MODEL BASED CALIBRATION FOR IMPROVING FUEL ECONOMY OF A TURBOCHARGED DIESEL ENGINE

by

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Fuel economy is the key performance for the vehicle besides emission, which has been compulsory controlled by the legislation. For the electronic controlled Diesel engines, the mentioned properties could be satisfied not only by engine design but also by engine performance tuning. Fuel economy may be influenced by many coupled factors, such as injection timing, speed, load and under the limitation of cylinder peak pressure and exhaust temperature. To achieve a high efficient calibration, a model based calibration was performed on a four cylinder electronic unit pump Diesel engine with exhaust gas recirculation. The objective of the study is to solve the complexity of the interactions among the engine running parameters and the best fuel economy performance in order to meet under the restriction of NO_x emission performance. The study was carried out in four stages. First, the experiment design has been proposed to identify designed experiment operating points and weighting factors. Second, two-stage statistical engine responses and boundary models have been established. Third, the global optimization and European steady-state cycle operating point optimization have been carried out. Finally, the bench test has been conducted on the Diesel engine. The global operating points results show that the fuel consumption rate has decreased at most test operating points by model based calibration. The fuel consumption rate has decreased by 3.5%, and 13 mode cycle test results indicate that the proposed model based calibration method is effective and can improve the fuel efficiency by 2.72% compared with the traditional calibration.

Key words: *Diesel engine, fuel economy, model based calibration, optimization, statistical modeling*

Introduction

In order to meet stricter emission regulations and higher demand for low fuel consumption and better dynamics performance, engine electronic systems are made to be more complicated with more electronic parameters. Fuel economy efficiency is one of the most important parameters for Diesel engine. Engine with good fuel economy can reduce the cost of vehicles and saves the oil resource and reduce emission [1, 2].

Increased complexity in engine technology has driven the need for optimized calibration techniques. The architectures have involved more control variables and degrees of freedom than over, which results in a greater difficulty for studying interactions of physical processes [3]. However, the traditional calibration method is becoming too time consuming and ultimately expensive, which has led to the rise of statistical modeling and design of experiments (DoE)

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techniques that allow for visual realization of parameter interactions, which aids in calibration generation [4, 5].

The traditional calibration method separately optimizes each parameter step by step. However, it can not fully grasp the mutual influence relations among the parameters of electric control parameters. Therefore, the optimized result has lower robustness [6]. The fuel economy, power performance requirements and national emission regulations become stricter, which speeds up the development of the electronic control technology of Diesel engine [7-9]. The model-based calibration method uses mass experiment data to acquire the regression model and combines the mathematical optimization theory with control parameters [10-12].

Millich *et al*. [13] have proposed a highly efficient calibration by the charge control to decrease the emission of NO_x. Kianifar *et al*. [14] have proposed an efficient DoE strategies to minimize expensive testing. Mosbach *et al*. [15] have used the experimental design technique to do new experiments with the aim of decreasing the uncertainty in the parameter estimation. In order to solve the coupling of different parameters, Prucka [16] explained that it could get the high efficiency and strong repeatability when combined with the model based calibration experiment. Other researchers also have used two-stage regression approach to establish the transient engine model for calibration [17].

The purpose of this study is to propose the model based fuel economy calibration method via establishing two-stage statistical model and optimizing the parameters under the premise of meeting emission constraints. To get the most suitable experiment data distribution, the V-optimal design experiment method has been proposed. To predict each control parameter response output, the two-stage statistical model has been built and verified with reasonable precision. To improve the Diesel engine specific fuel consumption, the optimization strategy has been proposed and evaluated by ESC 13 mode test cycle experiment. The traditional calibration method costs over thousands of experiment times and increases the cost and workload. However, the model-based calibration method has less times of experiment and greatly reduce the workload with high efficiency and strong repeatability, it just costs several hours to complete the work.

Table 1. The main technical parameters of YC4E170 Diesel engine

Item	Parameter
Type	Water cooled, 4-stroke cycle
Cylinders	4
Cylinder × stroke [mm]	110 × 112
Displacement [L]	4.257
Compression ratio	17.5 : 1
Intake type	Supercharge, inter-cooling
Rated power [kW]	125

Experimental set-up and method

The introduction of test bench

In this study, an electronic unit pump (EUP) Diesel engine with exhaust gas recirculation (EGR) is employed on a dynamometer. The test bench consists of YC4E170 Diesel engine, dynamometer, sensors and emission measurement system. The main technical parameters of engine and schematic diagram of the experimental set-up are shown in tab. 1 and fig. 1. Combined with this equipment, it is convenient to carry out the engine test experiment and obtain the needed parameters.

