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A Method for real-time Combustion Metrics Estimation using Wiebe Model in Diesel Engine

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Abstract

Combustion closed-loop control is an important technology for intelligent energy saving and emission reduction of internal combustion engines. The real-time feedback of combustion indicators plays an important role in the accuracy and rapidity of closed-loop control. However, the calculation of the combustion midpoint based on the complete heat release rate curve often consumes more computing resources. In order to speed up the calculation speed, this paper proposed a method that the Wiebe model combined with neural network prediction combustion metric. Firstly, we match the Wiebe basis function for different working conditions by analyzing the heat release rate curve. then the RLS-DE algorithm is developed to identify the heat release rate curve with high precision, and the BP neural network combined with the Wiebe model parameters is used to calculate CA50. Finally, in the HIL real-time simulation environment, the calculation accuracy and calculation speed of the algorithm are verified. The results show that the use of different Wiebe basis functions combined with the RLS-DE algorithm can fit the heat release rate curves under different working conditions with high precision, and the fitting error is within 5%. The CA50 prediction algorithm based on the parameters of the Wiebe model has a different calculation accuracy under different loads. The algorithm error is 6%-8% at low load, and the error is 2%-4% under high load conditions. It is developed in the cRIO-9047 real-time computing platform. The algorithm time-consuming is 8-12 us, which has high real-time performance and engineering application value.

Abbreviations		***Symbols***	
RLS-DE	Recursive Least Squares- Differential Evolution	α	Premixed combustion proportional coefficient
BP	Back Propagation	a	The efficiency factor
CA50	Crankshaft Angle when the cumulative heat release reaches 50% (°CA)	φ	Crank angle degree
HIL	Hardware In Loop	τ	The delay angle between premixed combustion and diffusion combustion
ECU	Electronic control unit	Qp	Total heat release of premixed combustion
EGR	Exhaust gas recirculation	Qsum	Total heat release of fuel combustion
°CA	Crank angle degree	$\ddot{A}\varphi_{CA0-CA90}$	Combustion duration
CA05	Crankshaft Angle when the cumulative heat release reaches 5% (°CA)	x_b	Combustion fraction of each degree
CA90	Crankshaft Angle when the cumulative heat release reaches 90% (°CA)	a_p	Efficiency factor of premixed combustion
RLS	Recursive Least Squares	$\Delta\varphi_p$	Premixed combustion duration
SST	Total Sum of Squares	m_p	Premixed combustion quality factor
SSR	Regression Sum of Squares	a_d	Efficiency factor of diffusion combustion
SSE	Error Sum of Squares	m_d	Diffusion combustion quality factor
ANN	Artificial neural network	h(k)	Sample vector
LM	Levenberg-Marquardt	θ	Parameter vector to be identified
DE	Differential Evolution	e(k)	Error term
HRR	Heat Release Rate	θ_{LS}	Make the criterion function obtain the minimum value
Subscripts		$J(\theta)$	The criterion function
p	Premixed combustion	$\hat{\theta}_{LS}$	The estimated value of θ_{LS}
d	Diffusion combustion	K(k)	The adaptive gain matrix
		P(k)	The covariance matrix
		I	Identity matrix
		ε	Sufficiently small positive real vector

Introduction

The situation of energy saving and emission reduction of internal combustion engines is grim. At the same time, internal combustion engines are evolving in the direction of intelligence. Low temperature combustion mode and combustion closed-loop control are key features of the intelligence of internal combustion engines. The internal combustion engine that adopts the advanced low temperature combustion mode can obtain a good compromise in the trade-off relationship between fuel consumption and emission, but the internal combustion engine that realizes the low temperature combustion mode is often accompanied by cycle fluctuations and the non-uniformity of each cylinder. Since Jan-ola Olsson of Lund University in 2001 [1] proposed closed-loop combustion control for low-temperature combustion mode, more and more scholars have developed combustion stability control based on cylinder pressure sensors. The control based on cylinder pressure is actually the adjustment of the heat release rate curve in order to obtain better consistency of each cylinder and a more stable combustion state. The heat release rate control is one of the most common, simple and effective means to realize the control of the combustion process, but the real-time control of the heat release rate curve is often limited by the computing power of the computing platform.

The traditional engine combustion feedback control is generally based on the cylinder pressure sensor installed on the engine to measure the cylinder pressure signal, and transmit the cylinder pressure signal to the PC [2-4], which is calculated combustion metrics, and then sends the index to the ECU through the serial bus. The ECU changes the control variables, such as EGR rate, Premix Ratio, Inject Timing, to make the combustion state reach to the ideal state. There are two problems in this control framework. Firstly, the amount of cylinder pressure signal data is large, data communication consumes a lot of time and takes up a lot of CPU resources. Secondly, the current cycle combustion metrics used for next cycle injector parameters regulation, which is susceptible to random disturbances, and the control error will be amplified. The above problems can be avoided by realizing the online calculation of the combustion state through the algorithm upgrade. Data-based models or hybrid-driven methods are widely used by researchers because of their faster computing speed.

The model algorithm is divided into three types, physics-inspired control-oriented models (COM) [5-7], purely data driven or machine learning based control models [8-10], amalgamate physical and machine learning based models [11-14]. The research on the modeling of the combustion process of internal combustion engines has been continuously improved and perfected. The combustion simulation of internal combustion engines is generally divided into zero-dimensional models, quasi-dimensional models and multi-dimensional models. From the essence of the performance simulation accuracy of the whole machine, there is no difference between the simulation of the zero-dimensional combustion model and the quasi-dimensional model or the multi-dimensional model. Due to the rapidity and accuracy of the zero-dimensional model calculation, some scholars [15-16] still conduct research on it in the performance simulation of the whole machine, among which the most widely studied zero-dimensional model is the Wiebe model.

Iven Wiebe proposed a semi-empirical model, which described the in-cylinder combustion process by establishing a mathematical relationship between the crank angle and the heat release rate. The proposal of the Wiebe combustion model has greatly promoted the research process of engine combustion process simulation. After more than 70 years of development, the Wiebe model has developed from the single Wiebe model based on statistics to the current dual Wiebe and multi-Wiebe combustion models of internal combustion engines. In practical engineering applications, different types of internal combustion engines often use different forms of Wiebe combustion models. Among them, in commercial simulation software, the single Wiebe combustion model is generally used in the construction of the combustion heat release rate model of gasoline engines [17]. However, many scholars [18-20] used the single Wiebe model in the simulation of the heat release rate of diesel engines with low strengthening index and low load.

