-427.

Raz A.K., Kenley C.R., DeLaurentis D.A., 2017, A System-of-Systems perspective for information fusion system design and evaluation. Information Fusion 35, 148-165.

Razmara M., Bidarvatan M., Shahbakhti M., Robinett III R.D., 2016, Optimal exergy-based control of internal combustion engines. Applied Energy 183, 1389-1403.

Mnks U., Trsek H., Drkop L., Genei V., Lohweg V., 2016, Towards distributed intelligent sensor and information fusion. Mechatronics, 34, 63-71.

Massone M., Gabrielli F., Rineisk A., 2017, A genetic algorithm for multigroup energy structure search. Annals of Nuclear Energy, 105, 369-387.

Giasemidis G., Haben S., Lee T., Singleton C., Grindrod P., 2017, A genetic algorithm approach for modelling low voltage network demands. Applied Energy, 203, 463-473.

Sun B.G., Tian H.Y., Liu F.S., 2014, The distinctive characteristics of combustion duration in hydrogen internal combustion engine. International Journal of Hydrogen Energy, 39(26), 14472-14478.

Verhelst S., 2014, Recent progress in the use of hydrogen as a fuel for internal combustion engines. International journal of hydrogen energy, 39(2), 1071-1085.