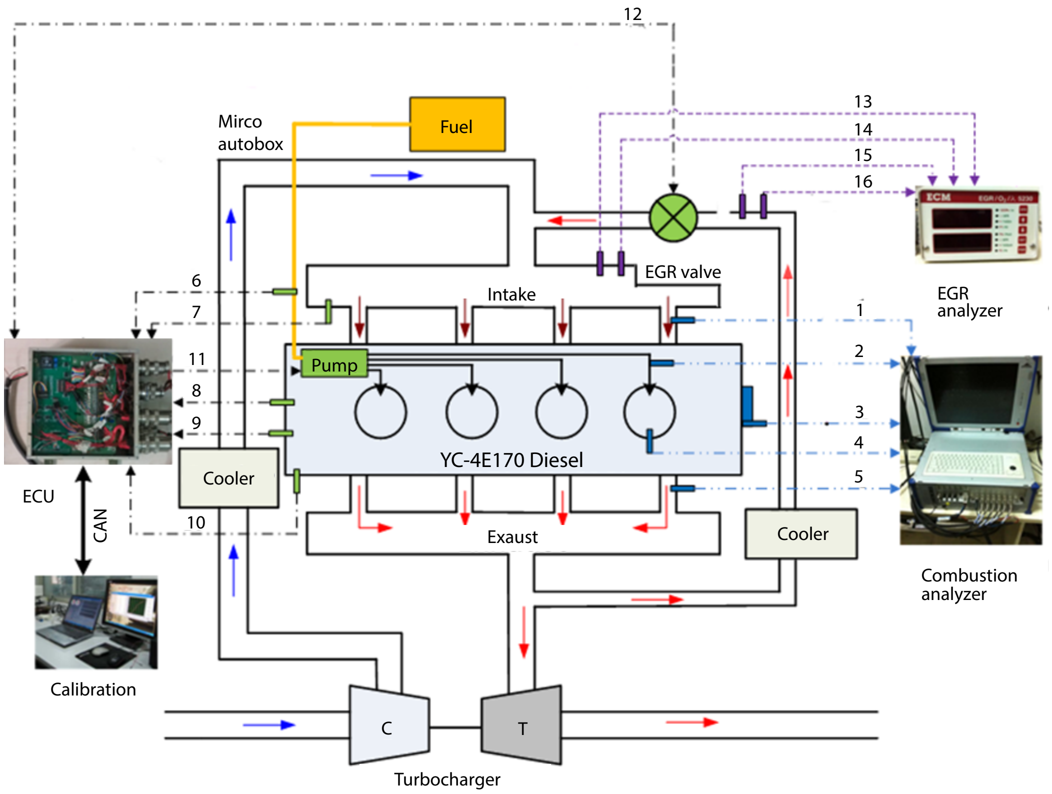

Figure 1. Schematic diagram of the experiment;
1 – intake pressure, 2 – injection pressure, 3 – encoder, 4 – cylinder pressure, 5 – exhaust pressure, 6 – fuel temperature, 7 – intake temperature, 8 – cam sig, 9 – crank sig, 10 – coolant temperature, 11 – injection control, 12 – EGR valve pos, 13 – steady intake pressure, 14 – intake O_2 PCT, 15 – exhaust O_2, 16 – steady exhaust pressure

Method

Table 2. Variable range of design experiment

Variable	Minimum	Maximum
Speed [rmin^{-1}]	1300	2300
Basefuelmass [mgstr^{-1}]	33	127
EGR valve rate [°]	0	90
Soi [°]	0	12

Modern Diesel engines have many degrees of freedom that must be simultaneously adjusted to optimize efficiency, emissions, and performance. Due to the complexity of the interactions among the input parameters, including speed, cycle fuel injection quantity, fuel injection advance angle (Soi) and EGR rate, traditional manual calibration methods will spend more time and cost on the process. Model based calibration can fully optimize a base-engine calibration to meet cycle-based emissions and fuel economy targets. Multiple models have been used to build a collection of local models at the discrete operating points.

This study uses the model-based calibration (MBC) toolbox of Matlab to make automatic calibration and optimization of YC4E170 ECP Diesel engine. This method mainly has three process steps: DoE, building two-stage model and calibration. In this study, several control parameters are chosen, as shown in tab. 2.