In some papers, the single Wiebe model combined with the modified MAP can better fit the combustion heat release rate curve. With the development of combustion theory of internal combustion engines and the emergence of high-strengthened internal combustion engines, the combustion process in diesel engine cylinders has been further refined, and is generally divided into two stages: premixed combustion and diffusion combustion [21, 22], double Wiebe function fits them well. However, in the medium and high load conditions, due to the large amount of fuel injection, the after-combustion phenomenon is obvious, which leads to the exposure of the limitations of the dual Wiebe combustion model fitting [23-25]. It is difficult to find a Wiebe basis function suitable for all operating conditions of diesel engines. Although the Wiebe model is widely used, most studies do not link the basis function of the Wiebe model with the characteristics of the engine heat release rate curve. Due to the close relationship between the Wiebe model and the combustion heat release rate, it is considered to realize the online identification of the Wiebe model through the pre-analysis of offline data and the cylinder pressure curve when the engine is running. The estimation of the combustion heat release curve, plays an important role in the evaluation of the combustion state parameters, speeding up the calculation speed, and realizing the on-board calculation of the combustion parameters.

In this paper, aiming at the prediction of combustion state, the algorithm research of online real-time prediction of combustion metrics of diesel engine under all working conditions is carried out. By analyzing the variation law of the heat release rate curve of the diesel engine under all operating conditions, the shape of the heat release rate curve is classified to achieve the basis function matching of the combustion model under all operating conditions. An algorithm, based.

Recursive Least Squares, Differential Evolution, Backpropagation Neural Network (RLS-DE-BP), to calculate the Wiebe model parameters online and estimate the combustion metrics CA50 is proposed. Finally, the developed algorithms and methods are verified in the HIL real-time compute plant. The verification results show that the method of reflecting the combustion state parameter CA50 through the Wiebe model parameter calculation is feasible, on-line calculation error is less than 8 %. The developed algorithm takes 8-12 us in the cRIO-9047 real-time computing platform, which effectively improves the real-time performance of the calculation.

A large operation regime heat release rate analysis in diesel engine

The experimental research of the six-cylinder, four-stroke, water-cooling, high-speed, turbocharged and direct-injection compression ignition diesel engine was carried out. Engine schematics and specifications are shown in Table 1.

Name	***Parameter***
Diesel engine type	In-line 4-stroke
Cylinder number	6
Bore (mm)	129
Stroke (mm)	155
Rated power (kW)	309
Rated speed (r/min)	1700
Maximum torque (N.m)	1675
Maximum torque-speed (r/min)	1300
Intake type	Boost intercooler
Compression ratio	16.5
Fuel system	High-pressure common-rail
Displacement (L)	12.155
Fuel properties	Light diesel oil

Table 1: Diesel Parameter.

In order to cover more features, the fuel injection timing, engine speed and engine load will vary widely during the test. The measuring device is a Kistler Kibox 2893B combustion device with an AVL GU22CK cylinder pressure sensor. The other equipment is the AVL 735 S, AVL MAI 60, which measures fuel consumption and emissions. The operation conditions are shown in Table 1. There are 101 test points, speed is changed from idling speed 800 r/min to 1700 r/min step by 100, torque is changed from 0 N.m to 1500 N.m step by 200 or 300 N.m. Inject timing is changed from 5 CA BTDC (Before Top Dead Center) to 20 CA BTDC step by 5 or 10. Each point runs 100 cycles.

Diesel engines have different fuel injection amounts under different loads, and the cylinder pressure curve, heat release rate curve and combustion characteristic parameters are often different. To reduce the algorithm error, the cylinder pressure curve and the change law of the heat release rate data under all working conditions are analyzed, and the conjecture of the cause of the combustion process is put forward according to the change characteristics of the heat release law.

Speed (r /min)	***Load (N.m)***	***Injection timing BTDC (CA)***	***Rail pressure (bar)***
8 00	0:300:600	5	8 00
9 00	0:300:900	5	8 00
1 000	0:300:1200	5	8 00
1 100	0:300:1200	5	8 00
1 200	3 00:200:1500	5,10,15,20	8 00
1 300	3 00:200:1500	5,15	8 00
1 400	3 00:200:1500	5,15	8 00
1 500	3 00:200:1500	5,15	8 00
1 600	3 00:200:1500	5,15	8 00
1 700	3 00:200:500	5:15	8 00

Table 2: Engine test condition table.

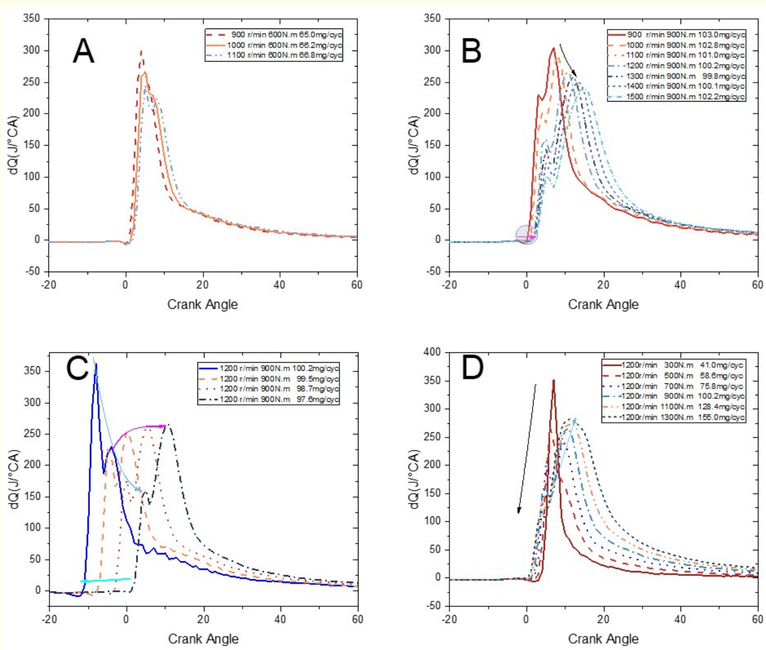

Figure 1: Variation law of heat release rate curve of engine under full operating conditions.

