The Rapid Development of Diesel Engines Using an Optimization of the Fuel Injection Control

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With concerns over preventing global warming, the usage of diesel engines, which have excellent thermal efficiency properties and are expected to reduce CO_2 emissions is attracting people's attention. Furthermore, nitrogen oxide and particulate matter emissions have been greatly reduced due to the development of emission reduction and combustion control technologies in recent years. To apply the latest combustion control technologies, optimization of the control parameters is required to achieve both exhaust gas suppression and heat efficiency improvement under various operation conditions. In this paper, we describe a method that optimizes the control parameters in actual engines such that they can operate at high efficiency and accuracy.

1. Introduction

Recently, the role of carbon dioxide (CO_2) in global warming has become an issue. To reduce CO_2 emissions, diesel engines have been re-evaluated for automobile applications, and various manufacturers have focused their efforts on the research and development of automobile diesel engines. Controlling exhaust gas has been greatly strengthened. On the other hand, exhaust gas regulations have been greatly strengthened in Japan, the United States, and Europe. In Europe, where diesel cars are more popular, the implementation of Euro 6 is scheduled to take effect in 2014, as shown in **Fig. 1**. Equivalent regulations are to be implemented in Japan and the United States. Therefore, a further reduction in exhaust gases, especially nitrogen oxide (NOx) and particulate matter (PM), will be required. For this reason, the technological development of a new generation of environmentally friendly diesel engines has been promoted.

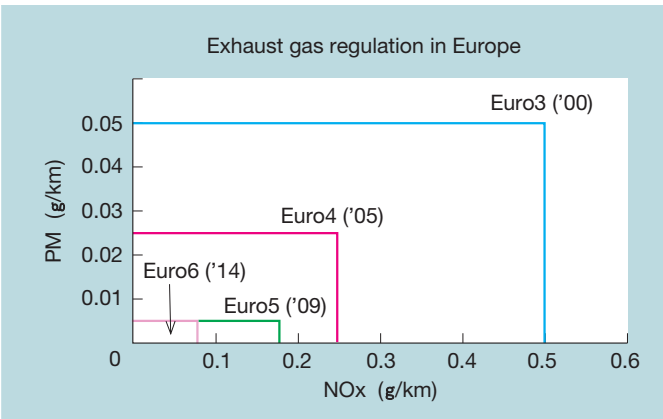

Fig. 1 Exhaust gas control in Europe
Implementation of Euro 6 is scheduled for 2014. Similar regulations are to be implemented in Japan and the United States.

Several major technologies support the latest clean diesel engine, such as exhaust gas recirculation (EGR), common-rail fuel injection systems, and variable geometry turbochargers. To improve the engine performance and reduce the amount of exhaust gas, these control devices must function properly and the control parameters must be efficiently optimized. The conventional trial-and-error method of engine testing has already been thoroughly examined.

In this work, we investigated an optimization method that enables quick calibration of the control parameters and accurate setting of the optimal values by combining engine testing and a response surface model (RSM)[1] with the optimization method.

2. Hybrid optimization using an RSM

An RSM describes the input/output relationship of the system in terms of how the output data are related to the input data. An RSM can make use of polynomial and neural networks. If a high-accuracy model can be established, predictions and optimizations can be performed efficiently. The basic procedure for the hybrid optimization of an engine experiment and the subsequent analysis by an RSM is as follows.

(1) Set the ranges and levels of the engine operating conditions and control parameters, and determine the test combinations (create an orthogonal array, apply the design of experiments methodology).

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(2) Following the orthogonal array, conduct the engine tests and measure the response values, such as the exhaust gas emissions.
(3) Create a response surface model from the combinations of test conditions and response values.
(4) Using the RSM, implement an optimization calculation to determine the control parameters that yield the desired exhaust gas characteristics.
(5) Perform a confirmation test on an actual engine using the optimal solution.

The orthogonal array is a method that provides a combination of test conditions that can thoroughly investigate the response characteristics of the parameter space with the least number of tests. Because the engine characteristics were non-linear, an orthogonal array of a three-level system, such as L18, L27, and L36 was basically used and an orthogonal array of a multi-level system of four levels or more was used in some cases.