Table 3. Evaluation value of optimal design

Type	D-value	V-value
D-optimal	3.385005	0.111284
V-optimal	3.144824	0.087565

Design of experiment

The DoE includes classical design, space filling, and optimal experiment design. Compared with the other two methods, optimal experiment design needs few test points and has higher efficiency. It can get the most reasonable test points distribution of selected model by statistical calculation. It can reduce statistical modeling error before experiment. Consequently, the optimal experiment design was chosen.

There are three kinds of optimal experiment design: D-optimal design, V-optimal design, and A-optimal design. The calculation basis of D-optimal design is to minimize the multinomial coefficient vector error. The aim of V-optimal design is to minimize the mean prediction error variance. Because A-optimal design is more difficult than D- and V-optimal -design in inversion calculation and the optimal result has lower precision, therefore D- or V-optimal design was chosen to get the global operating points distribution, which is shown in figs. 2 and 3.

The MBC toolbox can give the evaluation criterion of D- and V-optimal experiment design at the same time. The evaluation value of two optimal designs is shown in tab. 3. If the D-value is bigger or V-value is smaller, then the optimal experiment design is more efficient. Different optimal designs have the same optimal trend as a whole. However, it has contradiction in local part because of the different algorithm. From tab. 3, when D-value decreases, relatively, less than V-value, the V-value decreases obviously. Therefore, the V-optimal design was selected.

In order to evaluate the model, ten groups of global test points were chosen as the validation points and then the simulation degree could be observed combined with the engine performance. The validation value of D- and V-optimal, is respectively, 1.15189 and 0.74787.

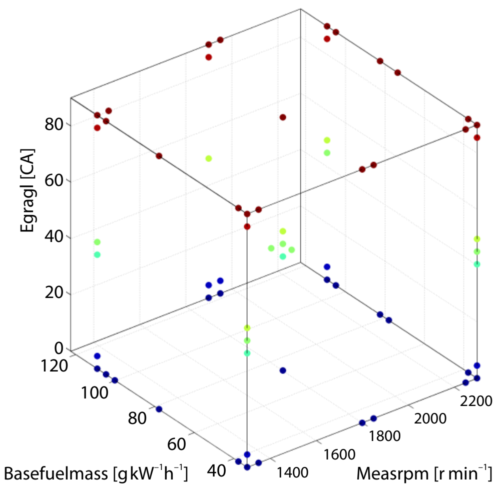

Figure 2. The D-optimal distribution of test points

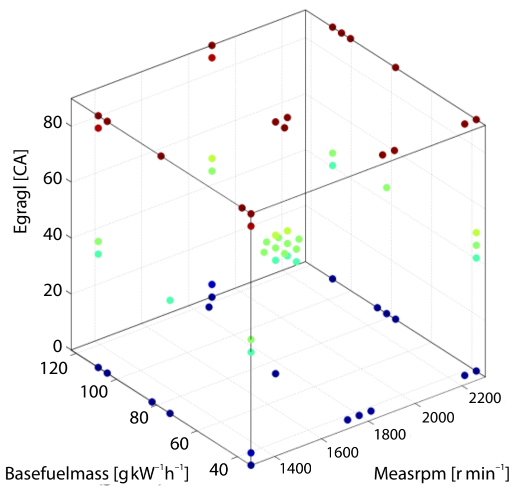

Figure 3. The V-optimal distribution of test points

Acquire engine performance database

According to the engine GT-Power simulation model and the acquired operating points, the engine input and output performance database could be gotten, including 65 groups of global test points. In each global point, seven groups of Soi were scanned, and the total number of test points is 455. The four input variables include speed, cycle fuel mass, EGR valve rate, and Soi. The simulation collected data include torque, power, EGR rate, A/F, NO_x emission mass, emission temperature and erupting pressure.

In order to improve the reliability, it is necessary to need validation data of statistical model, including ten global test points. Each point needs to be scanned by seven groups of Soi and be obtained by the bench test. Some unreasonable points have been wiped off, including erupting pressure beyond 165 bar and turbo emission temperature beyond 1023 K.

Statistical modeling

It is important to establish the two-stage statistical model for forecasting Diesel engine response model in model based engine calibration. In this paper, calibration has two steps process. In the first step, these parameters, including engine speed, cycle fuel mass and EGR valve rate, remain unchanged. In order to get the relationship between the engine performance and the Soi, the Soi was scanned. In the second step, by changing those parameters and scanning Soi again, the influence rule between engine performances with Soi could be obtained when global condition changed. The two-stage model was established in MBC toolbox, including local and global model. The local model gives a curve fitting for local variable Soi. Figure 4 shows the two-stage statistical model.