Figure 1.A and Figure 1.B respectively show the change law of heat release rate with speed when the fuel small and high. Based on literature [26, 27], it can be known that the heat release rate of premixed combustion is greater than that of diffused combustion. In general analysis, the first peak of heat release rate curve represents the premixed combustion heat release intensity, and the second peak of heat release rate represents the diffusion combustion heat release intensity. It can be seen from Figure 1.A and B the first and second HRR peak decrease with the speed increase. the HRR curve width grows with the speed increase. It is inferred that the fuel, which atomized and vaporized, has less time mix up with the air. The premixed combustion mixture concentration decrease, the rest of fuel for diffusion combustion increase. It makes the HRR shape changed. It is concluded that the heat release ratio of premixed combustion will decrease and the heat release ratio of diffusive combustion will increase with the increase of rotational speed. The Figure 1.C is the change law of HRR with injection timing and the Figure 1.D is the change law of HRR with engine load. In Figure 1.C the premixed combustion release heat increases with the injection timing forward, and the cycle fuel consumption grows. It is concluded

that advanced inject timing allows the fuel mix with the air long time the premixed combustion mixture concentration increase, the HRR first peak increase. This inference is consistent with the inference of speed changed, which the mix time influence the value of HRR first peak. In Figure 1.D, the cycle fuel increase with the engine load, the HRR shape shows different change lows with others. It can be clearly observed that the first peak value of the heat release rate curve gradually decreases, the beginning point of combustion slightly moves forward, the shape of the heat release rate curve widens, and the second peak value of the heat release rate gradually increases. At this time, the test conditions ensure that the fuel and gas mixing time is the same, but the shape of the heat release rate curve changes as the total oil volume increases. It is speculated that the starting point of combustion moves forward due to the increase of the overall concentration of fuel in the cylinder, and at the same time, the increase of fuel concentration makes the diffusion combustion happen in advance and the premixed combustion ratio decrease. Through analysis Figure 1 can be concluded that the HRR shape changed with the absolute time of fuel and gas mixture, premixed combustion mixture quality percentage of total fuel quality. The shape of the heat release rate curve can be caused by engine speed, engine fuel injection timing and engine cycle fuel injection quantity the relative relationship between the three factors of judgment.

Through the analysis of the combustion heat release rate in the full range of working conditions, it can be found that the heat release rate curve shows a relatively complete change rule under different load conditions of 1200 r/min. Analysis of the change law of the combustion state parameters, inference and matching and verification of the fitting basis functions for the transformation process of the combustion state. At 1200 r/min, from 25% load to 100% load, the variation law of combustion characteristic parameters is shown in Figure 2. The combustion onset is mainly distributed between 1-3°CA and is hardly affected by the load increase. With the increase of load, the combustion midpoint CA50 was delayed from 4.1°CA to 15.6°CA, and the heat release was more concentrated under low load conditions; the combustion duration was extended from 62 °CA to 81 °CA. According to the change law of the heat release rate curve at the typical operating point of 1200 r/min, different heat release stages and heat release modes are analyzed, and the whole process is divided into four stages.

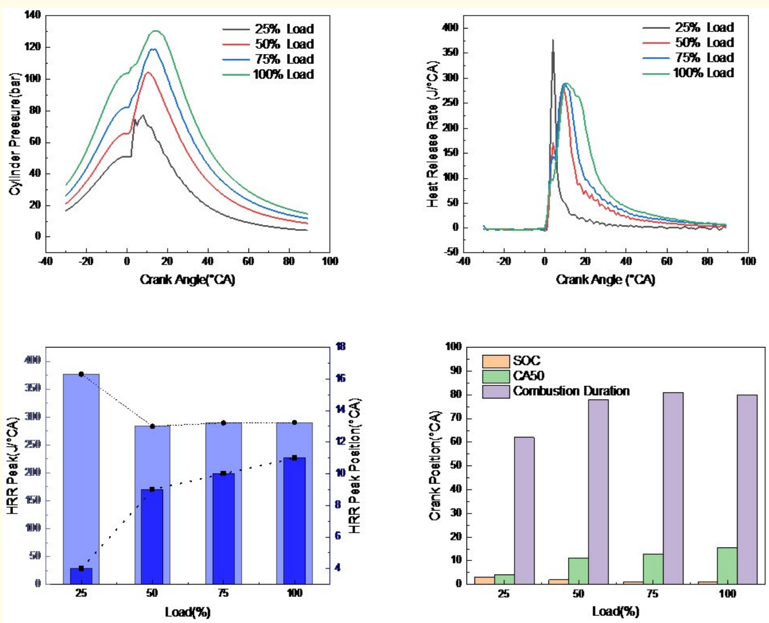

Figure 2: Variation law of combustion state parameters in different modes.

The first stage, the heat release rate curve at this stage appears in the working conditions of low speed and low load. In this stage, the fuel injection amount is small, and the concentration of combustibles in the cylinder is low. After the fuel is injected into the cylinder, the atomization time is sufficient, and the air is sufficient mixed to form a relatively uniform combustible mixture, and then fully combusted and rapidly released heat. The combustion mode at this stage is mainly premixed combustion, the fuel consumption is low, the heat release is concentrated, the heat is released rapidly in a short duration, the peak heat release rate is high, and the pressure rise rate curve is steep. The absolute value of the cylinder pressure small, higher thermal efficiency, worse emission performance, and the heat release rate curve exhibits a unimodal characteristic.

The second stage, there are two main reasons for the transition of the combustion process to this stage. Reason 1, with the increase of rotational speed, the time required to rotate through the same crankshaft angle becomes shorter. When reaching the position of the same combustion condition, the mixing time of fuel and air becomes shorter, diffusion combustion appears due to insufficient mixing. It will take the same time, but greater crank angles, resulting in a longer combustion duration. Reason 2, as the load increases, the amount of fuel injected into the cylinder increases. At this time, a small part of the fuel is mixed with air to form a combustible mixture, but the relative mass is higher than the amount of premixed oil in the first part, and the combustion can start earlier. In the premixed combustion stage, the proportion of diffusive combustion heat release is generally lower than that of premixed combustion. The heat release rate curve in this stage presents a bimodal characteristic.

The third stage, with the increase of engine speed and load, the circulating fuel injection amount further increases, and the combustion duration further increases. The fuel concentration in the cylinder is further increased, it is easier to ignite, the premixed combustion occurs slightly earlier, diffusion combustion is more likely to occur, and the proportion of fuel for diffusion combustion is higher, longer time for both combustions to take place simultaneously. the proportion of premixed combustion gradually decreases and the proportion of diffusion combustion increases. The exothermic rate curve at this stage exhibits bimodal characteristics, but the exothermic peak of the premix combustion exotherm becomes less obvious.

The fourth stage, as the fuel injection volume continues to increase, the proportion of fuel for premixed combustion is further reduced, and premixed combustion and diffusion combustion can almost start simultaneously. In the later stage of combustion, all of them are diffusion combustion, and even post-combustion occurs. The combustion duration of the heat release rate curve at this stage is long, the shape of the curve is wider, and the second peak point becomes gentler than the peak shape of the first three stages. At this time, the fuel in the premixed combustion stage can be ignored, but the peak heat release rate brought by the post-combustion stage or the continuous diffusion stage should be considered. This stage can be fitted with the three Wiebe function. If the heat release in the premixed stage is ignored, it can be Fitting was performed using dual Wiebe functions.

From the above analysis, it can be found that the shape of the heat release rate curve of the diesel engine presents obvious stage characteristics. Due to the shape differences exhibited by the staged features, a single basis function cannot be used in the heat release rate fitting process to obtain good results. According to the change of the exothermic shape characteristics, the exothermic rate curves of the four stages are matched with different Wiebe functions as the basis functions for fitting.