The polynomial expression model was used as an RSM. **Figure 2** shows the method used to create the model. Starting from the first-order polynomial, the accuracy of the model was improved by sequentially adding or deleting second- or higher-order terms. To further improve the model accuracy, the weight of each term on the model accuracy was analyzed using the t-test.[2] The t-test is a statistical method that rejects a term when the standard error of the term coefficient is large and bears no significance. Furthermore, to address the model accuracy before and after adding or deleting a term, the Akaike information criterion (AIC)[2] was calculated before and after the addition or deletion. If the value decreased after a term was added, the model accuracy had improved and that term was chosen. The AIC is an index that suppresses the excessive fitting accuracy by using multiple terms and is a standard that can be used to analyze which model, out of multiple models, is the most robust and the most accurate; the sum of the accuracy of the model and the number of terms serve as an evaluation function. It is not an absolute standard, but an index for determining relative high or low numerical values. The process terminates when the squared multiple correlation coefficient, adjusted for a degree of freedom that expresses how closely the model fits a given data point, meets or exceeds a given value. With this method, an optimal polynomial expression model can be obtained by automatically executing the calculation, by computer, based on the given data. For the case of a complete polynomial that uses all of its terms, it is necessary to conduct more tests than the number of the terms. However, if the above method is used, an orthogonal array can be adopted with fewer tests; therefore, the efficiency of the tests is greatly improved.

3. Adoption of the optimization method during a two-stage injection

3.1 Verification of the accuracy of the response surface

To confirm the effectiveness of the method described in Section 2, the method was adopted for a two-stage injection consisting of a main injection plus a pre-injection. There were five control variables: rail pressure (Pcr), pre-injection quantity (PreQ), pre-injection period (Pre-interval), main injection timing (MainIT), and EGR rate. Six responses were measured: NOx, HC, CO, PM emissions, brake specific fuel consumption (BSFC), and noise. The adopted test conditions were (i) speed of rotation = 1,500 min^{-1} and cylinder internal

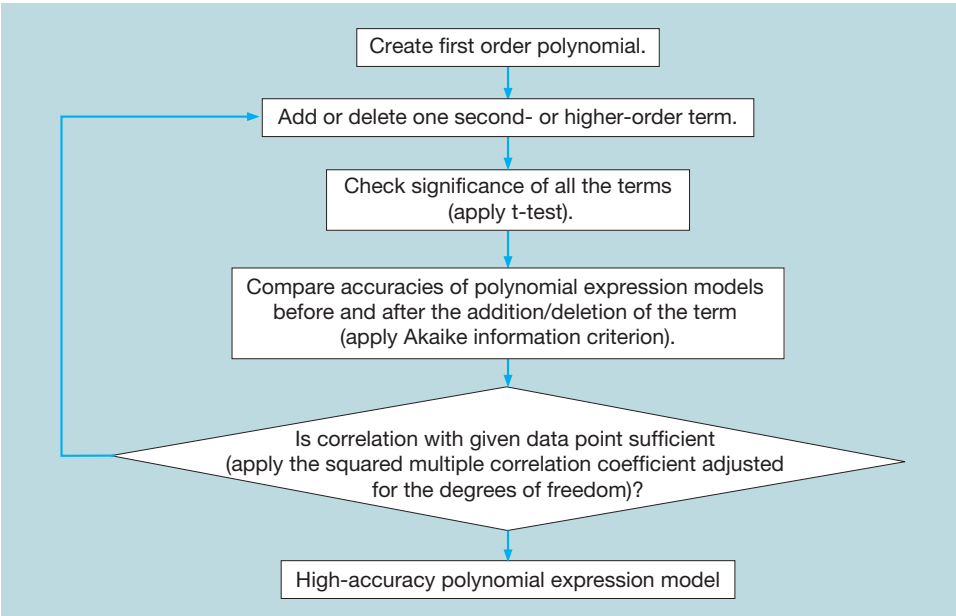

Fig. 2 Creation of an RSM
The terms of a polynomial expression model are chosen based on a statistical method to improve the model accuracy.

