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Stepwise 방식을 이용한 압축 착화 디젤 엔진의 반응 표면 모델 구축

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Construction of Response Surface Model for Compression Ignition Engine Using Stepwise Method

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Abstract >> In recent years, compression ignition engine has been equipped with some control devices such as common rail injection system and turbocharger. In order to control the large number of input parameter appropriately in consideration of NOx, HC and engine power as the engine output objectives. The model construction which reproduces the characteristic value of NOx, HC and engine power from input parameter is needed. In this research, the stepwise method was applied to construct the compression ignition engine model. By using the preliminary experimental data of single cylinder compression ignition engine, the prediction model of NOx, HC and engine power on single injection compression ignition engine was built and compared with the main experimental data.

Key words : Compression Ignition(압축착화), Diesel(디젤), Stepwise(계단식), Response surface model(반응면 모델)

Nomenclature

x_1 : injection timing, deg.CA
x_2 : Crank angle, deg
x_3 : Cylinder pressure, bar
y_1 : NOx, ppm
y_2 : HC, ppm
y_3 : engine power, kW
β_0 : coefficient constant
β_i : the coefficient on the x_i predictor
β_{ij} : the coefficient on the xi predictor x_j predictor
β_{ii} : the coefficient on the xi predictor 2 order
p : the total number of predictors
e_i : the error term

1. Introduction

The one of main problem in the compression ignition engine is engine performance and the exhaust gas emission such as NOx and HC. NOx and HC emissions are harmful not only for human health but also for the environment. Many approaches have been proposed to reduce these emissions[1-2]. In recent years, compression ignition engine has been equipped with some control devices such as common rail injection system and turbocharger[3]. However, this is not guarantee that the results obtained from the engine with these equipments is satisfy as an optimal results. Therefore, a technology which sets the multiple input parameter of these control devices optimally is needed. Response surface method (RSM) is one of the method that can be used to optimize several input parameters of the control devices of compression ignition engine.

Actually, RSM is a collection of mathematical and statistical techniques for building an empirical model. By using design of experiments carefully, the objective of RSM is to optimize a response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests in which several variations are made in the input variables in order to identify the reasons for changes in the output response.

Originally, this method was introduced by G. E. P. Box and K. B. Wilson in 1951[4]. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response. Box and Wilson suggested by using a second-degree polynomial model to do this. They acknowledge that this model is only an approximation, but they used it because such a model it is easy to estimate and applied, even when only a little information is known about the process.

Statistical approaches such as RSM can be employed to maximize the production of a special substance by optimization of operational factors. In contrast to conventional methods, the interaction among process variables can be determined by statistical techniques[5].

One of the kind of the response surface model is stepwise regression method. Some of the researcher used the stepwise method for their research. In order to control the large number of input parameter appropriately in consideration of the engine performance and exhaust gas components as the engine output objectives, a response surface model construction which reproduces the characteristic value of engine performance and exhaust gas components from some input parameter is needed[6-9].

In this research, the stepwise method is applied to some input parameter to build the response surface model of compression ignition engine. In the construction of the response surface model, the method of approximating by a polynomial model based on experimental data is used. The experimental data of single cylinder compression ignition engine to build a predictive model of engine performance and exhaust gas component.

In order to control the large number of control parameter appropriately in consideration of NOx, HC and engine power as the engine output objectives, the model construction which reproduces the characteristic value of NOx, HC and engine power from control parameter is needed. In this research, the stepwise regressions method was applied to construct the compression ignition engine model. Using the experimental data of a single cylinder compression ignition engine, the prediction model of NOx, HC and engine power in single injection compression ignition engines was built.

2. Construction of Modeling

In this study, the stepwise regressions method is used to construct the mathematical modelling of the single injection compression ignition engine.

2.1 Stepwise Regression Method

Stepwise regression method is one method to get the best model of a regression analysis. Actually, this method is a combination of methods of forward and backward method, variable first entry is the variable correlation is highest and significantly dependent variable, the variable that makes the second is the variable correlation partial highs and is still significant, after specific variables into the model of the other variables that is in the models evaluated, if there is a variable that is not significant then the variable is issued[4]. The dependent variable is sometimes also called the predictand, and the independent variables are called the predictors. The model is fit such that the sum-of-squares of differences of observed and predicted values is minimized.

2.2 The Mathematical Model Equation

The model expresses the value of a predictand variable as multilinear function of one or more predictor variables and an error term:

$$y_i = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \sum_{i=1}^{p} \beta_{ij} x_i x_j + \sum_{i=1}^{p} \beta_{ii} x_i^2 + e_i \qquad (1)$$

Where, y_i is the predictand variable in observation i. β_0 is the coefficient constant. β_i is the coefficient on the x_i predictor β_{ij} is coefficient on the x_i predictor x_j predictor. β_{ii} is coefficient on the x_i predictor 2 order. p is the total number of predictors. e_i is the error term.