The first-stage combustion mode is mainly premixed combustion, and the heat release rate curve has only one peak, so a single Wiebe function can be used to obtain a better fitting effect. At this stage, the premixed combustion proportional coefficient α=1, the efficiency factor a =4.605 can be found, and the combustion interval is set from CA05 to CA90. The basis function for the first-stage heat release rate curve fitting, as in Eq (1).

$$x_b(\varphi) = 1 - \exp\left(-a\left(\frac{\varphi - CA05}{\Delta\varphi_{CA05-CA90}}\right)^{m+1}\right) \quad (1)$$

x_b combustion fraction, dimensionless number; ϕ instantaneous crank angle, °CA; *CA05* crank angle at start of combustion, °CA;

Δϕ crank angle interval corresponding to combustion duration, °CA. *a* Efficiency factor, dimensionless number; *m* combustion quality factor or shape factor, dimensionless number. The second stage and the third stage are both premixed combustion and diffusion combustion coexist, and the curves are in the form of double peaks. The shape of the heat release rate curve cannot be accurately modeled using a single Wiebe function, so double Wiebe function is used to fit it. In this stage, the combustion interval is set from CA05 to CA90, the hysteresis angle τ of the second stage is set for 3-5 °CA, other is set for 5-8 °CA, and the basis function of the heat release rate curve fitting of them are shown in equation 2.

$$x_b(\varphi) = \alpha\left(1-\exp\left(-a_p\left(\frac{\varphi - CA05}{\Delta\varphi_p}\right)^{m_p+1}\right)\right) + (1-\alpha)\left(1-\exp\left(-a_d\left(\frac{\varphi - CA05 - \tau}{\Delta\varphi_{CA05\sim CA90} - \Delta\varphi_p}\right)^{m_d+1}\right)\right) \quad (2)$$

$$\alpha = \frac{Q_p}{Q_{sum}} \quad (3)$$

In the formula, Q_p is the cumulative heat release rate of premixed combustion, J; Q_{sum} is the total heat release of fuel combustion, J.

The combustion mode of the fourth stage is the most complex, and the shape of the heat release rate curve conforms to the fitting characteristics of the three Wiebe functions. However, considering the real-time requirements of the calculation parameters and the extremely small proportion of premixed combustion, ignoring the fluctuation of the combustion rate caused by the early premixed combustion, the dual Wiebe function with hysteresis angle is still used to simulate the fourth stage. combine. At this stage, set the combustion zone to CA05 to CA90, the hysteresis angle τ is set as 18-20 °CA. The basis function of the heat release rate curve fitting in the fourth stage is shown in the formula (2). It is worth noting that in the fourth stage, α is the ratio of diffusion + premixed combustion to the total heat release. At this time, the first term of the Wiebe function fitting is diffusion The heat release rate of the combustion stage, the second term is the heat release rate of the post-combustion stage, due to the prolongation of the combustion duration, it is necessary to increase the error compensation function to correct it at the second peak point.

Model and parameter identification algorithm

In order to improve the accuracy of the combustion model based on the Wiebe function, it is necessary to identify the unknown empirical parameters in the model. As a basic method for parameter estimation, the least squares method has fast convergence speed and is easy to implement. In this section, the Recursive Least Squares (RLS) method will be used to realize the online identification of the Wiebe combustion quality coefficient m. Since the efficiency factor a is easily affected by external conditions, it is difficult to identify it by the RLS. Therefore, the Differential Evolution algorithm is selected to calculate it in this paper.

Identification of combustion quality coefficient m

$$y(k) = h^T(k)\theta + e(k) \quad (4)$$

$$\theta = [\theta_1, \theta_2, \ldots, \theta_N]^T \quad (5)$$

$$h(k) = [-y(k-1),\ -y(k-2),\ \ldots,\ -y(k-n_a),\ u(k-1),\ u(k-2),\ \ldots,\ u(k-n_b)]^T \quad (6)$$

In the formula, $h(k)$ is the sample vector; θ is the parameter vector to be identified; $e(k)$ is error term. while $k = 1, 2, \ldots, L$ forms a system of linear equations.

$$y_L(k) = H_L(k)\theta + e_L(k) \quad (7)$$

in

$$y_L = \begin{bmatrix} z(1) \\ z(2) \\ \vdots \\ z(L) \end{bmatrix}, \quad H_L = \begin{bmatrix} h(1) \\ h(2) \\ \vdots \\ h(L) \end{bmatrix}, e_L = \begin{bmatrix} e(1) \\ e(2) \\ \vdots \\ e(L) \end{bmatrix}$$

The criterion function that defines the least squares method is

$$J(\theta) = \sum_{k=1}^{N} [y(k) - h^{\mathrm{T}}(k)\theta]^2 \qquad (8)$$

Minimizing the criterion function will make the criterion function obtain the minimum value of θ, denoted as θ_{LS}, and the specific calculation is shown in the formula (9).

$$\hat{\theta}_{LS} = (H_L^{\mathrm{T}} H_L)^{-1} H_L^{\mathrm{T}} y_L \qquad (9)$$

The above algorithm is rewritten into a recursive form of online computing, as shown in the formula (10).

$$\begin{cases} \hat{\theta}(k) = \hat{\theta}(k-1) + K(k)\left[y(k) - h^T(k)\hat{\theta}(k-1) \right] \\ K(k) = \dfrac{P(k-1)h(k)}{1 + h^T(k)P(k-1)h(k)} \\ P(k) = \left[1 - K(k)h^T(k) \right] P(k-1) \end{cases} \qquad (10)$$

where, $\hat{\theta}_k$ is the parameter vector to be identified; $K(k)$ is the adaptive gain matrix; $P(k)$ is the covariance matrix; $h(k)$ is the input vector of the sample system; $y(k)$ is the output vector of the sample system. $P(0) = \alpha I$, $\hat{\theta}(0) = \varepsilon$, α are sufficiently large positive real numbers ($10^4 \sim 10^{10}$); ε zero vector or sufficiently small positive real vector.

