

Article

Study on the Effect of Parameter Sensitivity on Engine Optimization Results

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Abstract: The effects of six control parameters, intake valve opening timing (IVO), exhaust valve opening timing (EVO), compression ratio (CR), engine speed, intake temperature, and intake pressure on engine output power, indicated specific fuel consumption (ISFC), and nitrogen oxides (NOx) emissions, are analyzed through engine simulation. The six parameters were categorized into two groups based on the degree of influence: high influence (EVO, speed and intake pressure) and low influence (CR, IVO and intake temperature). The relationship between these two groups of parameters and power, ISFC and NOx emissions was explored. Optimization was carried out for each of the two groups of parameters, and the optimization of the high impact parameters resulted in a higher diversity and wider distribution of the solution set. On the other hand, the optimization of the low-impact parameters resulted in a more concentrated distribution of the solution set, while better reflecting the trade-off between the optimization objectives. For the optimal solutions for both sets of parameters, the high-impact parameters provided significant optimization performance compared to the standard operating conditions. Although power and ISFC were optimized, the optimal solution for the low-impact parameter performed poorly with a significant increase in NOx emissions. Therefore, the parameters should be evaluated for optimization using high impact parameters to improve engine performance.

Keywords: engine optimization; Box–Behnken design; response surface methodology; sensitivity analysis; MOPSO



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1. Introduction

As the International Maritime Organization imposes increasingly stringent limits on pollutant emissions and carbon emissions from ships, it is increasingly important to improve the performance of marine engines and reduce pollutant emissions [1]. Traditional marine engines are mainly diesel engines, whose high NOx and particulate emissions are not only harmful to human health, but also difficult to adapt to the increasingly stringent regulatory requirements [2]. Natural gas, as a clean energy source with high calorific value, low sulfur emissions and low particulate emissions, has become an alternative fuel choice with significant advantages [3]. Understanding how to improve engine performance and reduce pollutant emissions has become a research focus.

Many studies have been conducted on the impact of the combustion process on natural gas engines performance and emission performance [4]. Kahila et al. [5] simulated the ignition and combustion process of a diesel pilot-ignited natural gas–air mixture using large eddy simulation and classified the combustion process into five phases. Khatamne et al. [6] investigated the in-cylinder pressure variations with different loads, different natural gas premixing ratios and heat release rate variations. The lower reactivity of the natural gas

causes a delay in the start of combustion at high natural gas premix ratios. Kozarac et al. [7] investigated the effect of load and injection timing on hydrocarbon emissions. The fuel-rich zone under low load conditions produced higher hydrocarbon emissions, and the increase in turbulence intensity in the combustion chamber after increasing the load resulted in lower hydrocarbon emissions. Poorghasemi et al. [8] explored the effect of injection cone angle on pollutant generation. Increasing the injection cone angle resulted in a more complete combustion of the mixture and a reduction in the generated carbon monoxide emissions. You et al. [9] investigated the effect of an excess air ratio on NOx emissions. Increasing the excess air ratio can inhibit the production of NOx. Yang et al. [10] studied the particulate emissions in the exhaust gas of a natural gas engine. The main particulate emissions were all large particles. Based on these studies, changes in engine operating conditions lead to changes in combustion processes, which in turn lead to changes in engine performance and pollutant emissions. Therefore, optimization of engine operating conditions is necessary [11].

Traditional engine optimization is based on a large number of experiments, and although the results are accurate, the experimental process of the engine optimization takes a lot of time and is costly. Therefore, the current research and optimization of engines are mainly carried out by means of simulation [12]. Through a small amount of experimental data obtained from experiments to establish the engine simulation model, the combination of simulation and statistics and machine learning methods has become the mainstream of the current research [13]. It has good engine prediction accuracy, and a well-trained model can reduce the time required to calculate the engine performance under different operating conditions under the premise of ensuring accuracy [14]. Combining the prediction model with the optimization algorithm can quickly find the parameter settings with the best performance for the engine [15].

Most of the optimization studies for engines first select the control parameters to be optimized and then select the optimization objectives. Liu et al. [16] selected ISFC, NOx emission and methane escape as the optimization objectives, and optimized the shape of the combustion chamber and the injection parameters of the engine through a computational fluid dynamics simulation combined with genetic algorithms. The optimization results demonstrated the trade-off relationship between the optimization objectives, and the improved combustion chamber shape could reduce the NOx emission but would sacrifice the other two optimization objectives. Ma et al. [17] optimized the parameters of a natural gas/diesel engine, and innovatively introduced decision preference in the optimization process. The decision preference controlled the direction of population development in the optimization algorithm, which made the final optimization results more in line with the expected goals. Park et al. [18] established a one-dimensional simulation model of a natural gas engine, selected the experimental points using Latin hypercube sampling, and investigated the effect of natural gas substitution fractions on the performance and emissions of the engine by using RSM. Finally, the engine torque, fuel consumption rate and emission parameters were optimized. Stoumpos et al. [19] simulated and optimized the exhaust gas recirculation and air bypass system of a natural gas/diesel dual-fuel engine. The optimized dual-fuel engine was able to meet the International Maritime Organization's "Tier III" standard for NOx emissions in diesel-only operation. Roy et al. [20] innovatively combined a meta-model with a genetic algorithm. The meta-model developed has reliable accuracy and the engine performance after optimization using genetic algorithm achieves the expected results. Motlagh et al. [21] optimized seven injection parameters of a natural gas/diesel engine based on the OpenFOAM software and explored the effect of injection parameters on combustion and pollutant generation processes.

