Multi Information Fusion Diagnosis Method for Diesel Engine Based on Optimized ANFIS

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Abstract. A novel diagnosis method based on optimized subtraction clustering ANFIS (adaptive neural fuzzy inference system) algorithm is proposed in order to improve the accuracy and reliability of diesel engine fault diagnosis. The improved analytic hierarchy process (AHP) and subtractive clustering algorithm are combined to form a new ANFIS network suitable for multi information fusion diagnosis. The initial clustering centers of subtractive clustering algorithm and reasoning rules of ANFIS are automatically optimized by AHP algorithm without relying on expert experience. The effectiveness of the novel algorithm is investigated on the example of multi information fusion diagnosis of diesel engine, and the results indicate that the proposed method can eliminate the disadvantages of more inference rules, slow convergence speed and low diagnostic accuracy of the conventional ANFIS algorithm under multiple input parameters, which means this new method can effectively improve the accuracy of diesel engine fault diagnosis with the advantages of more fusion parameters and less calculation.

1. Introduction

Diesel engine is one of the most important power machineries and its safe and stable operation is extremely important for daily work. A lot of great damages are caused in the severe accidents of the malfunction of diesel engine. Because of multi parameter variable, time-varying and nonlinear parameter, it is difficult to carry out fault diagnosis of diesel engine. It is an urgent need for the safety and economy of diesel engine to quickly and accurately estimate the work condition of diesel engine [1,2].

In recent years, with the advantages of self-learning ability, artificial neural network has been extensively used in diesel engine fault diagnosis [3-6]. Zabihi-Hesari presents a condition monitoring and combustion fault detection technique for a 12-cylinder diesel engine based on vibration signature analysis using fast Fourier transform, discrete wavelet transform, and artificial neural network [3]. A novel fault detection and diagnostic method of diesel engine by combining rule-based algorithm and Bayesian networks (BNs) or Back Propagation neural networks (BPNNs) is proposed [4]. Wang presents a Bayesian network-based approach for fault isolation in the presence of the uncertainties [6]. However, the neural network still has some disadvantages, such as slow convergence speed, local minimum value, lack of explicit expression between levels, and difficult to determine the network structure, which limits the application and development of neural network in diesel engine fault diagnosis.

ANFIS (adaptive neural fuzzy inference system) combines the advantages of neural network and fuzzy reasoning. This algorithm has the advantages of strong self-learning ability, visualization of
fuzzy reasoning rules, clear structure and good stability, and has been widely used in fault diagnosis. The excellent operation of ANFIS in classifications, fault detection and pattern recognition tasks have been proved by many researchers works [7-10]. Tightiz put forward an intelligent method for diagnosis and classification of power transformers faults based on the instructive Dissolved Gas Analysis Method (DGAM) based on ANFIS [9]. However, traditional ANFIS has the problem of overflow of multi parameter input training rules in practical application due to its own structure limitation. In the condition of multiple input parameters, the number of fuzzy rules increases exponentially with the increase of input parameters, especially in the complex nonlinear relationship of multi parameter input of diesel engine fault diagnosis. In [10] Artificial Neural Network (ANN) and ANFIS techniques were hybridized by Grey Wolf Optimizer (GWO) to develop the predictive models for predicting the CS of Normal Concrete (NC) and High-Performance Concrete (HPC). The reduction method of reasoning rules and the optimization method of algorithm need to be further studied.

Aiming at the above problems, a multi information fusion diagnosis method for diesel engine based on optimized subtraction clustering ANFIS algorithm is proposed. The improved analytic hierarchy process (AHP) and subtractive clustering algorithm are combined to form a new ANFIS network suitable for multi parameter input. The comparison matrix is generated from the residuals of input parameters and historical data, and the initial clustering center of subtraction clustering algorithm is determined by using AHP, which solves the problems of large number of rules, slow convergence speed and low diagnostic accuracy of conventional subtraction clustering ANFIS algorithm under the condition of multi-parameter input. The investigations indicate that the new method can realize the automatic optimization of the algorithm reasoning rules without relying on expert experience. This method has the advantages of more fusion parameters and less calculation, and can effectively improve the accuracy of diesel engine fault diagnosis.