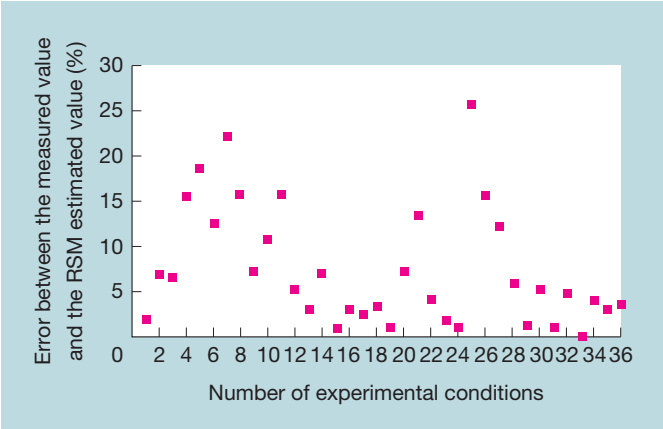

Fig. 3 Confirmation of the accuracy of the RSM
This figure shows the errors between the measured value and the RSM estimated value at the test conditions in the orthogonal array. The prediction accuracy of the response surface is sufficient.

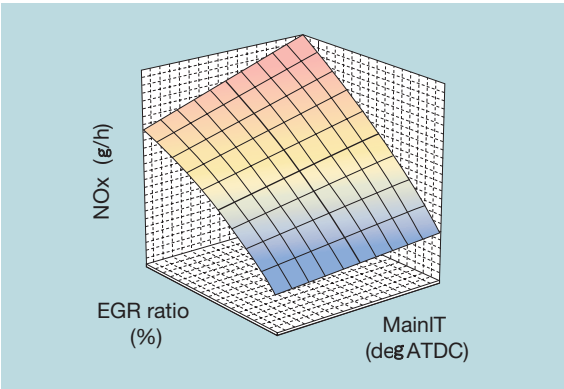

Fig. 4 One example of a response surface
The figure provides a visual understanding of the engine characteristics. MainIT and EGR rate are control parameters and NOx is the response characteristic.

pressure Pme = 0.4 MPa, and (ii) speed of rotation = 2,000 min^{-1} and cylinder internal pressure Pme = 0.7 MPa. For the engine test to yield the response surface, we used an L36 orthogonal array of three levels with five control variables.

First, we discuss the prediction accuracy of the response surface for test condition (i). The accuracy of the fit of the created response surface to the sampling point can be assessed with the squared multiple correlation coefficient adjusted for the degrees of freedom; its value is R^2 = 0.95 for any response value. For example, NOx has a model with excellent accuracy for the respective test conditions, as shown in **Fig. 3**. **Figure 4** shows the response surface for NOx when the MainIT and the EGR rate were taken as control variables. Visualizing the response surface aids in understanding the parameter space for engine control. Furthermore, in **Fig. 5** the results are compared with the measured values, along with four control variables whose response values are different, in order to verify the prediction accuracy of the response surface. For any of the responses, excellent prediction accuracy was obtained quantitatively.

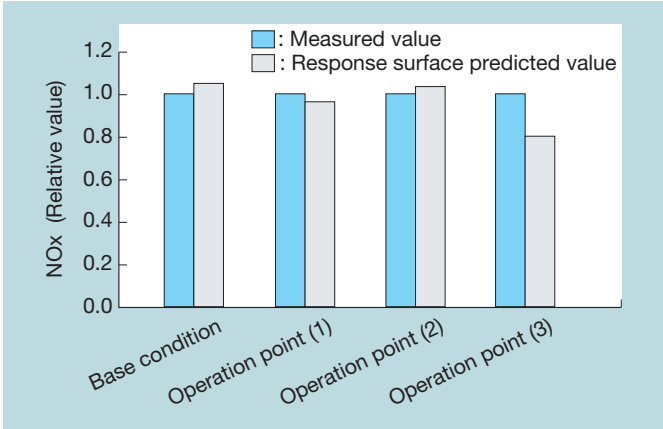

Fig. 5 Comparison between RSM predictions and measured values
The prediction accuracy is excellent for all conditions. The measured value is 1.0.

3.2 Application of the optimization method

Next, the optimization method was applied using the created response surface. The optimization was based on the simulated annealing (SA) method. The SA method determines the optimal solution in a large domain by avoiding a local solution when the existence of multiple local optimal solutions is expected. To minimize the NOx emissions, the optimization was implemented under the restrictions of setting upper limit values to the PM and BSFC on the response surface created based on the data from test condition (ii). As a result, we obtained a condition that reduced NOx emissions by 11% compared to conventional conditions. When we executed a confirmation test, we obtained approximately the expected result. The optimization calculations on the response surface could be performed quickly because the optimization was implemented using a given polynomial. Accordingly, efficient engine control optimization could be achieved without executing a trial-and-error test only if a response surface that satisfied the prediction accuracy could be created.