In summary, the current optimization research methods for natural gas engines are mainly as follows: firstly, selecting the engine control parameters for the study, then exploring the effects of the control parameters on engine performance and emissions and finally optimizing the control parameters. However, due to the different mechanisms of the control parameters for the combustion and pollutant generation process, the different

control parameter changes impact the engine performance and emission indexes to different degrees. Studying the engine using simulation modeling has the advantage of reducing the research cost, and engine simulation is chosen as the research method in this paper. This paper first evaluates the degree of influence of control parameters on performance and emission parameters, then classifies the control parameters according to the degree of influence, and explores the differences in the results of optimizing two groups of parameters with high and low degrees of influence, respectively.

2. Methodology

2.1. Research Framework

Figure 1 shows the research framework of this paper, including the following steps: (1) model building, (2) parameter sensitivity analysis, (3) parameter classification and (4) optimization comparison.

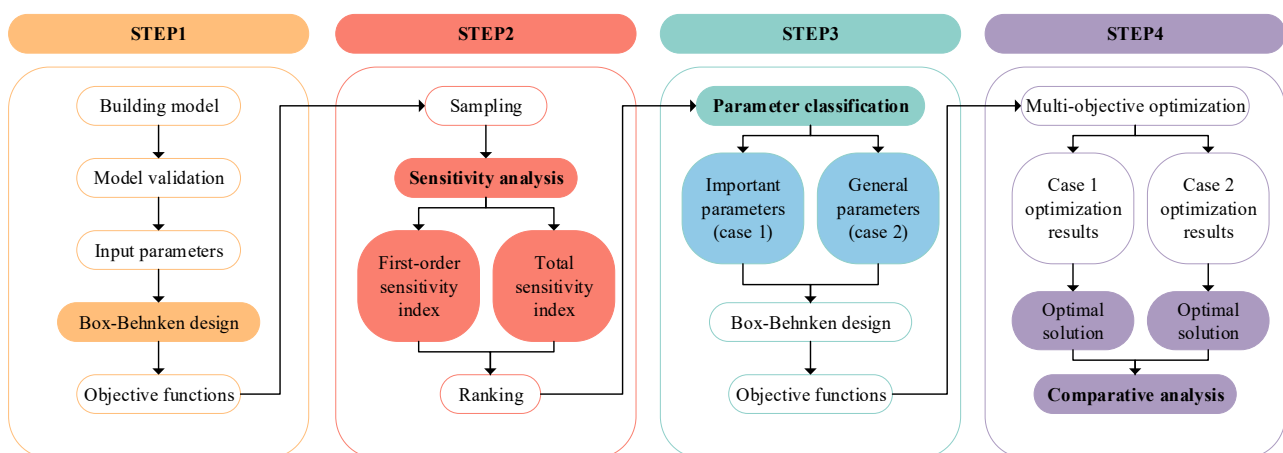


Figure 1. Research framework.

2.2. Engine Simulation Model Building

AVL-BOOST is an engine simulation software focused on engine simulation. The target engine is the Wärtsilä 9L34DF engine. The target engine is designed by Wärtsilä Group of Finland and manufactured by CSSC Power (Group) Corporation Limited. The main engine parameters are shown in Table 1. As a marine dual-fuel engine, it has both diesel and dual-fuel modes. The diesel mode is the same as the compression ignition diesel engine. In dual-fuel mode, natural gas is used as the main energy source and a small amount of diesel fuel is used as pilot fuel. The engine simulation software built in AVL-BOOST R2019.2 is shown in Figure 2.

Table 1. Engine parameters.

Parameters	Values
Engine type	four-stroke
Cylinder configuration	Inline 9 cylinders
Cylinder bore (mm)	340
Stroke (mm)	400
Compression ratio	12.6
Speed (r/min)	750
Power (kW)	4500
Intake valve opening timing (° CA)	300
Exhaust valve opening timing (° CA)	130
Intake air temperature (K)	323
Intake pressure (bar)	4.53

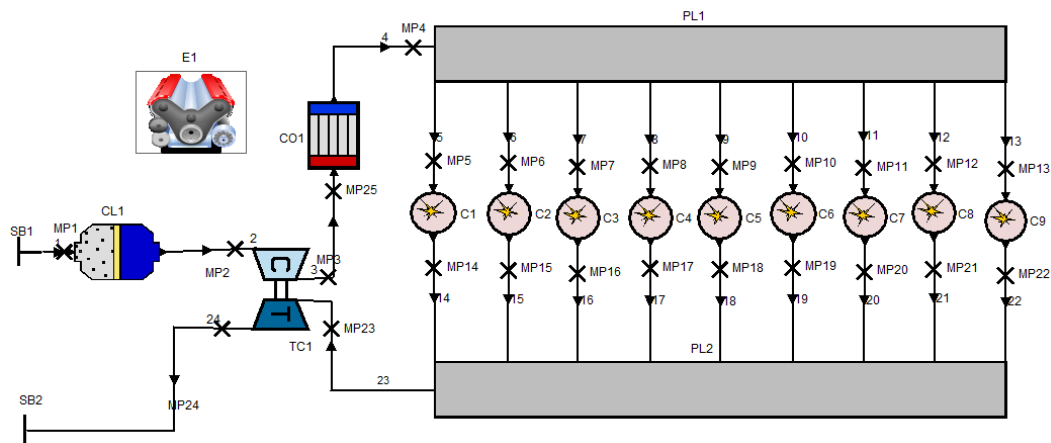


Figure 2. Engine modeling in AVL-BOOST.