The model (1) is estimated by least squares, which yields parameter estimates such that the sum of squares of errors is minimized. The resulting prediction equation is:

$$\hat{y_i} = \hat{\beta_0} + \sum_{i=1}^{p} \hat{\beta_i} x_i + \sum_{i=1}^{p} \hat{\beta_{ij}} x_i x_j + \sum_{i=1}^{p} \hat{\beta_{ii}} x_i^2 \qquad (2)$$

Where, the variables are defined as in (1) except that "^" denotes estimated values. The error term in equation (1) is unknown because the true model is unknown. Once the model has been estimated, the regression residuals are defined as:

$$\hat{e_i} = y_i - \hat{y_i} \qquad (3)$$

Where, y_i is the observed value of predictand in observations i and $\hat{y_i}$ is the predicted value of predictand in observations i.

The difference between the observed value y_i and the predicted value $\hat{y_i}$ would on average, tend toward 0. For this reason, it can be assumed that the error term in equation (1) has an average or expected value of 0 if the probability distributions for the dependent variable at the various level of the independent variable are normally distributed. The error term can therefore be omitted in calculating parameters[5].

Then, the sum of squared residuals (SSE) equation is:

$$SSE = \sum_{i=1}^{n} \hat{e_i^2} \qquad (4)$$

Where, n is the number of observation. The sum of squared regression equation is:

$$SSR = \sum_{i=1}^{n} (\widehat{y_{i-\bar{y_i}}})^2 \qquad (5)$$

Where, $\bar{y_i}$ is the mean of the y values. In the case of simple regression, the formulas for the least squares estimates are:

$$\beta = [\beta_0 \beta_1 \beta_2 \dots \beta_p]^T = (X^T X)^{-1} XY \qquad (6)$$

$$X = \begin{vmatrix} 1 & x_{11} & x_{12} & .. & x_{1p} \\ 1 & x_{21} & x_{22} & .. & x_{2k} \\ .. & .. & .. & .. & .. \\ 1 & x_{n1} & x_{n2} & .. & x_{np} \end{vmatrix} \text{and } Y = \begin{bmatrix} y_1 \\ y_2 \\ .. \\ y_n \end{bmatrix}$$

$$R = \sqrt{1 - \frac{SSE}{SST}} \qquad (7)$$

$$F = \frac{\frac{SSR}{p}}{\frac{SSE}{(n-p-1)}} \tag{8}$$

$$t_j = \frac{\hat{\beta}_j}{\sqrt{c_{ij}\left[\frac{SSE}{n-p-1}\right]}} \tag{9}$$

$$c_{ij} = (X^T X)^{-1} \quad ij = 0,1,2,...,p \tag{10}$$

Where, F is the statistic value, t_j is relationship parameter R and t statistic value. The correlation coefficient R indicated that the matching level of the calculation datum by the regression equation and the original datum, the result is better when R is more close to 1. Statistic values indicate the significance of the multiple linear regression equation, whose values obey F distribution. On the condition of less effective regression analysis result, the statistics values of t correspond to non significant variables should be rejected in turn according to the value of t_j. Then the regression analysis will be carried out again with the remaining significant factors. Finally, the prediction model of output is identified.

3. Experimental Setup

In this research, the single cylinder compression ignition engine was used as experimental device to get the preliminary experiment data. Then, the preliminary experiment data was used to build the model.

3.1 Experimental Device

Combustion model can be applied to calculating many engine indices, BSFC (Brake Specific Fuel Consumption), gas emission, pressure, etc. In the cur-