4. Adoption of the optimization method during multi-stage injection

4.1 Accuracy degradation of a response surface subjected to multiple variables

Although we showed that an excellent optimal condition can be predicted if an appropriate response surface can be created, there are some cases where the appropriate response surface cannot be created if the number of injections is increased. Following are two cases where the appropriate response surface cannot be created.

(1) There is a large discrepancy between the optimal condition predicted from the initial response surface that was created from the orthogonal array and the confirmation test results.

(2) The calculated values of certain responses have negative values (values that cannot exist from a physical

viewpoint) based on the initial response surface created from the orthogonal array.

Insufficient accuracy of the response surface is the cause for both cases. The net mesh becomes rougher as the number of variables increase when we use the same size of orthogonal array. When the interaction between variables or non-linear parameters increases and the number of data points is not sufficient, either degradation of the prediction accuracy or a negative value occurs. Although the best response surface can be created for the given data with the method described in Section 2, there are some cases where degradation of the accuracy cannot be avoided where sampling data is not sufficient. In this work, the successive updating method described below was adopted to improve the prediction accuracy of the response surface.

4.2 Improvement of the response surface by successive updating

After creating the response surface described in Section 2, we checked to determine whether there was a negative response value. This checking was performed in a round-robin manner for all combinations of the respective three-level control variables. If negative values appeared, the maximum negative value was extracted for each response. Using this response surface, the optimal condition was determined using SA optimization. The engine test was performed using the condition of the extracted maximum negative value and the optimal condition. By adding the newly obtained test data to the initial orthogonal array test data, the response surface was recreated. When there were no negative values, the three control variables that were highly sensitive to the response value around the optimal condition were selected in addition to the optimal condition, and an L4 orthogonal array was created. The engine test was conducted with five additional test conditions, besides the optimal condition, and the response surface was recreated by adding these data. The L4 orthogonal array is an array of two levels of respective variables and was utilized for two purposes: first, to determine how close we were to the true optimal condition by investigating the response sensitivity around the optimal condition selected by the SA method; and second, to improve the prediction accuracy by increasing the number of data points around the optimal condition. If the expected optimal condition and the results of the confirmation test nearly agreed, the process was terminated, and the solution was deemed converged close to the optimal condition.

With this successive updating method, the optimal condition can be reached more quickly with fewer tests compared to the use of a large-scale orthogonal array.

4.3 Three-stage injection—the addition of after injection

We describe here the results from applying seven control variables, where two control variables, the quantity of the after injection and the injection timing, were added to the two-stage injection described in Section 3. The minimization of NOx emissions was selected as the optimization parameter under the following constraints: set the upper limit values of CO, PM, fuel consumption, and noise. No negative values were identified after creating a response surface from an L36 orthogonal array; therefore, the optimal condition was determined using SA optimization. The engine test was performed by adding five conditions together with the L4 orthogonal array conditions, using the rail pressure, main injection timing, and EGR rate as variables, whose sensitivities to NOx were high around the optimal condition that varied at two levels. By incorporating these results, the response surface was recreated, and the optimal condition was determined using SA optimization. When the confirmation test was performed after this first updating, the prediction accuracy was improved, as shown in **Fig. 6**, and a highly accurate optimal condition was obtained.

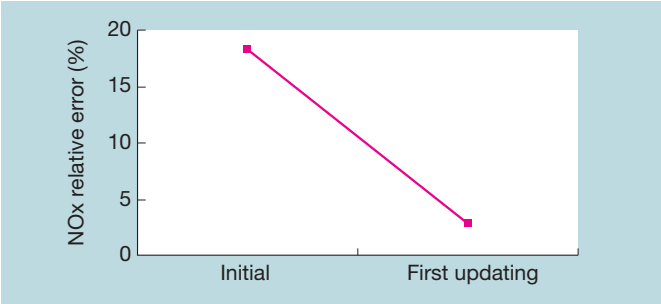

Fig. 6 Improvement of RSM prediction accuracy during the addition of an after injection

By updating the RSM once, the prediction accuracy of NOx improved. The relative error is shown using the measured value as the standard.