The validity of the simulation model established in AVL-BOOST under different load conditions is verified using test data. The performance and emission data of the engine under different operating conditions were obtained from the engine performance test at the shipyard. The engine simulation model was constructed based on the experimental data from the shipyard, and the diesel condition and natural gas condition were verified. Comparison of test and simulation data for engine power, brake mean effective pressure (BMEP), indicated specific fuel consumption and NOx emissions under diesel operating conditions are shown in Figure 3.

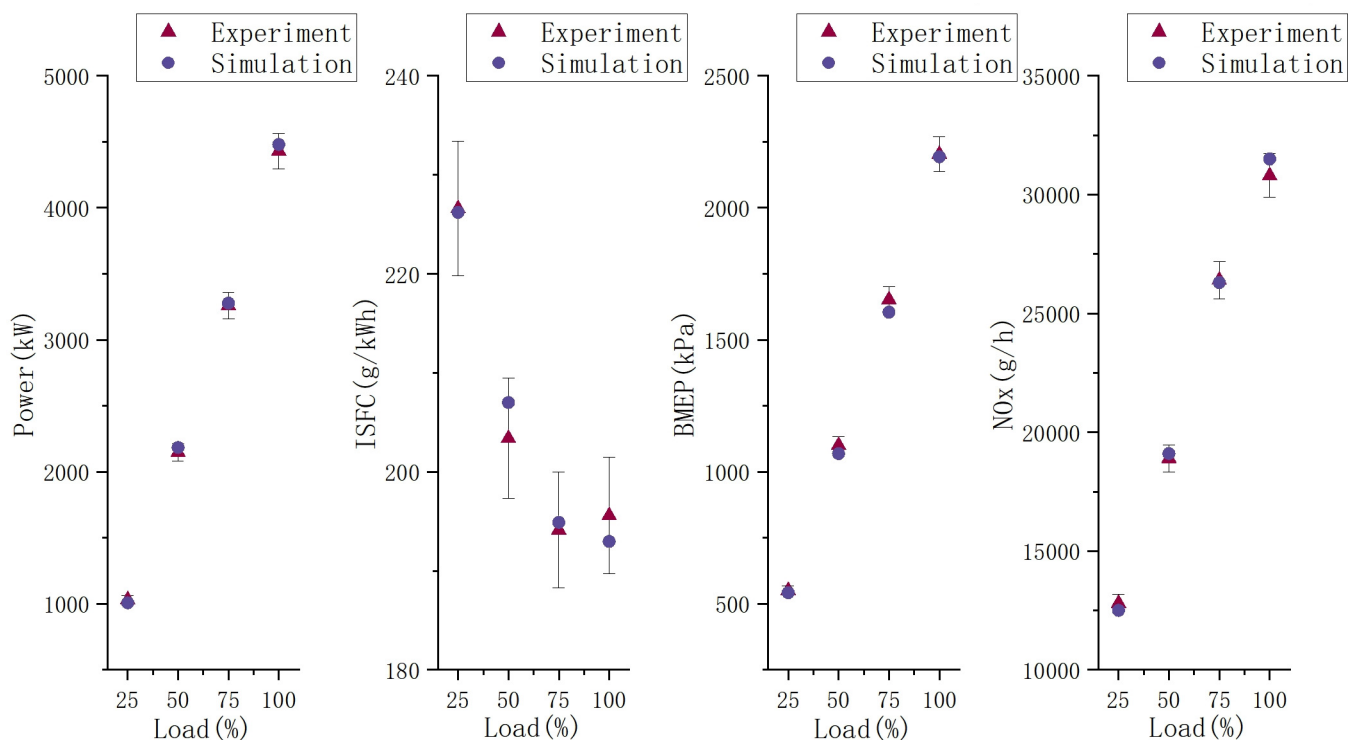


Figure 3. Comparison of experimental and simulated numerical values in diesel mode.

Comparison of experimental and simulation data under natural gas conditions is shown in Figure 4. The target accuracy error under both conditions is less than 3%, which proves the reliability of the modeling.