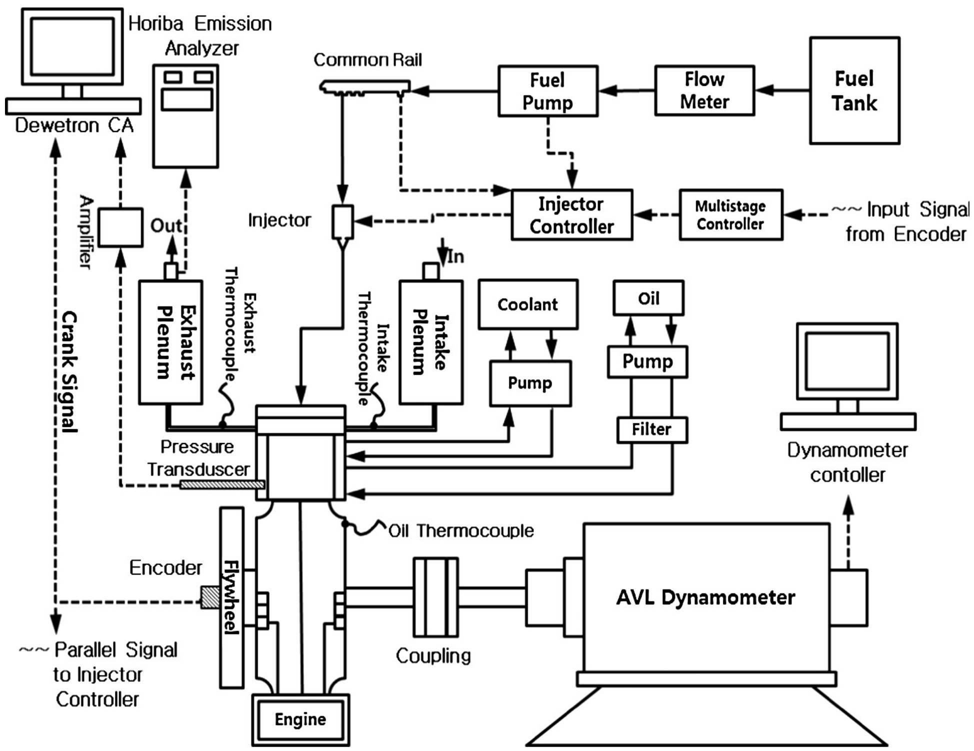

Fig. 1. Single cylinder compression ignition engine schematic view

Table 1. Specification of a diesel engine

Displacement	498 cm^3
Bore × Stroke	83 mm × 92 mm
Crank radius	43.74 mm
Con-rod length	145.8 mm
Compression ratio	19.5
Valve system	SOHC 4 valve
Fuel system	Electronic common rail

Table 2. Compression ignition engine control parameters

Control Parameter	Meaning	Unit	Variation Range
x_1	injection timing	deg.CA	-60,-50,-40,-30,-20
x_2	Crank angle	deg.	-360-360
x_3	Cylinder pressure	bar	0.95-75.5

Table 3. Optimization objectives

Optimization Objective	Meaning	Unit
y_1	NOx	ppm
y_2	HC	ppm
y_3	Engine Power	kW

Table 4. The example input and output data obtained from compression ignition engine

No	Injection timing	crank	Cylinder pressure	NOx	HC	Power
	degCA	deg	bar	%	ppm	kW
	x_1	x_2	x_3	y_1	y_2	y_3
1	-20	-360	1.1512516	1488	4492	2.476
2	-20	-350	1.1054752	1488	4492	2.476
3	-20	-340	1.0627506	1488	4492	2.476
4	-30	-360	1.1917561	2408	1776	2.476
5	-30	-350	1.130721	2408	1776	2.486
6	-30	-340	1.0971516	2408	1776	2.486
7	-40	-360	1.1633093	2865	1111	1.423
8	-40	-350	1.1236365	2865	1111	1.423
9	-40	-340	1.0992224	2865	1111	1.423
10	-50	-360	1.1516832	1479	4314	1.099
...	...	...	...	...	...	...
...	...	...	...	...	...	...
260	-50	-350	1.1272691	1479	4314	1.099
261	-50	-340	1.0875963	1479	4314	1.099
262	-60	-360	1.1209823	331.3	6809	1.137
263	-60	-350	1.0904647	331.3	6809	1.137
264	-60	-340	1.0355331	331.3	6809	1.137
265	-60	-330	1.0172225	331.3	6809	1.137

rent research, polynomial model is constructed, and only NOx and HC are taken as optimization objectives. These objectives are formulated from groups of experiment data. The experiments with single injection are performed on a compression ignition engine experimental device included the compression ignition engine schematic view (in Fig. 1) whose specifications are listed in Table 1.

3.2 Experimental Condition and Result

A single cylinder water-cooled, naturally aspirated, 4-cycle diesel engine with 498 cm3 of displacement and an SOHC 4 valves system was used to carry out the engine test. The engine control parameters are set as Table 2 and the engine optimization objectives are listed as Table 3. Table 4 shows the some examples data was obtained from compression ignition engine. In Table 4, x_1, x_2, and x_3 as control parameters (input). Then, y_1, y_2 and y_3 represents the characteristic value of the optimization objective (output). In this study, the model was built with 3 input variables where each variable have 265 data and 60 data used to test this model. All the data got from experimental. In this study, the author only want to show the accuracy of the prediction model of the NOx, HC and engine power as the output variable.