When identifying the Wiebe combustion quality coefficient, the Wiebe function needs to be linearized first, and a single Wiebe function is taken and linearized by the formula (11).

$$(m+1)\ln\frac{(\phi - \phi_0)}{\Delta\phi} + \ln a = \ln\left(-\ln\left(1 - x_b\right)\right) \qquad (11)$$

Combined with (4, 10, 11) the basic idea of the parameter recursive algorithm, the recursive least squares method can be used to realize the online identification of the dynamic characteristics of the m value, and the m value can be finally determined by the formula (12).

$$\hat{m} = \hat{\theta}_{LS} - 1 \qquad (12)$$

Identification of efficiency factor a

For the single Wiebe model, the value of *a* can be calculated by the combustion fraction at the end of the combustion; but for the dual Wiebe model, since there are both the premixed combustion efficiency factor *ap* and the diffusion combustion efficiency factor *ad*, the differential evolution algorithm is used to compare ap and ad performs search calculations. Differential Evolution (DE), as a random parallel search algorithm, has the advantages of low complexity, easy implementation, fast convergence and strong robustness. The basic algorithm flow is as follows:

Create an initial population

$$\left\{xi(0)\middle| x_{j,i}^{L} \le x_{j,i}(0) \le x_{j,i}^{U}, i=1,2,...N; j=1,2,...D\right\} \quad (13)$$

$$x_{j,i}(0) = x_{j,i}^{L} + rand(N,D)\cdot(x_{j,i}^{U} - x_{j,i}^{L}) \quad (14)$$

In the formula, *N* is the population size; D is the solution space dimension; $x_{j,i}^{L}$, $x_{j,i}^{U}$ are the upper and lower bounds of the value range. In the formula, $x_{j,i}(0)$ is the j_{th} gene of the i_{th} individual of the 0th generation in the population.

Each individual is evaluated, and the goodness of fit of the heat release rate curve is selected as the fitness function to evaluate the pros and cons of each individual. The goodness of fit can characterize the fit of the regression line to the experimental data. Usually, the coefficient of determination R^2 is used to measure the pros and cons of the curve fitting effect, and R^2 is the closer to 1, the better the curve fitting effect.

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_{i=1}^{N}\left(\hat{y} - y_i\right)^2}{\sum_{i=1}^{N}\left(y_i - \bar{y}\right)^2} \quad (15)$$

Among them, SST (Total Sum of Squares) represents the total sum of squares, SSR (Regression Sum of Squares) represents the regression sum of squares, and SSE (Error Sum of Squares) represents the residual sum of squares. The relationship between the three is: SST=SSR +SSE. In the formula, $\hat{y}$ is the fitting value, that is, the calculated value of the heat release rate through the Wiebe function; y_i is the value to be fitted, that is, the experimental value of the heat release rate; $\bar{y}$ is the mean value to be fitted. By calculating and comparing the value of the fitness function *f* of each individual, the position corresponding to the maximum value of *f* is denoted as the optimal position *xbest*.

The random vector difference method is used to achieve individual mutation, which is expressed as DE/rand/1, where rand indicates that the current mutated vector is a random vector, and 1 indicates that the number of difference vectors in the algorithm is 1, such as formula (16).

$$v_i(g+1) = x_{r1}(g) + F\cdot[x_{r2}(g) - x_{r3}(g)] \qquad r_1 \ne r_2 \ne r_3 \quad (16)$$

In the formula, *F* is the amplification factor, which is generally taken as 0≤F≤2.

By adjusting *F*, the population convergence speed is changed. If *F* is too large, the population convergence speed will be slowed down. otherwise, the population convergence speed will be accelerated. This study takes *F*=0.4. In order to make the population have diversity, it is necessary to perform crossover operation on the population according to the formula (17).

$$uj,i(g+1) = \begin{cases} v_{j,i}(g+1), rand(1,D) \ge CR \\ x_{j,i}(g), \text{otherwise} \end{cases} \quad (17)$$

where CR is the crossover probability, 0 ≤ CR ≤ 1, and the boundary parameter of 0.1 is taken in this paper. The operation process is shown in Figure 3.

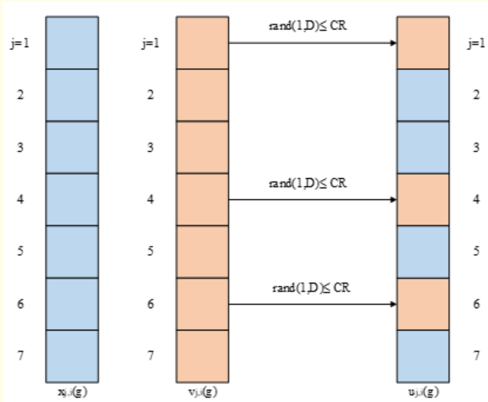

Figure 3: DE algorithm crossover operation process.

Finally, the greedy algorithm is used to search for the optimal solution, and the population individuals after differential mutation and crossover operations are selected. The specific calculation is shown in the formula (18).

$$x_i(g+1) = \begin{cases} u_i(g+1), f(u_i(g+1)) \leq f(x_i(g)) \\ x_i(g), otherwise \end{cases} \quad (18)$$

On-line identification of combustion metrics

Some studies [28] have shown that the parameters in the Wiebe model are related to the operating parameters of the engine, and the changes in the parameters in the Wiebe model can reflect the changes in the combustion state. The accumulate heat release rate reaches 50% (CA50) is used as a feedback parameter reflecting the change of combustion parameters during combustion control. In order to establish the nonlinear mapping relationship between Wiebe model parameters and CA50, an artificial neural network (ANN) method was used. In this study, the error back propagation algorithm (Back Propagation, BP) of the multi-layer feedforward network is used, the BP neural network establishes the nonlinear mapping relationship between the Wiebe model parameters and the CA50, and directly gives the CA50 value of the combustion control through the combustion parameters.

The goal of BP neural network training is to make the output value of the grid approach the expected output value. The mathematical expression of its hidden layer is shown in the formula (19).

$$y = f\left(\sum_{i=1}^{m} w_i x_i\right) \quad (19)$$

In the formula, ω_i is the weight, x_i is the input vector of the *ith* neuron, $f(\bullet)$ is the activation function of the neuron. To apply the BP algorithm, it is necessary to determine the input and output thresholds a and b of each layer, the number of neurons in the hidden layer m, and the number of network layers *L*. The weights W_{ij} and W_{jk} are initialized, and the excitation function and iteration are determined. rate, the excitation function selects the sigmoid transfer function. Applicative (20, 21) computation of hidden layer parameters and output layer results.

$$H_j = f(\sum_{i=1}^{n} W_{ij} x_i - a_i) \qquad (20)$$

$$y_k = \sum_{j=1}^{L} H_j W_{jk} - b_k \qquad (21)$$

Calculate and output the result, get the error, and change the weight error in the process of backward pass by iterating continuously. The Levenberg-Marquardt (LM algorithm) is used to train the network, and the convergence speed of the network is adjusted by introducing a variable factor λ, which can improve the operation speed while reducing the amount of calculation.

In summary, the flow of the entire algorithm is described in the following Figure.