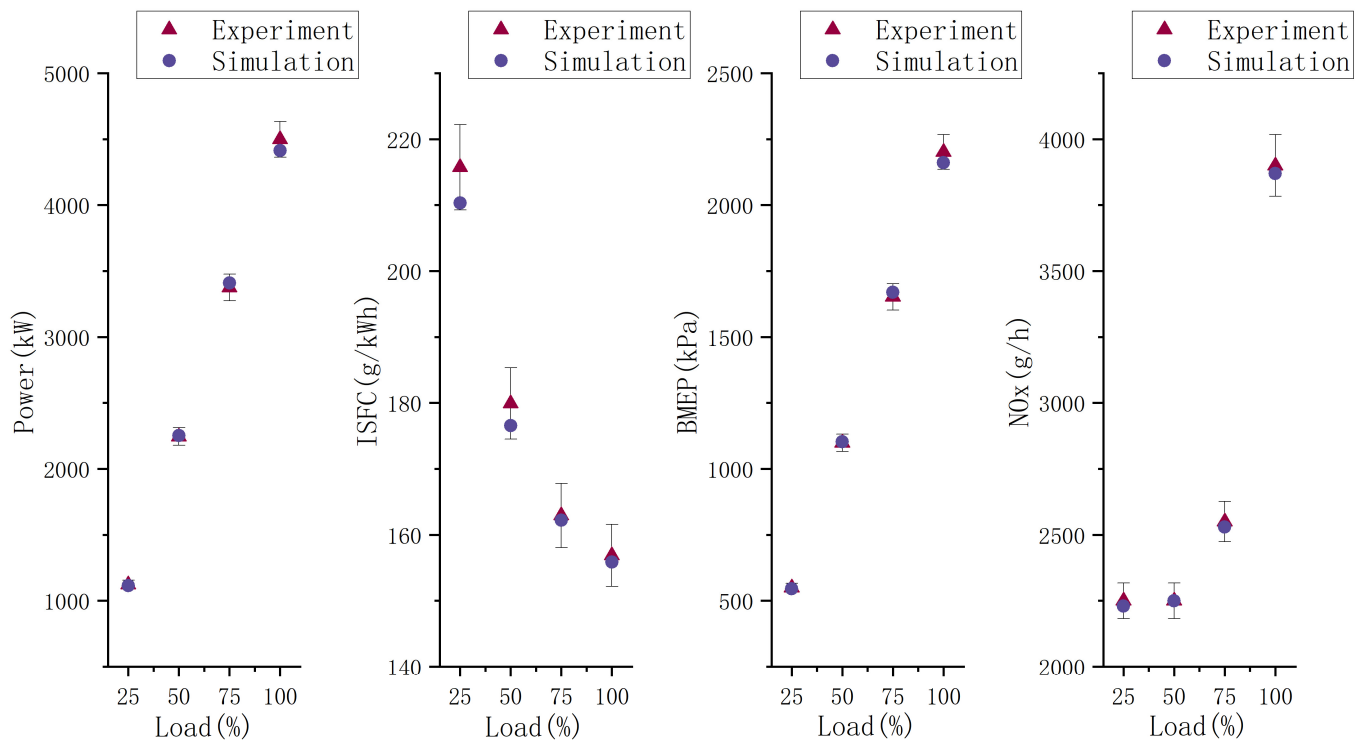


Figure 4. Comparison of experimental and simulated numerical values in natural gas mode.

2.3. Experimental Design and Response Surface Methodology

Box–Behnken design (BBD) is a type of response surface design for efficient estimation of first and second order coefficients. The number of experiments (N) for BBD is defined as $N = 2k(k - 1) + c$ where k is the number of design variables and c is the number of centroids. All the levels of the design variables were categorized into three levels (−1, 0, 1) with equal intervals between the levels. The coded values of the BBD for the three-variable condition are shown in Table 2.

Table 2. Three-factor BBD experimental matrix.

X1	X2	X3
0	1	1
0	0	0
−1	0	−1
0	1	−1
0	−1	−1
−1	−1	0
0	−1	1
1	−1	0
−1	1	0
−1	0	1
1	1	0
1	0	−1
1	0	1

Response surface methodology (RSM) is used to obtain mathematical relationships between response parameters and design variables. As a statistical method, RSM is widely used in internal combustion engine calibration [22]. Application of the BBD method allows RSM to obtain accurate predictive performance with a reduced number of experiments [13].

Equation (1) shows the fitted general second-order polynomial response surface mathematical model.

$$y = \beta_0 + \sum_{i=1}^m a_i x_i + \sum_{i < j}^m b_{ij} x_i x_j + \sum_{i=1}^m c_i x_i^2 \quad (1)$$

where y is the response parameter; x_i is the value of the design variable; m is the number of design variables; β_0 is the constant term; a_i is the coefficient of the primary term; b_{ij} is the coefficient of the cross term; and c_i is the coefficient of the quadratic term.

In order to evaluate the fitting accuracy of RSM, R^2 , R^2_{adj} and R^2_{pred} were introduced to assess the fitting accuracy of the equation. The closer R^2 , R^2_{adj} and R^2_{pred} converge to 1, the higher the accuracy [23]. R^2 describes the extent to which the input variables explain the output variables.

$$R^2 = 1 - \left[\frac{SS_{residual}}{SS_{residual} + SS_{model}} \right] \quad (2)$$

where, $SS_{residual}$ is the residual sum of squares; SS_{model} is the regression sum of squares. R^2_{adj} offsets the effect of sample size on R^2 and responds only to the goodness of fit of the regression equation.

$$R^2_{adj} = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1} \quad (3)$$

where n is the number of samples and p is the number of design variables. R^2_{pred} determines the predictive superiority of the regression equation.

$$R^2_{pred} = 1 - \frac{PRESS}{SS_{residual} + SS_{model}} \quad (4)$$

where $PRESS$ is the sum of squared prediction residual errors.