4. Simulation results & discussion

The purpose of this study is to predict NOx, HC emission and engine power of the single cylinder compression ignition engine fuelled with diesel. In this study only three input data were using which are: injection timing, crank angle and cylinder pressure. Then, to output data of NOx and HC emission and engine power are predicted as the output. This condition is a little bit different with several study, whereas they always using more than five input data and also output predicted data[10,11]. However, this study can be as a proof by using limited data input the predicted data can be obtained precisely. Basically, in the stepwise method, if increasing amount of data input is used, thus, more dominant data input can be addressed which one is influenced to the model. This condition can be obtained from the result of predicted model. For example, if the predicted model was built using only four variables, thus that four variables are the most influencing variable to the model. This can be detected by using value of multiple correlation coefficient (R) and statistic value (F). Even though R value is same, but F value will be different. Therefore, the model which has higher F value is better than other, even though only using a few of variable input. Three variable input were used to built NOx, HC emission and engine power model in this study, due to the difficulty to obtain data input that has direct correlation with NOx, HC emission and engine power. However, on both prediction which are NOx, HC and engine power, have R and F value more than 0.9. On both model R value is more than 0.92. Even though only three input data were used, but the ideal predicted model can be develop very well. On three of model, only one variable to develop NOx, HC and engine model were used. This condition show that this variable is the most dominant to develop NOx, HC emission and engine power model.

The predicted results of NOx, HC emission and engine power are evaluated using correlation coefficient.

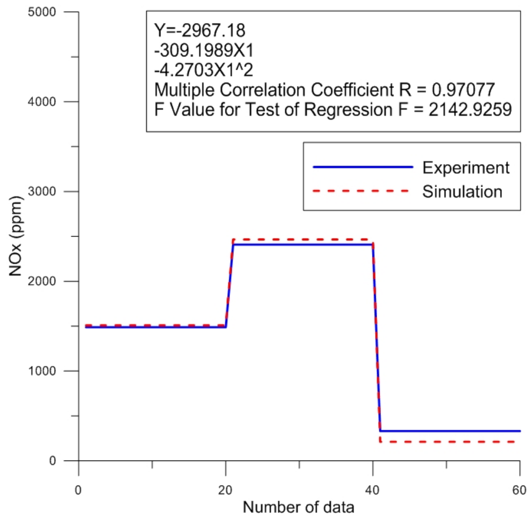

Fig. 2. The prediction and experiment of NOx

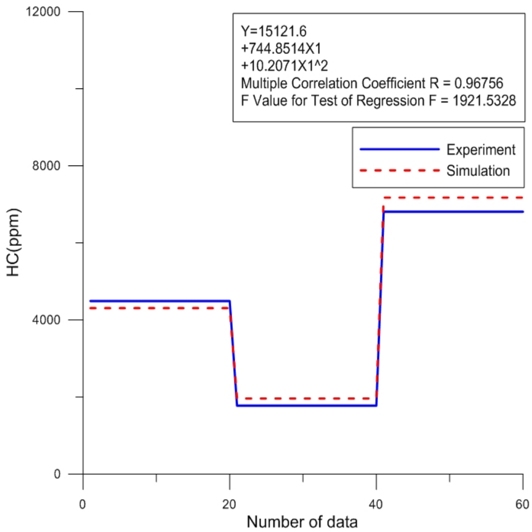

Fig. 3. The prediction and experiment of HC

The predicted result, experiment data and absolute error of NOx, HC emission and engine power is showed in Fig. 2, Fig. 3 and Fig. 4. The predicted value and actual measurement of NOx, HC emission and engine power by stepwise method considering multicollinearity are shown in Fig.2, 3 and 4. The multiple correlation coefficient of NOx is 0.97077, multiple correlation coefficient of HC is 0.96756 and multiple correlation

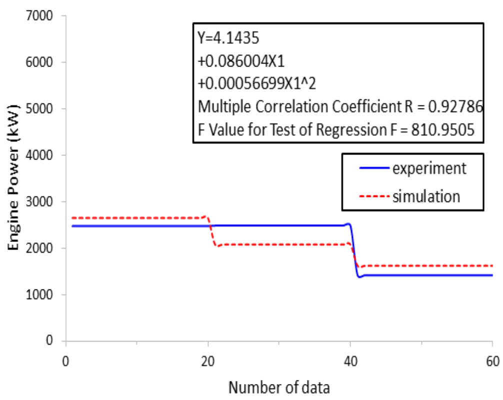

Fig. 4. The prediction and experiment of engine power

coefficient of engine power is 0.92786. Based on these results, it shows that the accuracy of these model is a high. It can be regarded that stepwise method considering multicollinearity can effectively estimate the objectives.