2. ANFIS Algorithm Structure

2.1. Basic Principle and Network Structure of ANFIS

ANFIS combines the advantages of neural network and fuzzy reasoning, and the learning and self-adaptive method of ANFIS is realized by changing fuzzy rules and the fuzzy membership function in rules. The commonly used single fuzzy expression method is if-then expression method.

\[
\text{if } x_1 \text{ is } A_1^1, x_2 \text{ is } A_2^1, \ldots, \text{ then } y = Z_1
\]

where \( x_1, x_2, \ldots, x_k \) are the input parameters, \( A_1^1, A_2^1, \ldots, A_k^1 \) are fuzzy subsets. The rule is improved by Takagi kobay and transformed into a function expression to get the mathematical relation model Sugeno model which is convenient for training.

\[
\text{if } x_1 \text{ is } A_1^1, x_2 \text{ is } A_2^1, \ldots, \text{ then } y = Z_1 = f(x) = a_0 + a_1 x_1 + \cdots + a_k x_k
\]

where: \( A_1^1, A_2^1, \ldots, A_k^1 \) are fuzzy subsets, \( a_i \) is the parameter value, \( Z_i \) is the output.

The membership function, premise parameters and fuzzy rules of fuzzy reasoning are determined by learning, and the structural errors are reduced by training and modifying parameters. A typical two input ANFIS structure is exhibited in Figure 1.
Figure 1. Typical structure of ANFIS.

ANFIS network structure is divided into five layers, including fuzzy layer, rule generation layer, rule collation layer, deblurring layer and output layer.

Layer 1: This layer is the fuzzification layer, which divides the input data according to the membership degree. The expression is as follows:
\[ R_{A_i} = \mu_{A_i}(s_1), R_{B_i} = \mu_{B_i}(s_2) \]  \( i = 1,2 \)  \( (3) \)

where \( A_i, B_i \) are fuzzy representations, \( \mu_{A_i}(s_1) \) and \( \mu_{B_i}(s_2) \) \( i = 1,2 \) are membership functions of \( s_1, s_2 \) respectively. Bell type selection function, and the expression is as follows:
\[ \mu_1(s_i) = \left(1 + \frac{|s_i + c_i|}{a_i}\right)^{2b_i}^{-1} \]  \( i = 1,2 \)  \( (4) \)

where \( \{a_j, b_j, c_j\} \) is a set of advanced parameters, whose values are constantly updated by feedback in the training stage, and finally form the conclusion parameter set in the rules.

Layer 2: The function of this layer is to realize the operation of fuzzy sets in the first layer. The output of the first layer is represented as points in this layer. After the calculation of this layer, the output is the algebraic product of the signal, and the output result of each point is expressed as a rule applicability. The expression is as follows:
\[ Q_i = \mu_{A_i}(s_1) \times \mu_{B_i}(s_2) \]  \( i = 1,2 \)  \( (5) \)

Layer 3: Normalize the excitation intensity of each rule, the node of this layer is also a fixed node, and the output is the applicability of the rule and all rules. The expression is as follows:
\[ \bar{q}_i = \frac{Q_i}{Q_1 + Q_2} \]  \( i = 1,2 \)  \( (6) \)

Layer 4: All nodes in this layer are adaptive to calculate the output of each rule. The expression is as follows:
\[ \bar{q}_i f_i^2 = \bar{q}_i (a_i s_1 + b_i s_2 + c_i) \]  \( i = 1,2 \)  \( (7) \)

Layer 5: This layer is the output layer, which is used to calculate the sum of all the transmitted signals as the output signal. The expression is as follows:
\[ f = \sum_{i=1}^{2} \bar{q}_i \]  \( i = 1,2 \)  \( (8) \)

For the advanced parameter modification, find a suitable set of parameters such that \( \bar{J} = min\Sigma(f - \bar{f})^2 \), where \( f \) is the actual output, \( \bar{f} \) is the model output.

The premise parameters of ANFIS are trained by back-propagation algorithm, and conclusion parameters are trained by linear least squares estimation algorithm.
2.2. Subtractive Clustering Algorithm

Subtractive clustering (SCM) is a density algorithm, which is used to estimate the number of clusters and cluster centers in a group of data. The specific method is to take each data as the possible cluster center of data, and then calculate the possibility of data as cluster center according to the density of surrounding data. The higher the density of surrounding data, the more likely the data will be selected as the center. The remaining data center is selected according to the possibility of the next data center. The basic steps of subtraction clustering are as follows [11]:

Considering the input parameter data to form n-dimensional data points, the identification data points have been normalized to the hypercube space, and the density function at \( x_i \) of each parameter data is defined as:

\[
M(i) = \sum_{j=1}^{N} \exp \left( -a \| x_i - x_j \|^2 \right)
\]

where \( M(i) \) is the density index of the point, \( a \) is the ratio of curvature \( \gamma \) of exponential function curve to \( r_a \) square of cluster center radius, and the data points outside the radius contribute little. After calculating the density index of each data point, the cluster center is found according to the index value.

\[
M_k(i) = M_{k-1}(i) - M_{k-1}^* \exp \left( -\beta \| x_i - x_k \|^2 \right), \quad \beta = \frac{\gamma}{rb^2}
\]

where: \( M_k(i) \) is the density of the \( k \)th cluster center, \( x_i \) is the modified data point. After modifying the density value of each data point, the data point with the maximum density is set as the cluster center.