2.4. Sobol Method

Sensitivity analysis is an analytical method used to determine the key factors affecting the performance of a system. The Sobol method is a sensitivity analysis method based on variance decomposition. This method quantifies the variance of each input variable and considers the interactions between the variables [24]. The first order sensitivity index S_i is a measure of the effect of individual parameters on the output. The total order sensitivity index S_{Ti} is a measure of the contribution of the combined effect of a single parameter and other parameters to the output, including its first order effects (inputs varying individually) and all higher order interactions. The formulae for S_i and S_{Ti} are as follows:

$$S_i = \frac{D_i(Y)}{Var(Y)} \quad (5)$$

$$S_{Ti} = 1 - \frac{D_{-i}(Y)}{Var(Y)} \quad (6)$$

where $Var(Y)$ represents the total variance of the objective function and $D_i(Y)$ represents the first-order variance of the parameters. $D_{-i}(Y)$ represents the interaction of all parameter variations excluding the objective parameter.

2.5. Optimization Method

The multi-objective particle swarm optimization (MOPSO) algorithm is a commonly used heuristic algorithm for dealing with multi-objective optimization problems. Combining particle swarm algorithms and multi-objective optimization techniques can find optimal solutions in different objective functions [25]. By simulating the social cooperation and individual competition behaviors of bird flocks and fish schools and guiding the particle swarm to evolve to the global optimum based on the currently searched optimal solution, it has a very fast convergence speed. Jin et al. [26] and Cong et al. [27] both optimized

the engine using MOPSO and obtained good optimization results. Figure 5 shows the computational flow of the MOPSO algorithm.

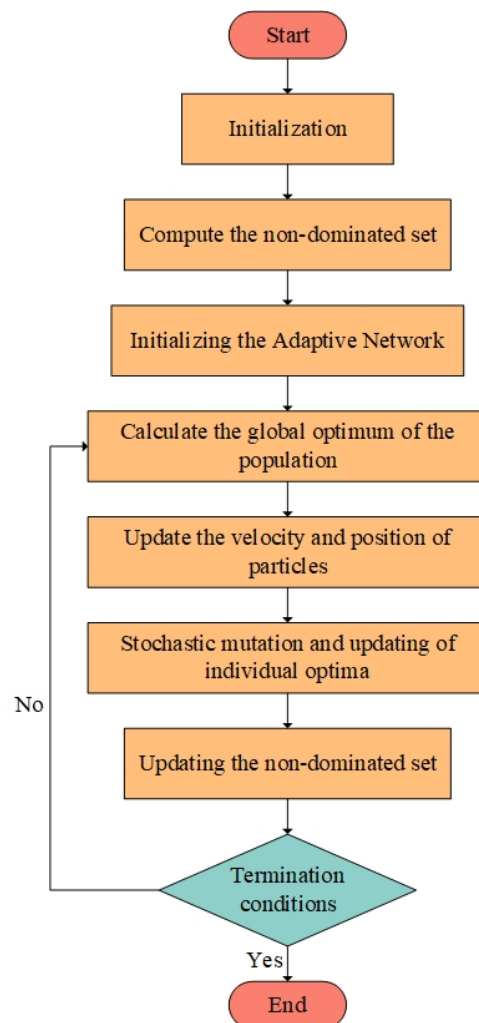


Figure 5. Flowchart of MOPSO algorithm calculation.

The RSM is combined with MOPSO so that the mathematical relationships between the response parameters fitted in the RSM and the design variables are brought into the optimization algorithm to achieve the optimization of the engine.

3. Results and Discussion

3.1. Sensitivity Analysis

Figure 6 illustrates the first-order and total-order sensitivity indices to power for the six parameters evaluated by applying the Sobol method. The parameter with the largest effect on power is the engine speed. The first- and total-order sensitivity indices are 81.55% and 81.56%, respectively. The next most influential parameter is EVO with first- and total-order sensitivity indices of 13.35% and 13.28%, respectively. All other parameters have first-order and total-order sensitivity indices of less than 5% and have relatively little effect.

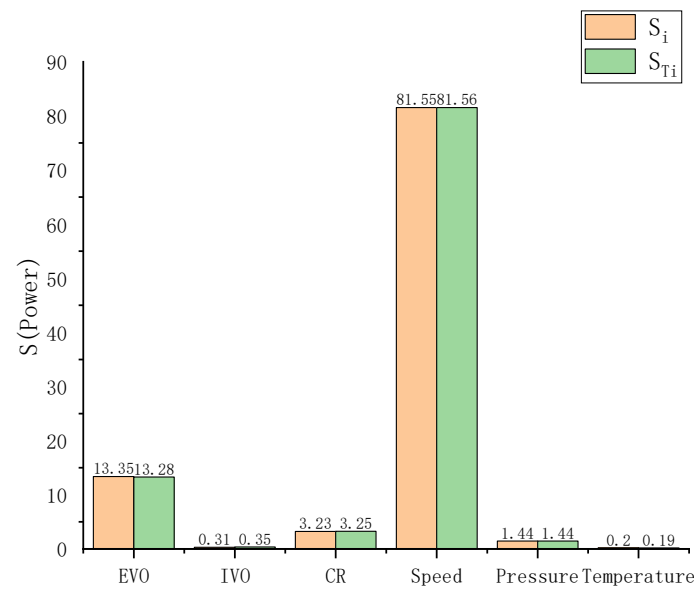


Figure 6. Comparison of first-order and total-order sensitivity indices for the power parameters of the Sobol method.