The test in this study was conducted by using only a single type of fuel that is diesel fuel. The results show the satisfy comparison between experiment and simulation. In the near future, this work is possible to applied and predict the combustion and emission characteristics of diesel engine running on low temperature combustion fueled by gasoline-biodiesel blends. Stepwise method is the one of efficient and simple method to develop NOx, HC emission and engine power of compression ignition engine.

5. Conclusions

Based on the experiment data, in order to control the large number of control parameter appropriately in consideration of NOx, HC emission and engine power as the engine output objectives, the model construction which reproduces the characteristic value of NOx, HC emission and engine power from control parameter is needed. In this study, the stepwise method considering multicollinearity was applied to construct the polynomial model order 1 and order 2. The accuracy of predictions made using stepwise method models considering multicollinearity depends on how well the regression function fits the data, there should be regular checks to see how well a regression function fits a given data set. This can be done through regular updates to ensure that the error values are always below a pre-specified error threshold. In this paper, we have reported our predicting model of NOx, HC emission and engine power in single injection compression ignition engines by stepwise method considering multicollinearity. This paper shows that the predictive accuracy by stepwise method considering multicollinearity is high. This is proved by the single correlation coefficient 0.92 or more and F value is very high. It can be regarded that the stepwise method can effectively estimate the objectives. In order to improve exhaust emissions and fuel efficiency in a compression ignition engine, in the future, we use particle swarm optimization (PSO), one of optimization techniques to find the optimal engine operating condition efficiently.

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References

1. P.K. Karra, S.C. Kong, "Diesel Engine Emissions Reduction

Using Particle Swarm Optimization", Combustion Science and Technology, vol. 182:7,Taylor and Francis, pp. 879-903. 2010.

2. T. Kitamura, T. Ito, J. Senda and H. Fujimoto, "Mechanism of Smokeless Diesel Combustion with Oxygenated Fuels Based on The Dependence of The Equivalence Ratio and Temperature on Soot Particle Formation", Int. J. Engine. Research, 3, pp.223-248, 2002.
3. Z. Lu, M. Ogawa and H. Ogai, "Response Surface Modeling of Multiple Injection Diesel Engine", The 54th Conference of the Automatic Control Federation, Toyohashi University of Technology, November 19-20, 2011.
4. Box, G. E. P., and K. B. Wilson. "On the Experimental Attainment of Optimum Conditions". Journal of the Royal Statistical Society. Series B (Methodological) 13, no. 1 pp. 1-45, 1951.
5. Asadi, Nooshin; Zilouei, Hami. "Optimization of Organosolv Pretreatment of Rice Straw for Enhanced Biohydrogen Production using Enterobacter Aerogenes". Bioresource Technology. 227: 335-344. doi:10.1016/j.biortech.2016.12.073, March 2017.
6. J. B. Hurke and A. S. Padalkar, "Performance Optimization of CI Engine Fuelled with Waste Fried Oil Methyl Ester-Diesel Blend Using Reponse Surface Methology", Fuel, pp.266-273, 2014.
7. C. Poompipatpong and A. Kengpol, "Design of a Decision Support Methodology Using Response Surface for Torque Comparison: An Empirical Study on An Engine Fueled with Waste Plastic Pyrolisi Oil", Energy, pp. 850-856, 2015.
8. N. Zhou, Z. Huang and F. Tuffner, "A Modified Stepwise Linear Regression Method for Estimating Modal Sensitivity", IEEE Power and Energy Society General Meeting, pp. 1-7, 24-29 July 2011.
9. N. Amral, C.S.Ozveren and D. King, "Short Term Load Forecasting using Multiple Linear Regression", 42nd International Universities Power Engineering Conference, pp.1192-1198, Brighton, 4-6 Sept. 2007.
10. Apaslan Atmanli, Bedri Yuksel, Erol Ileri and A. Deniz karaoglan. "Response Surface Methodology Based Optimization of Diesel-n-Butanol-Cotton Oil Ternary Blend Ratios to Improve Engine Performance and Exhaust Emission Characteristics". Energy Conversion and Management, pp. 383-394, 2015.
11. B. Rajesh Kumar, S. Saravanan, D. Rana and A. Nagendran. "Combined Effect of Injection Timing and Exhaust Gas Recirculation (EGR) on Performance and Emissions of a DI Diesel Engine Fuelled with Next Generation Advanced Biofuel-Diesel Blends using Response Surface Methodology". Energy Conversion and Management, pp.470-486, 2016.