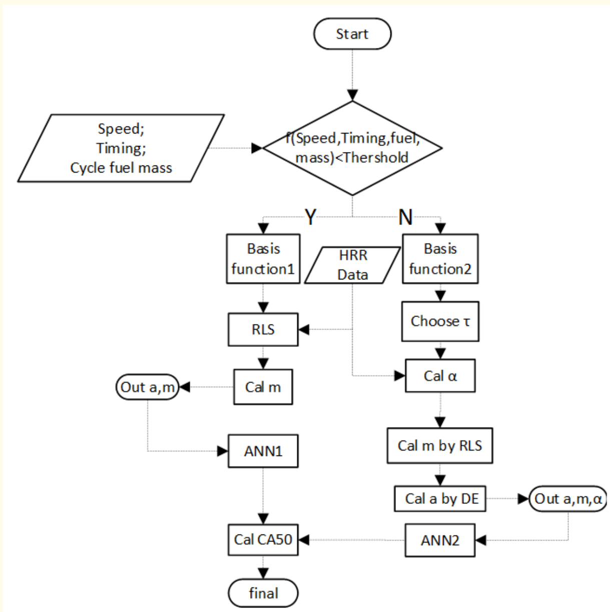

Figure 4: Combustion model classification identification and combustion state parameter algorithm flow chart.

Algorithm verification and result discussion

Accuracy comparison of simulation results of heat release rate curve

Based on the basis functions of the heat release rate curve fitting at different stages determined in the first section, combined with the least squares algorithm and the differential evolution algorithm, the heat release rate curves of the four stages were trained and fitted respectively. In this study, the parameters of the combustion model are calculated by means of statistical analysis of data, and the confidence level of the calculation model is analyzed. Through the normal distribution analysis of the Wiebe combustion quality coefficient *m*, the 95% confidence interval of the *m* value is obtained, which is used as the judgment condition for the recursive stop of the RLS algorithm. Table 1 gives the mean, standard deviation and 95% confidence interval of *m* value under different working conditions.

Load	Mean	standard deviation	95% confidence interval
25%	-0.2348	0.0241	[-0.2395, -0.2301]
50%	-0.0839	0.0147	[-0.0868, -0.0810]
75%	0.0188	0.0138	[0.0161, 0.0215]
100%	0.1572	0.0156	[0.1542, 0.1603]

Table 3: Statistical properties of *m* values.

Through the analysis of the *m value* probability parameter, it is set that when the difference between the iteratively calculated *m value* and the average value of the *m value* trained by the LS algorithm is satisfied |m(k+1)-m(k)|<0.0005, the iteration stops and the *m value* is output. The convergence rate of the RLS algorithm is shown in Figure 5 and the fitting results of the heat release rate calculated in Figure 6.

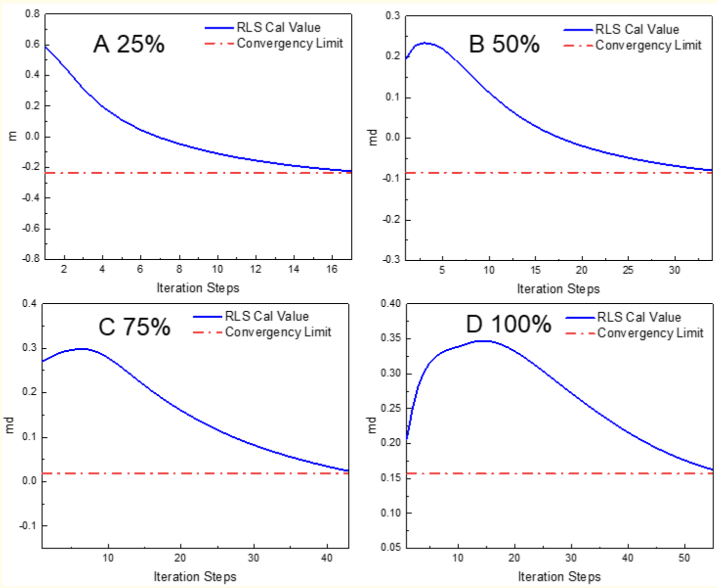

Figure 5: Different load RLS convergence curve.

From Figure 5 the iteration durations of the final output *m value* at 25%, 50%, 75%, and 100% load are 17 °CA, 34 °CA, 43 °CA, 55 °CA, respectively. The number of iteration steps under different working conditions is less than the combustion duration under different working conditions, and the online identification of *m value* is completed in the combustion process in one cycle, so the online parameter identification in a single cycle can be realized. The validity of the calculation results is calculated by model reconstruction, and the fitting effect is shown in Figure 6. The results show that the goodness of fit under 25%, 50%, 75%, and 100% loads R^2 are 95.86%, 96.84%, 95.59%, and 97.22%, respectively, and the goodness of fit is greater than 95%. The fitting results of the heat release rate curve are satisfactory, especially at the undulating position of the heat release rate curve. The method can effectively characterize the shape change of the heat release rate curve.

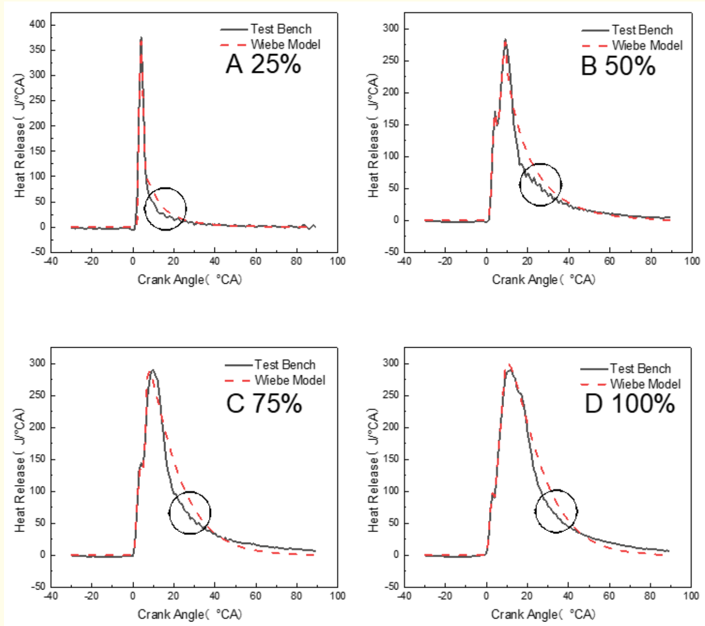

Figure 6: Wiebe function fitness result in different load.

Estimated of combustion metrics

In this study, the feature parameters of the Wiebe function are used as input feature parameters to train the neural network, in which there are 70 training sets, 15 validation sets and 15 test sets. The number of layers in the BP neural network is 3 and the number of hidden neurons is 10. The input of the network is fuel injection timing, premixed combustion shape coefficient m_p, diffusion combustion shape coefficient m_d, premixed combustion efficiency factor a_p and diffusion combustion efficiency factor a_d. The output is CA50. The neural network regression curve of the combustion process parameter CA50 is shown in Figure 7, It can be seen from the Figure that the output data are distributed on both sides of the regression line, and the whole is close to the regression curve. The overall goodness of fit of the experimental data R^2 is 97.72%, which indicates that the established neural network model has a good goodness of fit.