The first-order and total-order sensitivity indices of the six parameters of ISFC are shown in Figure 7. EVO is the most important parameter with first-order and total-order sensitivity indices of 55.28% and 55.81%, respectively. Next, engine speed also has a significant effect. Both the first- and total-order sensitivity indices of CR and intake pressure are also greater than 5%, again possessing a non-negligible influence effect.

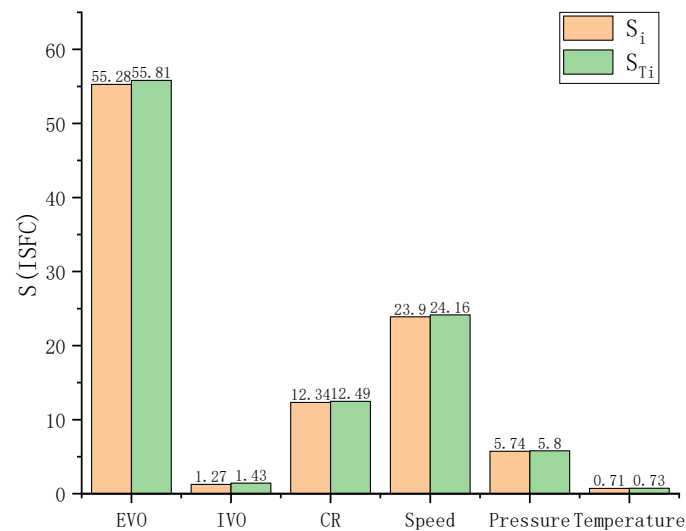


Figure 7. Comparison of first-order and total-order sensitivity indices for the ISFC parameters of the Sobol method.

The first-order and total-order sensitivity indices of the parameters for NO_x are shown in Figure 8. The engine speed has the largest influence, with first-order and total-order sensitivity indices of 46.31% and 46.35%, while the difference between the sensitivity indices of intake pressure and engine speed is only less than 10%, and the first-order and total-order sensitivity indices of intake pressure are 38.56% and 39.08%, respectively. The relative influence of intake air temperature and CR is limited, while that of EVO and IVO is almost negligible.

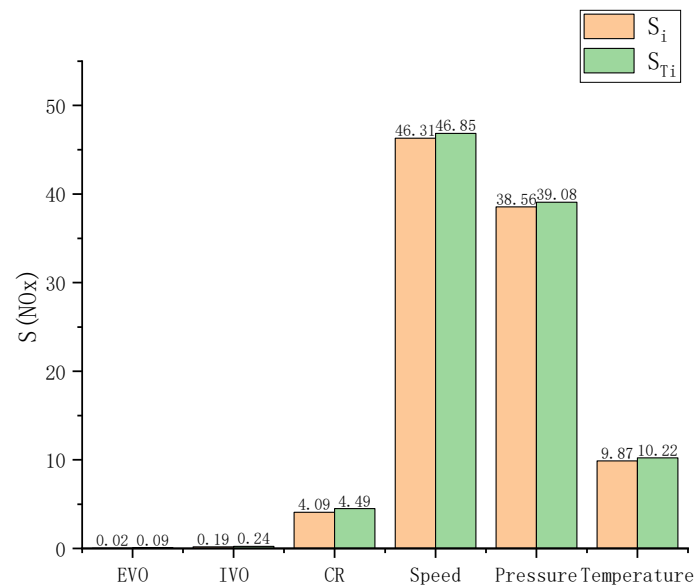


Figure 8. Comparison of first-order and total-order sensitivity indices for NOx parameters of the Sobol method.

The degree of influence of different control parameters on the performance parameters varies considerably. The six control parameters are divided into two groups, one for the parameters with high influence (Case1) and one for the parameters with low influence (Case2). The parameters selected for Case1 are engine speed, EVO and intake pressure, while the parameters selected for Case2 are IVO, CR and intake temperature. The range of parameter variation is shown in Table 3.

Table 3. Scope of the parameter study.

Parameter	Scope
EVO (° CA)	100–150
IVO (° CA)	260–300
CR	12–15
Speed (r/min)	600–800
Intake pressure (bar)	4.5–5.5
Intake temperature (K)	315–335

3.2. RSM Results

Based on the BBD method, the experimental design was carried out for Case1 and Case2, respectively, and numerical simulation tests were conducted using AVL-BOOST. The response surface functions for *Power*, *ISFC* and *NOx* were obtained by analyzing the experimental results. The response surface functions obtained for Case1 based on the coding factors are shown in Equations (7)–(9), where *A*, *B* and *C* represent EVO, rotational speed and inlet pressure, respectively. The response surface functions obtained for Case2 are shown in Equations (10)–(12), where *E*, *F* and *G* represent IVO, CR and inlet temperature, respectively.