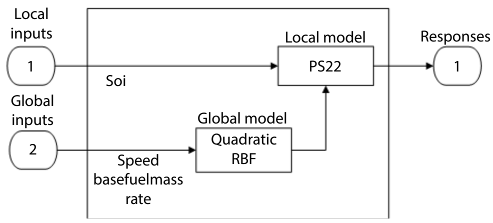

Figure 4. Two-stage statistical model between global model with local model

Local model provides regression factors for global model, the curve has the biggest torque and panel point (the Soi corresponding to the biggest torque). Global model is the best curve fitting for the panel point and Soi in each test.

Firstly, 436 groups of data were imported into MBC toolbox. Local model usually adopts polynomial spline function. It can be defined:

$$T_q = \beta_0 + \sum_{a=2}^{c} \beta_{\text{low\_}a} \left(Soi - k\right)_-^a + \sum_{b=2}^{h} \beta_{\text{high\_}b} \left(Soi - k\right)_+^b \tag{1}$$

$$\left(Soi - k\right)_- = \min\left\{0, \left(Soi - k\right)\right\} \tag{2}$$

$$\left(Soi - k\right)_+ = \max\left\{0, \left(Soi - k\right)\right\} \tag{3}$$

where T_q is responding torque, Soi – the injection advance angle, k – the panel point position, β_0 – the biggest torque point, and $\beta_{\text{low\_2}}$, β_{high} – the fitting constant, and k, β_0, $\beta_{\text{low\_2}}$, $\beta_{\text{low\_}c}$, $\beta_{\text{high\_}h}$ are the local model regression coefficient. The global model adopts hybrid RBF model, which is local approximation network. It needs a small number of weight and threshold to correct. Besides, its rate of convergence is fast and calculated amount is small, moreover, it has the robustness property and can avoid the local minimum. The global model mathematical expression is shown: $h = [n, Q, \text{EGR}]^T$, n is speed, Q is cycle fuel mass, EGR is EGR valve rate.

$$k = m_0 + \sum_{i=1}^{3} m_i h_i + \sum_{i=1}^{3}\sum_{j=i}^{3} m_{ij} h_i h_j + \text{RBF} \tag{4}$$

$$\beta_0 = n_0 + \sum_{i=1}^{3} n_i h_i + \sum_{i=1}^{3}\sum_{j=i}^{3} n_{ij} h_i h_j + \text{RBF} \tag{5}$$

$$\beta_{\text{low\_2}} = l_0 + \sum_{i=1}^{3} l_i h_i + \sum_{i=1}^{3}\sum_{j=i}^{3} l_{ij} h_i h_j + \text{RBF} \tag{6}$$

$$\beta_{\text{high\_2}} = r_0 + \sum_{i=1}^{3} r_i h_i + \sum_{i=1}^{3}\sum_{j=i}^{3} r_{ij} h_i h_j + \text{RBF} \tag{7}$$

Validation criterion

Whether the established model is good or not could be evaluated by the fitting degree between the model and data. Generally, it could be verified by the root mean squared error (RMSE). If the fitted value in each test data is smaller, the RMSE will be rather smaller. In order to prevent the test data over fitting, (predicted sum of squares) PRESS RMSE was put forward as the average value of RMSE. If PRESS RMSE value is bigger than RMSE value, the model will occur data over fitting and need be established again.

Global model was selected as hybrid RBF model, including four eigenvalues, k (knot), β_0 (max), $\beta_{\text{low\_2}}$, $\beta_{\text{high\_2}}$. The linear part of RBF selected the quadratic polynomial. In this paper, we have compared the data imitative effect by different number of cores for RBF. The final selected result and statistical evaluating index are shown in figs. 5-8.