The termination conditions are as follows:

\[
\frac{M_{k-1}}{M_i^*} < \delta \quad \text{where: } 0 < \delta \leq 1
\]

The difference between using subtractive clustering method and not, to generate ANFIS structure, is that the fuzzy rules generated by data center are more consistent with the relationship between input and output data. The number of fuzzy rules is \( r = \prod_{i=1}^{m} n_i \), where: \( m \) is the number of input parameters, \( n_i \) is the number of membership functions of corresponding parameters.

When the fuzzy reasoning model is generated by subtractive clustering algorithm, the rule model more in line with the input and output data can be reasonably obtained, which can effectively avoid the combinatorial explosion problem of setting the structure manually.

However, in subtraction clustering, it is still necessary to set the training parameters according to the number of parameters, or to set the four training parameters (range of influence, square face, accept ratio, reject radio) required by iteration. At present, the parameter setting of subtraction clustering method adopts the subjective setting method or iterative method, and the subjective setting method does not distinguish the fuzzy parameters; When the number of parameters is less (\( m < 6 \)), the method can find appropriate parameters and maintain a certain accuracy. However, when the number of parameters grow, the iterative dimension increases, which makes the algorithm difficult to run [12].

According to the principle and structure of ANFIS of subtractive clustering method, subtractive clustering method is mostly combined with subjective setting method and iterative method at present. Structural parameters are initially obtained after mechanism analysis, then iterative training parameters are determined, and structural parameters are trained through multiple iterations. This method needs subjective analysis process, more prerequisite parameters need to be optimized, and a lot of iterative process is needed to make the parameter fitting result good, which makes the model generation more complex.

2.3. Improved Analytic Hierarchy Process
Analytic hierarchy process (AHP) is a kind of decision-making method [13,14]. By comparing the importance of parameters and parameters, the parameters are sorted to obtain the weight value of parameters, and the parameters are determined according to the weight values. The traditional AHP is improved to calculate the weight of network input parameters by replacing the importance of parameters with the residual size of parameters. The evaluation matrix is constructed by the difference between input data and historical data, and the weight value of input parameters is calculated by AHP.

The parameter weight is judged according to the change degree of parameter. When the deviation between the operation parameter value and the normal operation parameter value is large, it means that the parameter has a great influence on the output result in the diagnosis process.

The AHP is used to obtain the weight value of parameters, including the following steps:

1. The input parameters are compared with the historical operation data to generate the difference.
2. The judgment matrix \( A = (a_{ij}) \) is generated according to the difference value. Find the eigenvalue and eigenvector of the judgment matrix.
3. The ratio of difference between element \( i \) and element \( j \) is \( a_{ij} \), then the ratio of factor \( j \) to factor \( i \) is

\[
A_{ji} = a_{ij}^{-1}
\]  

(12)

4. If the eigenvector corresponding to the maximum eigenvalue \( \lambda_{\text{max}} \) of \( A = (a_{ij}) \) is \( w = (w_1, \ldots, w_n)^T \), then \( a_{ij} = \frac{w_i}{w_j} \), where \( w \) is the parameter weight value.

According to the basic structure of AHP, the consistency of construction matrix \( A \) should be checked before obtaining the weight value

\[
CR = CI / RI
\]  

(13)

When \( CR < 0.1 \), the matrix is considered as consistent matrix, otherwise the matrix should be modified. The value of \( CI \) is calculated by the judgment matrix, and the value of \( RI \) can be obtained by looking up the random consistency test table of AHP or by matrix calculation.

Since matrix \( A \) is selected by the difference of parameters, it is not constructed according to the importance of the original analytic hierarchy process. The values of matrix \( A \) are taken as absolute values, and all data are between 0 to 1.

3. ANFIS Algorithm Model Based on Improved AHP and Subtractive Clustering

3.1. Algorithm Structure

The structure of the new ANFIS algorithm is shown in Figure 2, based on the Subtractive Clustering algorithm (Section 2.2) and the improved AHP (Section 2.3).