$$\begin{aligned}
 \text{Power} = & 4206.21 + 170.38 \cdot A + 411.39 \cdot B + 65.87 \cdot C \\
 & + 5.06 \cdot A \cdot B + 4.71 \cdot A \cdot C - 1.56 \cdot B \cdot C \\
 & - 106.84 \cdot A^2 - 16.01 \cdot B^2 - 4.41 \cdot C^2
 \end{aligned} \tag{7}$$

$$\begin{aligned}
 ISFC = & +153.92 - 5.93 \cdot A + 4.62 \cdot B - 2.12 \cdot C \\
 & + 0.33 \cdot A \cdot B + 0.011 \cdot A \cdot C + 0.48 \cdot B \cdot C \\
 & + 3.97 \cdot A^2 + 0.15 \cdot B^2 + 0.030 \cdot C^2
 \end{aligned} \quad (8)$$

$$\begin{aligned}
 NOx = & +3377.81 - 99.72 \cdot A + 1007.31 \cdot B - 779.08 \cdot C \\
 & - 231.24 \cdot A \cdot B + 8.22 \cdot A \cdot C - 246.52 \cdot B \cdot C \\
 & + 127.27 \cdot A^2 + 229.14 \cdot B^2 + 28.72 \cdot C^2
 \end{aligned} \quad (9)$$

$$\begin{aligned}
 Power = & +4443.91 + 19.46 \cdot E + 80.34 \cdot F - 13.05 \cdot G \\
 & - 0.23 \cdot E \cdot F + 3.88 \cdot E \cdot G - 1.22 \cdot F \cdot G \\
 & + 3.43 \cdot E^2 - 10.13 \cdot F^2 - 0.41 \cdot G^2
 \end{aligned} \quad (10)$$

$$\begin{aligned}
 ISFC = & +154.92 - 0.58 \cdot E - 2.42 \cdot F + 0.30 \cdot G \\
 & + 0.010 \cdot E \cdot F - 0.099 \cdot E \cdot G + 0.21 \cdot F \cdot G \\
 & - 0.015 \cdot E^2 + 0.27 \cdot F^2 - 0.092 \cdot G^2
 \end{aligned} \quad (11)$$

$$\begin{aligned}
 NOx = & +4235.99 - 65.39 \cdot E + 447.66 \cdot F + 290.12 \cdot G \\
 & + 11.52 \cdot E \cdot F + 1.22 \cdot E \cdot G + 8.95 \cdot F \cdot G \\
 & - 28.05 \cdot E^2 - 53.15 \cdot F^2 + 5.92 \cdot G^2
 \end{aligned} \quad (12)$$

In order to demonstrate the effectiveness of the combined RSM and MOPSO optimization method, the constructed response surface functions were evaluated. Table 4 shows that R^2 is very high ($R^2 > 0.99$), which indicates that the input data is effectively used to fit the response surface function. The value of R^2_{adj} is somewhat reduced compared to R^2 . This is because whenever more variables are added, whether or not there is a relationship between the added variables and the output variables, then R^2 either remains constant or increases. R^2_{adj} counteracts the effect of the number of samples on R^2 and therefore reflects the significance of the eigenvalues [28]. R^2_{pred} represents the magnitude of the response surface function's predictive ability with respect to the data [29]. The fact that the R^2 , R^2_{adj} , and R^2_{pred} for Case1 and Case2 are all greater than 0.9 proves that the response surface function has good predictive ability. Figures 8 and 9 show the response surface plots for Case1 and Case2, respectively.

Table 4. Response surface model accuracy assessment.

Parameter	Case1			Case2		
	Power	ISFC	NOx	Power	ISFC	NOx
R^2	0.9999	0.9995	0.9967	0.9998	0.9973	0.9998
R^2_{adj}	0.9997	0.9989	0.9924	0.9994	0.9938	0.9996
R^2_{pred}	0.9982	0.9924	0.9470	0.9967	0.9570	0.9975

As shown in Figure 8, with the increase in engine speed, the engine output power increases significantly; this is because the engine cycle injection volume and gas supply are certain, and the increase in speed makes the number of engine cycles per unit time increase, resulting in a significant increase in engine output power. The early EVO (100–110° CA) causes the high pressure gas in the combustion chamber to be released into the exhaust pipe in advance, resulting in an insufficient release of gas energy, and therefore lower engine power. Appropriately delayed EVO (110–130° CA) allows the gas energy in the combustion chamber to be fully utilized to push the piston to do work. However, excessively late EVO (130–150° CA) has a low effect on power because the gas energy in the combustion chamber has been fully utilized and there is little gas energy left before EVO to provide more output

energy. Increasing the intake pressure increases the in-cylinder pressure during combustion, increasing the work capacity of the gas in the cylinder, so output power is increased.