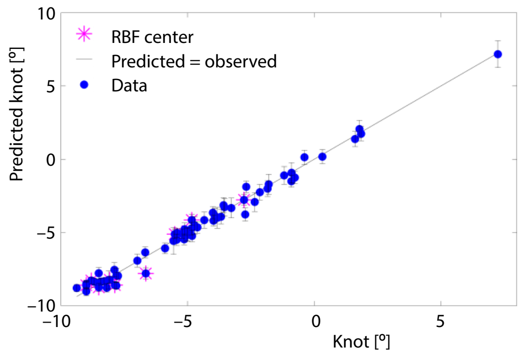

Figure 5. The k eigenvalue fitting value

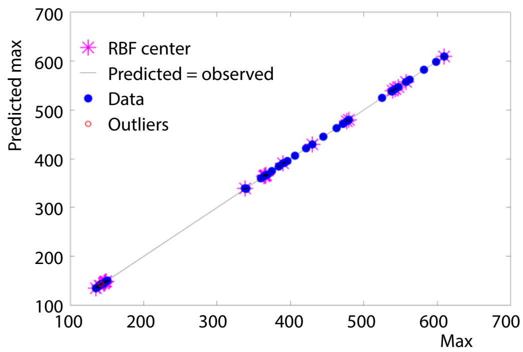

Figure 6. The β_0 eigenvalue fitting value

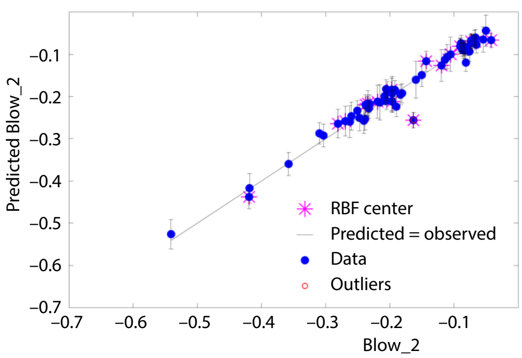

Figure 7. The $\beta_{\text{low\_2}}$ eigenvalue fitting value

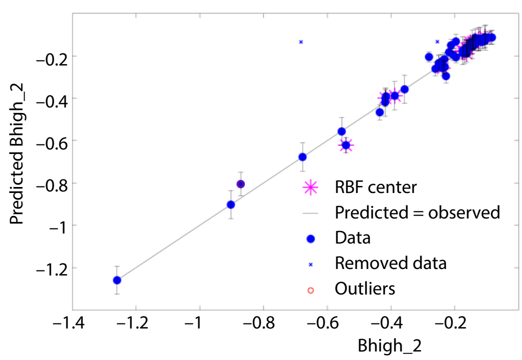

Figure 8. The $\beta_{\text{high\_2}}$ eigenvalue fitting value

If the number of cores of hybrid RBF model is more, the data will be more closely followed by the model, and the structure of model will be more complex. If the number of cores is more, it will make data over fitting and the efficiency of calculation would be low. Therefore, it is quite important to select suitable model complexity by the evaluation index, which is shown in tab. 4.

Table 4. Statistical value of evaluation index

Eigenvalue	Number of observing parameter	Number of model parameter	RMSE	PRESS RMSE	Number of RBF cores
k	64	16	0.461	1.059	10
β_0	63	32	0.624	0.909	30
$\beta_{\text{low\_2}}$	63	23	0.015	0.023	20
$\beta_{\text{high\_2}}$	61	25	0.027	0.106	10

From table 4, there is no much difference in RMSE and PRESS PMSE value of each global eigenvalue fitting model, and the RMSE value is quite small. Therefore, the two statistical indexes indicated that the data fitting between the model and data was quite good and is not over fitting, the modeling of global eigenvalue was successful.

Finally, we can get the fitting result of two-stage model and torque by the fitting between local model and global model. Figure 9 shows the relationship between the original torque data with the fitting curve of two-stage model. The green curve is the experiment result evaluated by the two-stage model, the green point represents the estimated value of model. The blue point is the original experiment point.

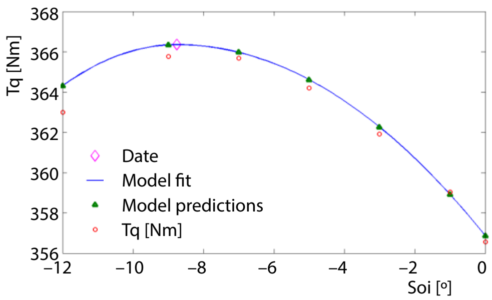

Figure 9. The torque fitting result of two-stage model

Finally, RMSE value of fitting two-stage model is 1.7, the validation RMSE is 6.33. Because the maximum torque of YC4E170 Diesel engine is equal to 590 Nm, such RMSE and validation RMSE value could be accepted, and the two-stage model fitting is successful.