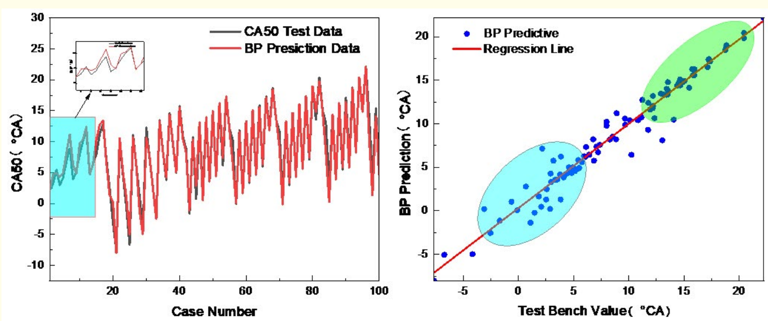

Figure 7: BP neural network predicts CA50 results.

Randomly select the heat release rate data of 100 cycles to verify the validity of the neural network calculation, compare the network output data with the combustion analyzer calculation data, and use the root mean square error RMSE to describe the deviation between the output results and the original data. It can be seen from Figure 7 that the BP neural network has a good prediction effect on CA50, and the root mean square error RMSE of the model's prediction of CA50 is 1.52 °CA, which meets the modeling requirements of the prediction model. The neural network model developed based on the algorithm can effectively realize the prediction of CA50, but the online computing capability of the calculation model needs to be further verified. Therefore, a real-time simulation platform is built to verify the developed algorithm.

Online simulation verification of real-time computing platform algorithm

In order to further illustrate the significance and engineering application value of the developed algorithm, the developed algorithm is loaded into the NI cRIO-9047 rapid prototype unit, and an engine real-time simulation platform (NI PXI-8880) is built to verify the accuracy of the developed algorithm and test the time-consuming calculation. The function of the engine real-time simulation platform is to output the cylinder pressure signal of the engine as a signal source, and cRIO-9047 is used as the algorithm execution platform. The algorithm test conditions are selected at 1200 r/min four steady-state operating points of 25% load, 50 % load, 75% load, and 100 % load for verification. In Figure 8.A, it is the 20 cycles error distribution under 25% load condition. It can be clearly seen that most of the errors are distributed between 6% and 8%. At this time, the relative error of the calculation of CA50 is relatively large. The absolute value of CA50 is small, resulting in a relatively large relative error in the calculation. Similarly, the calculation error of Figure 8.B is also significantly larger, which is due to the fact that when the load is lower than 50 %, the circulating fuel injection amount is small, and the value of CA50 is close to the top dead center. In Figure 8.C and D, as the load increases and the circulating fuel injection amount increases, the numerical characteristics of CA50 become larger, and the relative error also becomes smaller, which are distributed below 4% and 2%, respectively. Considering the random fluctuation characteristics of errors, the highest and lowest values of relative errors of 20 groups of data are removed, and the average relative errors of CA50 after removing extreme errors are 7.95%, 6.94%, 3.49%, and 1.98%, all of which are less than 8%, satisfying the general case of combustion state parameter estimation requirements. At the same time, if the closed-loop control of combustion is to be realized, it can generally be realized when the engine switches to high load conditions, so the relatively large error of this algorithm is acceptable at low load.

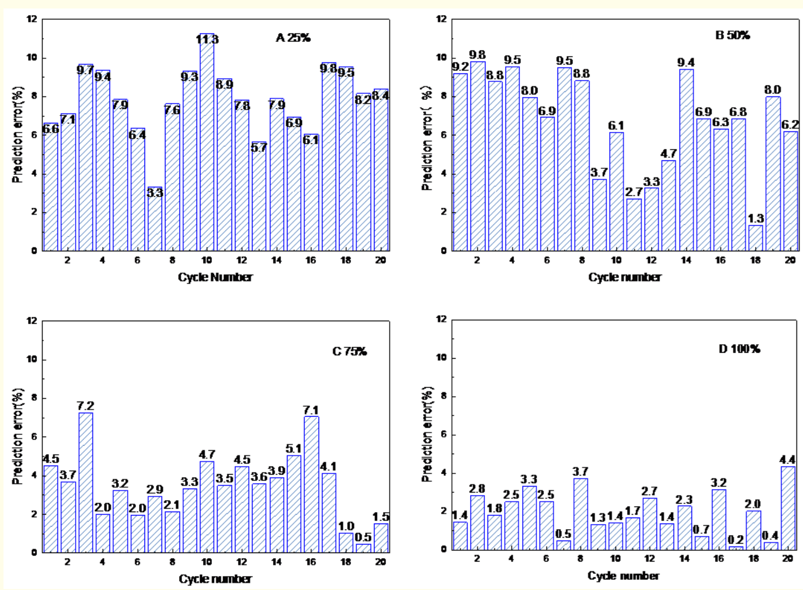

Figure 8: Prediction error of multi-cycle combustion parameters under typical operating conditions.

In addition to the calculation error, the calculation time is also a point that needs to be paid attention to in the development process of this algorithm. During the algorithm verification process, the calculation time in the process of 1000 engine cycles was collected and observed. It can be found that in the 4 cores 1.6G frequency The calculation time of the algorithm developed on the cRIO-9047 combined with the 40Mhz clock FPGA computing platform fluctuates between 8-12us, indicating that its calculation speed is fast and has certain engineering application feasibility.

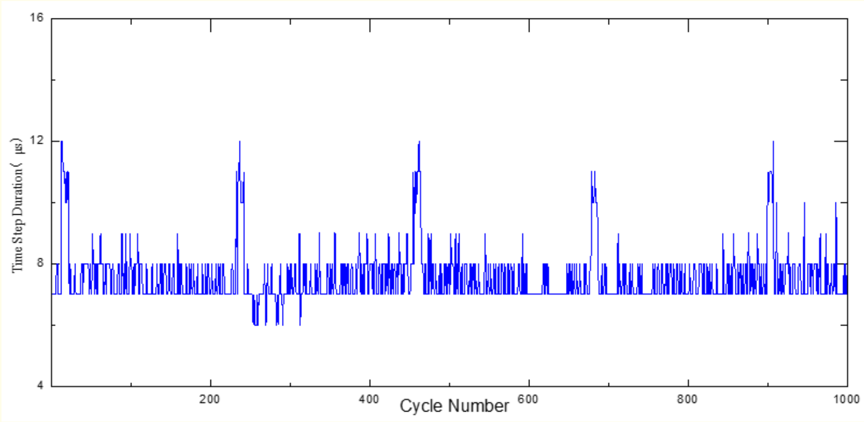

Figure 9: Real-time plant calculate time consume.