The number of fuzzy rules in ANFIS algorithm is \( r = m \times n \), where \( m \) is the number of input parameters and \( n \) is the number of membership degree. When the input parameter \( m \) and the number of membership degree increase, the number of fuzzy rules increases exponentially. In the case of multi parameter and membership, the conventional ANFIS algorithm is easy to cause the combination explosion of reasoning rules or dimension disaster, which makes it difficult to establish the model and run it normally.

When the number of input parameters is determined, the initial parameters optimization of ANFIS based on subtractive clustering method has a great impact on the diagnosis performance of the network algorithm. If the initial parameters are not optimized or not optimized well, it is easy to have problems of no optimization or poor initial parameters optimization in the process of network training, resulting in excessive calculation of the model and poor diagnosis accuracy.

This method uses AHP to optimize the initial parameters of ANFIS, which effectively avoids the problems of large amount of calculation and poor diagnosis accuracy caused by expert subjective experience method and iterative calculation method to determine the initial value of the network, and
realizes the fast and automatic optimization of algorithm reasoning rules without relying on expert experience, with the advantages of many fusion parameters and small amount of calculation.

Figure 2. Structure of ANFIS algorithm based on Improved AHP and subtractive clustering.

3.2. Algorithm Flow of Diagnosis Model

Based on the optimized ANFIS algorithm structure and diesel engine fault diagnosis data, the flow chart of fault diagnosis algorithm is exhibited in Figure 3.

Figure 3. Flow chart of diesel engine fault diagnosis algorithm based on the improved ANFIS.

The algorithm flow is divided into: data processing part, including data sorting, numbering, classification and normalization processing; The processing part of analytic hierarchy process includes the establishment of characteristic matrix of input parameters, calculation of eigenvalues and
eigenvectors, calculation of parameter weight value; ANFIS structure model generation and training, as well as detection data processing, model detection, parameter modification.

In order to facilitate data processing, the set $S$ is defined for the input parameters of system failure, and the fault symptom parameter set can be expressed as follows by Euclidean vector:

$S = \{s_1, s_2, ..., s_n\}$ Where: $n$ is the total number of fault symptom parameters.

A result fault set is defined for typical faults of diesel engine.

$Y = \{y_1, y_2, ..., y_m\}$ Where: $m$ is the total number of fault types.

The input fault symptom parameter set $S$ is normalized, and the input parameters are normalized within the range of $[0,1]$. In this paper, the method of maximum and minimum normalization is adopted:

$$s_k = \frac{(s_k - s_{\text{min}})}{(s_{\text{max}} - s_{\text{min}})}$$ (14)

where $s_{\text{min}}$ is the mean value of the data sequence; $s_{\text{max}}$ is the variance of the data.

According to the analytic hierarchy process described in Section 2.3, the weight values of each input parameter are obtained as the initial clustering center value of the subtractive clustering ANFIS network, and the subtractive clustering ANFIS network is generated. The network is trained with the trained data, and the output accuracy of the network is verified by the test data. The hybrid algorithm of the network training is combined with the least square method.

4. Example of Diesel Engine Fault Diagnosis

4.1. Establishment of Test Bench and Fault Case Setting

In this paper, 11 monitoring parameters of MTU 20V 956 diesel engine are used as training parameters and testing parameters. Fault types include: Normal operation $f_0$, Single cylinder misfire $f_1$, Exhaust pipe leakage $f_2$, Compressor fouling resistance $f_3$, Air filter blocked $f_4$, Poor lubrication $f_5$. These parameters are divided into training data and detection data, data group number and output number, as exhibited in Table 1.

| fault type | $f_0$ | $f_1$ | $f_2$ | $f_3$ | $f_4$ | total |
|------------|------|------|------|------|------|-------|
| Number of training groups $S'$ | 11   | 22   | 11   | 11   | 11   | 77    |
| Number of test groups $S''$   | 5    | 10   | 5    | 5    | 5    | 30    |
| Output number                  | 0    | 1    | 2    | 3    | 4    | …     |

4.2. Model Parameters

According to Section 4.1 fault example setting, the input fault characteristic parameter matrix is set as the training input parameter matrix. According to Section 2.3, the fault diagnosis procedure flow is established for data normalization and chromatography, and the fault diagnosis model of diesel engine based on ANFIS is established. The maximum training step is 200. The diagnostic accuracy of the model is verified by the test samples after the integration and normalization. The differences between the improved ANFIS and the conventional ANFIS are investigated by using the same samples.