4.4 Three-stage injection—the addition of pilot injection

Next, we describe the results obtained after adding a pilot injection instead of an after injection. When the existence of a negative value was investigated for the response surface created from the L36 orthogonal array, the prediction accuracy of PM was low, and many negative values were identified. Then, two additional tests were conducted by combining the condition of the maximum negative value and the optimal condition for the minimum NOx on this response surface, and the response surface was recreated. Since a negative PM value occurred even on the recreated response surface, additional tests were conducted using two conditions of the maximum negative values and the optimal condition, and the response surface was recreated again. At this point, the negative PM value disappeared. An L4 orthogonal array was created with the optimal condition, determined by the optimization calculation, using the rail pressure, main injection timing, and EGR rate as variables, whose sensitivities were high around the optimal condition. Five additional test conditions were determined. With a total of three successive updates for the response surface,

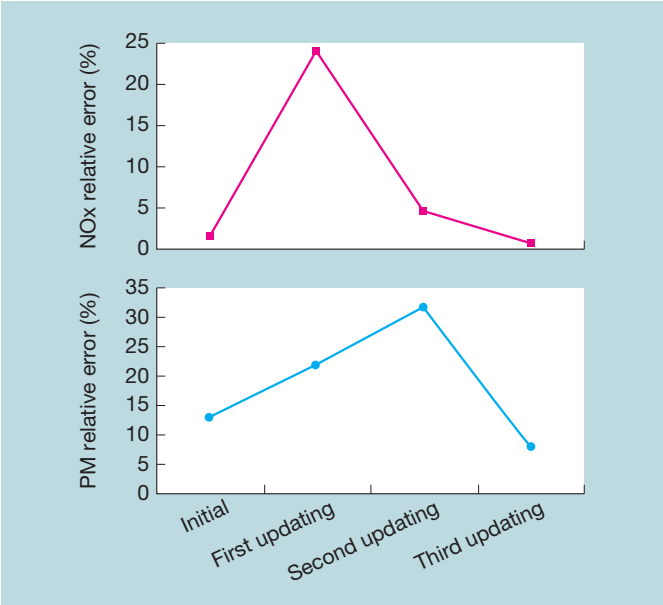

Fig. 7 Improvement of RSM prediction accuracy during the addition of a pilot injection

The prediction accuracy of NOx and PM was improved by updating the RSM three times. The relative error is shown using the measured value as the standard.

a converged value approximating the optimal condition was obtained.

Figure 7 shows the transition of the predicted and experimental NOx and PM values for the optimal condition. During the fourth confirmation test, the prediction accuracy of NOx and PM improved, and results below the constraint conditions could be obtained for the PM, CO, fuel consumption, and noise. There were seven control variables because of the addition of an after injection or a pilot injection. The reason for the larger degradation of the prediction accuracy and the need for three iterations for the pilot injection case is that the addition of the pilot injection affected the pre-injection and main injection due to the change of injection condition. The resulting strong interaction or non-linear actions significantly degraded the prediction accuracy. Since an after injection occurs subsequent to the pre-injection and main injection, it does not have a large effect on the engine combustion. This study has demonstrated that the accuracy improvement from successive updating of the response surface is effective when predicting the optimal condition during multi-stage injection by adding the minimum number of additional tests to the initial orthogonal array.

5. Conclusion

We demonstrated that the hybrid optimization method, which combines orthogonal array testing, an RSM, and optimization, is effective when optimizing the control parameters of the latest diesel engine, which has many control variables. Compared to conventional engine testing, approximately 54% of man-hour testing can be avoided by using the hybrid optimization method, as shown by the example of three-stage injection with the addition of a pilot injection. We plan to upgrade combustion control technology and the optimization method described in this paper to reduce engine exhaust gas emissions, measures for exhaust gas regulations during the transient period and maintain our customers' trust by developing an environmentally friendly engine.

References

1. R. H. Myers and D. C. Montgomery, Response Surface Methodology, John Wiley & Sons, Inc,(2001)
2. Sadao Ishimura, Multivariate Analysis: The Easy Way, Tokyo Tosho (2000) pp.2–57


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