The final four global eigenvalue mathematical model expression is listed:

$$\text{Knot} = -7.9765 - 2.4238n + 11905Q - 0.54598\text{EGR} + 2.7068n^2 - \\ -1.7187nQ + 1.8944Q^2 + 1.3983Q\text{EGR} + 1.4315\text{EGR}^2 + (\text{RBF} - 10) \tag{8}$$

$$\beta_0 = 322.2853 - 26.95885n + 219.1412Q + 2.235144n^2 - 27.21098nQ + \\ +7.963119n\text{EGR} - 10.43544Q\text{EGR} + 5.375736\text{EGR}^2 + (\text{RBF} - 30) \tag{9}$$

$$_{\text{ow\_2}} = -0.19312 + 0.054748n - 0.067004Q + 0.0020113\text{EGR} + \\ +0.03296n^2 + 0.056224Q^2 + (\text{RBF} - 20) \tag{10}$$

$$\beta_{\text{high\_2}} = -0.1885 - 0.055088n - 0.089732Q - 0.02176\text{EGR} + 0.016372n^2 - \\ -0.014038nQ - 0.031023Q\,\text{EGR} - 0.027937\text{EGR}^2 + (\text{RBF} - 30) \tag{11}$$

where n is the speed, Q – the cycle fuel mass, (RBF – 10) – the radial basis function with ten cores. So far, this part has established the two-stage statistical model of YC4E170 Diesel engine.

Optimization

The aim of optimization and calibration is to minimize the fuel consumption lowest under the premise of meeting the emission constraints. Due to the experiment equipment restriction, the emission constraint just took the NO_x emission as the criterion. It can be divided into two steps for the engine parameter optimization. The first step is global optimization, which gives the control parameter optimization value in all the experiment design space scale. In this step, the major uniform distribution operating points in experiment design space will be optimized, and the optimization result will be interpolated into a MAP figure in the whole operating points. The second step is local operating points weighed optimization. In order to meet the heavy duty vehicle Diesel engine emission demand, its emission must pass the ESC 13-mode test cycle experiment. In the optimization process, the target is the lowest fuel consumption rate and the constraint is the NO_x emission 13 mode test cycle weighed value.

This process belongs to single object optimization. It can be optimized by using the MATLAB CAGE toolbox.

Because the NO_x emission and fuel consumption of weighted optimization target refer to the sum of the whole driving cycle condition, instead of aiming at each single operating point. Consequently, it needs firstly to confirm weighting coefficient of engine different operating points, and the emission weighting coefficient usually satisfies with the national emission laws and regulations. This paper will optimize according to 13 mode operating points required by the CI engines of automobile emission laws and regulations, which is shown in tab. 5.

Table 5. The 13-mode test cycle weighting coefficient

Point	1	2	3	4	5	6	7	8	9	10	11	12	13
Load [%]	0	100	50	75	50	75	25	100	25	100	25	75	50
Weight	0.15	0.08	0.1	0.1	0.05	0.05	0.05	0.09	0.1	0.08	0.05	0.05	0.05

$$BSNOx = \frac{\sum [NOx_{\text{mass}}] W_i}{\dfrac{2\pi}{6000} \sum W_i n_i T_{tq}} \tag{12}$$

where W_i is the weighting value of operating point, Pe_i is the power of operating point.

To make the problem easier, the weighting coefficient adopted the same weighting distribution as the emission. It is important for the idle speed operating point and we need calibrate individually for the control parameter optimization. According to the regulation, the limiting value of NO_x emission is 5.0 g/kWh.

Result and discussion

Optimization result of parameters

In the process of parameters optimization, it exists the trade-off between the fuel consumption and NO_x emission. The main control parameters needed to be calibrated are fuel cycle mass, injection advance angle, EGR valve rate. Combined with the optimization, three control parameter global MAP picture could be gotten by the interpolation in CAGE toolbox. The final MAP of three parameters is shown in figs. 10-12. The whole calibration and optimization saves time and workload compared with the traditional process, and it is repeatable and increases the efficiency. Besides, it could obtain the global control parameter MAP picture.