4.3. Analysis of Model Diagnosis Results
4.3.1 Comparative Analysis of Diagnostic Accuracy. The initial value of the conventional ANFIS model is usually based on the expert experience and iterative calculation method, and the four optimized parameters are: range of influence = 0.5, square face = 1.25, accept ratio = 0.5, reject radio = 0.15. While the improved ANFIS proposed in this paper does not need to give the cluster center in advance, and its value is automatically given by the algorithm. The other parameters of the two networks are the same, and the training data and test data are identical. Based on the fault types and data samples of diesel engine in Table 1, the diagnosis result is shown in Figure 4, and the result error is shown in Figure 5.

From Figure 4 it can be seen that both two methods have good diagnostic accuracy for the four kinds of faults. In Figure 4, the actual fault type: 0 means normal condition, 1 denotes the fault of single cylinder misfire, 2 express the fault of exhaust pipe leakage, 3 represent the fault of compressor fouling and 4 means air filter blocked. For the fifth fault (5 in the figure means the fault of poor lubrication), the improved ANFIS in this paper has better diagnosis accuracy than the conventional ANFIS model, which is shown clearly from the error comparison analysis chart in Figure 5.

For the conventional ANFIS, it is necessary to point out that the initial value of cluster center was pre-optimized. Based on the previous principle of subtractive clustering ANFIS, the initial value of the clustering center has a great impact on the accuracy and calculation of the algorithm. In order to obtain high diagnostic accuracy, a lot of optimization work needs to be done in advance, including being familiar with the fault mechanism, judging the weight of each input parameter subjectively, and iterative calculating on basis of parameters. On the contrary, the improved ANFIS proposed in this paper can automatically obtain the initial value of subtractive clustering centers according to the input parameters. It does not need to set the initial value of the cluster centers and iterative optimization calculation according to the expert experience, and algorithm reasoning rules are automatically optimized with no expert experience.

Figure 4. Comparison of the diagnosis results between the improved ANFIS and the conventional ANFIS.

Figure 5. Error comparison between the improved ANFIS and the conventional ANFIS on the fault of poor lubrication.

4.3.2 Comparative Analysis of Calculation. In this paper. Table 2 displays the number of inference rules and the operation time of the two models. It is clear that the number of rules in improved ANFIS is greatly reduced compared with the conventional ANFIS. According to the operation time, it should be pointed out that the running time of the conventional ANFIS is the time of diagnosis operation after optimization of cluster center value, without calculating the time of initial value optimization process. However, the optimization process often goes through multiple iterations, and the time consumption is far more than the model diagnosis operation time. While the time of the improved ANFIS is whole time consumption the diagnostic process.
Table 2. Running time and rule quantity comparison of the two models.

|                     | Number of rules | Running time / s |
|---------------------|-----------------|------------------|
| The improved ANFIS  | 7               | 3.56             |
| The conventional ANFIS | 16             | 3.53             |

Figure 6 and Figure 7 displays the comparison of training error convergence process between the improved ANFIS and the conventional ANFIS method. The model in this paper approaches the convergence value after the 35th iteration, and the conventional ANFIS approaches the convergence value after 48 iterations. The training accuracy of the improved ANFIS is also better than that of the conventional ANFIS from the figure 7, in which the minimum error of the former is 0.00023 and the latter is 0.01565.

Figure 6. Comparison of the relationship between model training error and training steps.  
Figure 7. Minimum error convergence and convergence steps.

5. Conclusion
This paper proposed an improved ANFISN method for diesel engine based on the combination of the improve AHP and optimized subtraction clustering ANFIS algorithm. The effectiveness of the novel algorithm is investigated on the example of multi information fusion diagnosis of diesel engine, and the results indicate that the proposed method has high diagnosis accuracy for five typical faults of diesel engine, such as single cylinder misfire, exhaust pipe leakage, compressor fouling, air filter blockage and poor lubrication. Compared with the conventional ANFIS model, the number of fuzzy reasoning rules of the new algorithm is greatly reduced, the diagnosis accuracy is improved, the convergence speed of the network is accelerated, and the amount of calculation is reduced.

In addition, this novel method can also automatically adjust the model structure and reasoning rules according to the changes of the type and number of input parameters, and realize the automatic optimization of the algorithm reasoning rules under the condition of independent of expert experience. This method solves the problems of large number of rules, slow convergence speed and low diagnostic accuracy of the conventional ANFIS algorithm under the condition of multi parameters, so the application range of ANFIS algorithm on diesel engine fault diagnosis has been further expanded.

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