Figures 10 and 11 show the computational performance of the developed algorithm under steady-state and transient conditions, respectively. The tracking performance of the developed algorithm is evaluated under the state operating conditions. Figure10.A when it is stable in steady state after loading and unloading. The calculation error of CA50 at low load is still larger than that at high load. Figure 11 A shows that the speed is switched from 900 r/min-1000 r/min, and the load is changed from 0 N.m gradually increases to 900N.m according to different slopes. It is found that when the load increases with a larger slope, the dispersion of the calculated value of CA50 increases. When the load tends to be stable, the output of the calculated value of CA50 is relatively stable. The calculation tracking can be achieved when the load changes slowly, and the same phenomenon also occurs in the case of load shedding and deceleration.

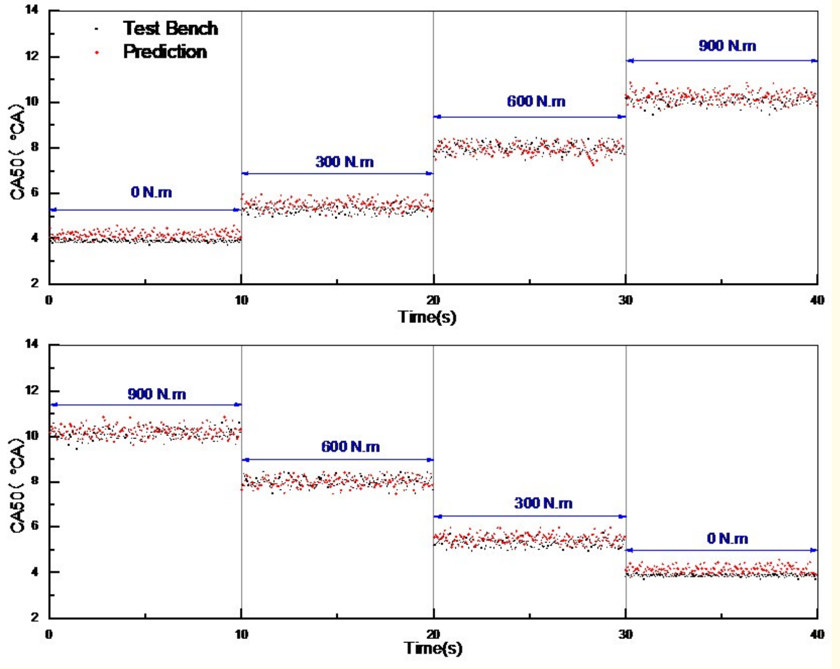

Figure 10: Comparison of real-time verification results under different steady working conditions.

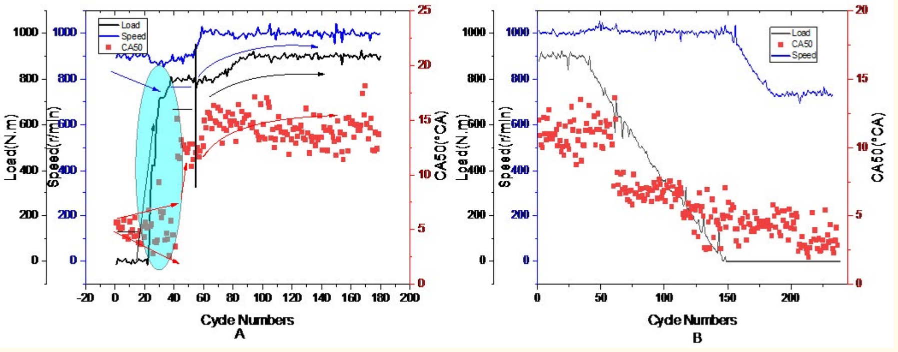

Figure 11: Transient switching condition CA50 tracking calculation.

Conclusion

The contribution of this research is mainly divided into two parts. The first part proposes a method to match the basis function of the Wiebe model based on the heat release ratio of premixed fuel, and according to the heat release rate of different working conditions, the phase delay value for different heat release stages is given. The second part develops the RLS-DE optimization algorithm for the established mathematical model, realizes the online calculation of the parameters of the Wiebe model, and establishes the BP neural network model to realize the prediction of the combustion metrics.

The major finding of the work is discussed below.

1. In the case of low circulating fuel injection and sufficient mixing time, the single Wiebe model can generally be used to fit the diesel heat release rate. With the increase of rotational speed and circulating fuel injection, the combustion obviously appears premixed and diffused. The two-phase nature of combustion requires dual Wiebe models to achieve a good fit. The difference in the proportion of premixed combustion oil under different working conditions determines the occurrence time of diffusion combustion, and the value of τ needs to be changed. The amount of circulating fuel injection is very large, and the fuel ratio of premixed combustion can be ignored when the speed is high, and the phenomenon of post-combustion will appear. At this time, the dual Wiebe model should also be used, but the first Wiebe model is to describe diffusion combustion. The second Wiebe model is used to describe the heat release law of post-combustion, and the corresponding τ is generally selected to be around 20 °CA.
2. The RLS-DE algorithm is used to fit different Wiebe basis functions, which has a good fitting effect. In the selected test conditions, 1200 r/min, 25%, 50%, 75% and 100% load The goodness of fit of the lower heat release rate curves R2 are 95.86%, 96.84%, 95.59%, and 97.22%, respectively, and the goodness of fit is greater than 95%, which meets the needs of engineering simulation. The BP neural network based on the Wiebe function has a good accuracy for the prediction of the CA50 parameters. After repeated testing of multiple operating conditions, the overall goodness of fit of the test data is R2 97.72 %, indicating that the established neural network model has good goodness of fit.
3. The algorithm is comprehensively verified in the real-time computing platform. The overall computing time is between 8 and 12 us. In the real-time computing platform, the average relative errors of CA50 under the four operating points are 7.95%, 6.94%, and 3.49%, 1.98%, respectively. the calculation accuracy and calculation time can meet the requirements of engineering calculation. In the real-time platform, when the speed and load change rapidly, the calculation accuracy of the CA50 will deteriorate. When applying the algorithm, the acceleration and deceleration rates and acceleration and deceleration rates should be considered to prevent sudden changes.

In the coming months, we will use the theory proposed in Section 1 to make more calculate. It can be found that the number of Wiebe functions is related to the proportion of diffusion combustion and premixed combustion in the combustion process. The PCCI combustion mode using multiple injections has an obvious two-stage heat release. According to the adjustment of different τ values, its mathematical model is established. The heat release law of the LNG dual-fuel engine with micro-injection ignition also has obvious two-stage heat release characteristics. The diesel rapid combustion in the early stage and the natural gas flame diffusion combustion in the later stage can be applied to the proposed model.

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