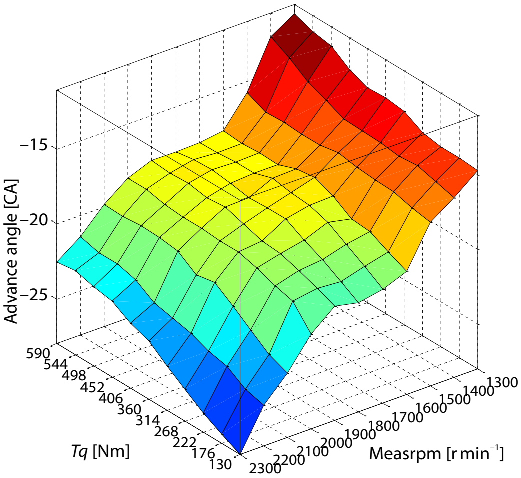

Figure 10. The MAP of cycle fuel mass

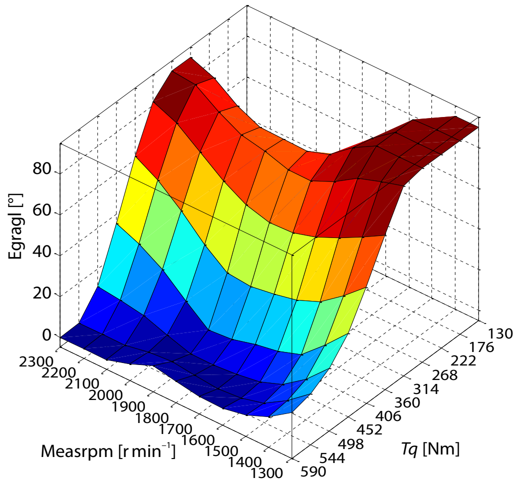

Figure 11. The MAP of fuel supply advance angle

Comparison of model based traditional calibration

The global operating test and 13 mode cycle test has been carried to compared the model based calibration with the traditional calibration. The global operating test has selected five speed conditions, (1600, 1700, 1800, 2000, and 2100 rpm) and four load conditions (25%, 50%, 75%, 100%).

The fuel consumption rate has been measured by the methods of traditional and model based calibration according to the experiment program. In figs. 13 and 14 is the fuel consumption rate results comparison by the two methods when speed is equal to 1600 and 2100 rpm.

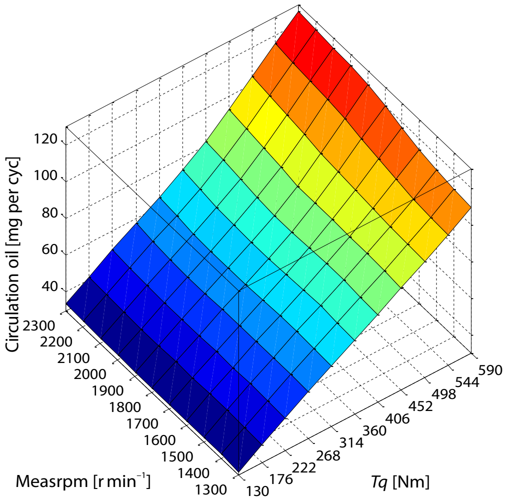

Figure 12. The MAP of EGR valve rate

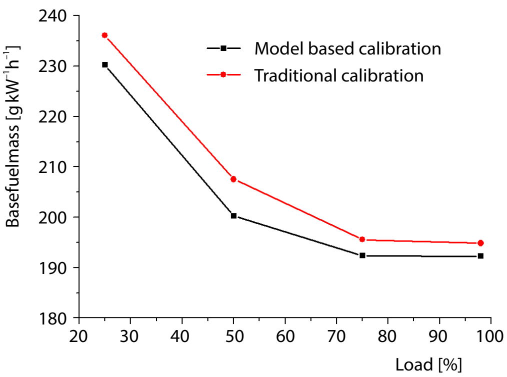

Figure 13. Comparison of fuel mass at 1600 rpm

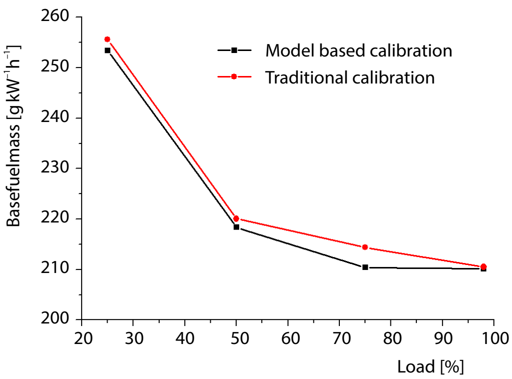

Figure 14. Comparison of fuel mass at 2100 rpm

From these figures, the fuel consumption rate in most test operating points by model based calibration are lower than by traditional calibration. At the 1600 rpm, 50% load operating point, the fuel consumption rate decreased by 3.5% at most. The test result shows that the economy efficiency of model based calibration is better and more effective than traditional calibration overall, it also indicates that traditional calibration has a further possibility to optimize.

Then the test bench experiment was carried out in order to verify 13 mode cycle local optimized results. Firstly we have confirmed the speed at point A, B, C.

$$A = n_{\mathrm{lo}} + 0.25\left(n_{\mathrm{hi}} - n_{\mathrm{lo}}\right) \tag{13}$$

$$B = n_{\mathrm{lo}} + 0.5\left(n_{\mathrm{hi}} - n_{\mathrm{lo}}\right) \tag{14}$$

$$C = n_{\mathrm{lo}} + 0.75\left(n_{\mathrm{hi}} - n_{\mathrm{lo}}\right) \tag{15}$$

where n_{lo} is the engine speed at the 50% of net power and n_{hi} is the engine speed at the 70% of net power. Finally, n_{lo} = 1100 rpm, A = 1500 rpm, B = 1900 rpm, C = 2300 rpm, n_{hi} =2700 rpm.

We have measured the biggest torque at the speed of A, B, C and at each speed, we selected the 25%, 50%, 75%, and 100% of torque as the measurement point. The optimized control parameters of test are fuel supply advance angle and EGR valve rate, which regarded the NO_x emission as the constraint in optimization process. The weighting value of NO_x 13-mode cycle test is less than 5 g/kWh. In figs. 15 and 16 are the test bench 13 mode cycle test results.

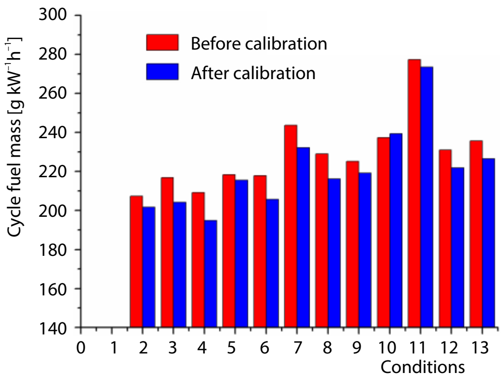

Figure 15. Fuel consumption comparison result

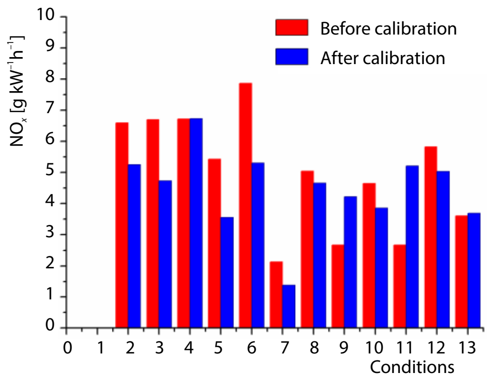

Figure 16. The NO_x emission comparison result

From these results, the fuel consumption at each operating point by model based calibration is lower than the traditional calibration. Among the 7$^{\text{th}}$ operating point, the fuel consumption decreased by 2.72% at most. On the other hand, the NO_x emission also decreased in most operating points. Combined with the weighting coefficient of 13-mode cycle test, the NO_x comprehensive emission of traditional calibration is 4.99 g/kWh, while the NO_x comprehensive emission of model based calibration is 4.86 g/kWh, the total of NO_x emission decreased. Therefore, the model based calibration method can improve the fuel economy of the EUP compared with the traditonal calibration.

Conclusions

This study proposes the model-based fuel economy calibration method for the EUP Diesel engine. The main conclusions are as following.

- V-optimal experiment design has better statistical property than D-optimal experiment design.
- Two-stage statistical model has been established to get the response model of control parameters.
- The test bench results showed that the fuel consumption rate decreases at majority of test operating points by model based calibration. The 13-mode cycle test results indicated that the proposed model-based calibration method is effective and can improve the fuel efficiency by 2.72% at most compared with the traditional calibration. The NO_x weight ratio emissions of 13-mode cycle test decreased from 4.99-4.86 g/kWh. The bench test fully verified and evaluated the effectiveness of the model-based calibration method.
- The whole calibration process can greatly lessen the test workloads compared with the traditional calibration and is repeatable and improve the work efficiency for the whole calibration.

In summary, the model based calibration is practical for improving fuel economic than the traditional calibration.

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Nomenclature

A/F – air/fuel
Basefuelmass – cycle fuel mass, [mgstr^{-1}]
CAGE – calibration and generation
CAN – controller area network
DoE – design of experiment
ECU – electric control unit
EGR – exhaust gas recirculation valve rate
ESC – European steady-state cycle
EUP – electronic control pump
MAP – mean effective pressure
MBC – model based calibration
n – speed, [rmin^{-1}]
PRESS – predicted sum of squares
Q – cycle fuel mass, [mgstr^{-1}]
RBF – radial basis function kernel
RMSE – root mean squared error
Soi – injection advance angle, [°CA]
Tq – responding torque, [Nm^{-1}]

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