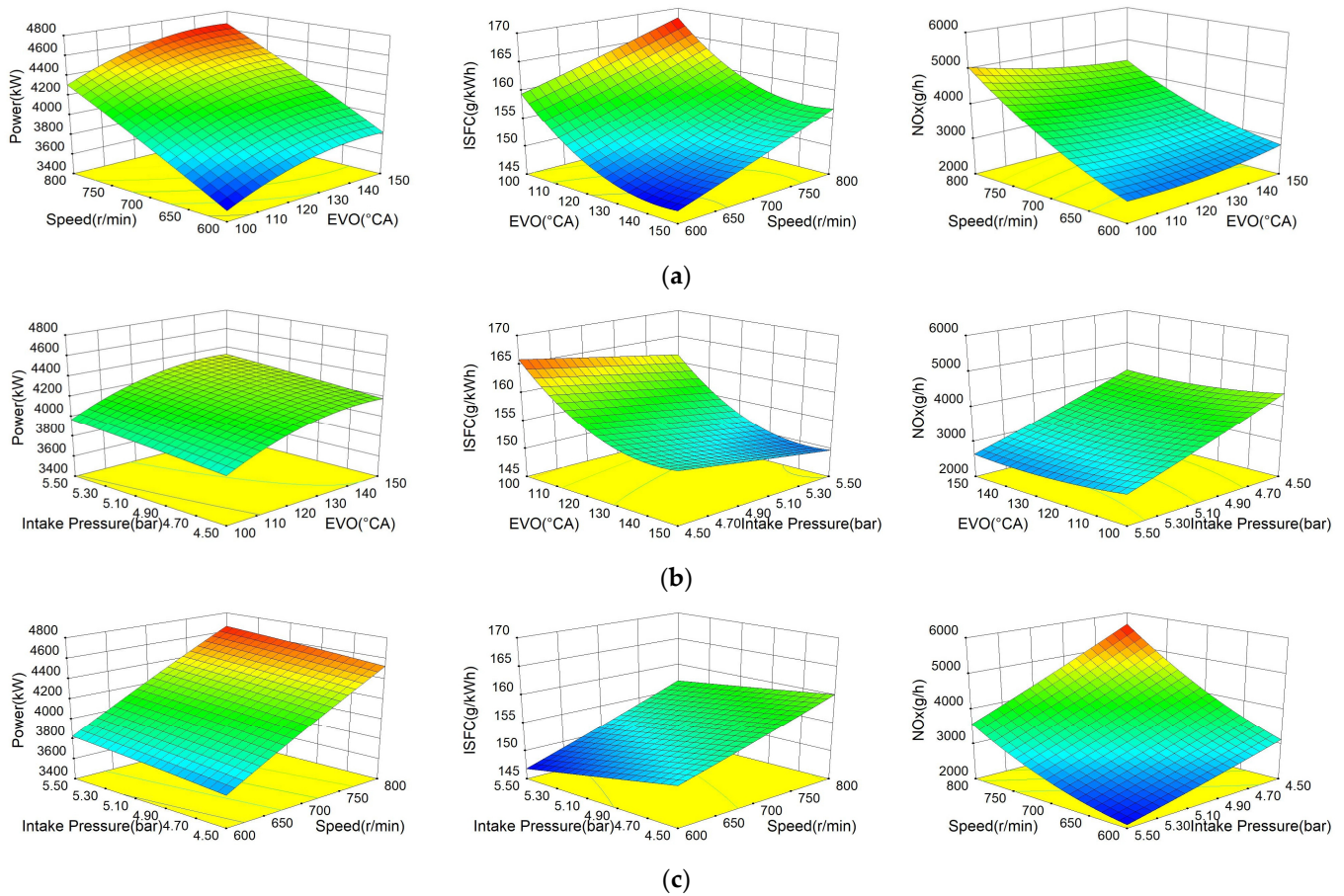


Figure 9. Response surface plots of power, ISFC and NOx for Case1 conditions: (a) intake pressure = 5 bar; (b) speed = 700 r/min; (c) EVO = 125° CA.

As shown in Figure 9, mechanical losses due to friction losses increase at high engine speeds, and therefore ISFC increases. The effect of EVO on ISFC is due to the same reason as that on power. Excessive early opening of the exhaust valve results in insufficient utilization of gas energy, which increases ISFC. Delaying EVO resulted in full gas energy release and reduced ISFC, while the increase in inlet pressure increased the oxygen content in the combustion chamber, which facilitated the rapid development of oxidative reactions in the combustion process. The rapid oxidation reaction reduces the combustion loss; therefore, the increased intake pressure can reduce the ISFC [30].

As shown in Figure 9, the increase in engine speed leads to a significant increase in NOx emissions. This is because the increase in rotational speed leads to an increase in the in-cylinder temperature increase rate and drastic temperature changes. The maximum in-cylinder temperature during combustion is increased. The NOx generation is mainly affected by the in-cylinder temperature, and the NOx emission increases exponentially as the in-cylinder temperature increases [31]. Therefore, increasing the engine speed leads to a significant increase in NOx emissions [32]. Delaying EVO allows a small amount of in-cylinder gas to remain in the combustion chamber, reducing the efficiency of the air exchange. The reduction in the amount of fresh air results in a lower maximum in-cylinder temperature for the combustion process, which results in lower NOx emissions [33]. The increase in intake pressure leads to an increase in the mass of the in-cylinder mass, which increases the total heat capacity of the in-cylinder mass. After the exothermic combustion of the fuel, the increase in the total heat capacity leads to a decrease in the in-cylinder

temperature, which destroys the main conditions for the generation of NO_x and reduces NO_x emissions.

As shown in Figure 10, the increase in CR is accompanied by a significant increase in output power. The high compression ratio implies a reduction in the volume of the combustion chamber, which allows the combustion process to develop rapidly, increasing the in-cylinder burst pressure and thus increasing the output power. Although high CR increases the output power, the rapid development of the combustion process increases the in-cylinder pressure on one hand and the in-cylinder temperature on the other hand, which leads to a surge in NO_x emissions [34]. ISFC increases under low CR conditions. This is because the output power obtained by consuming the same mass of fuel is lower under low CR conditions, which leads to the output of the same power at the cost of more fuel under low CR conditions.

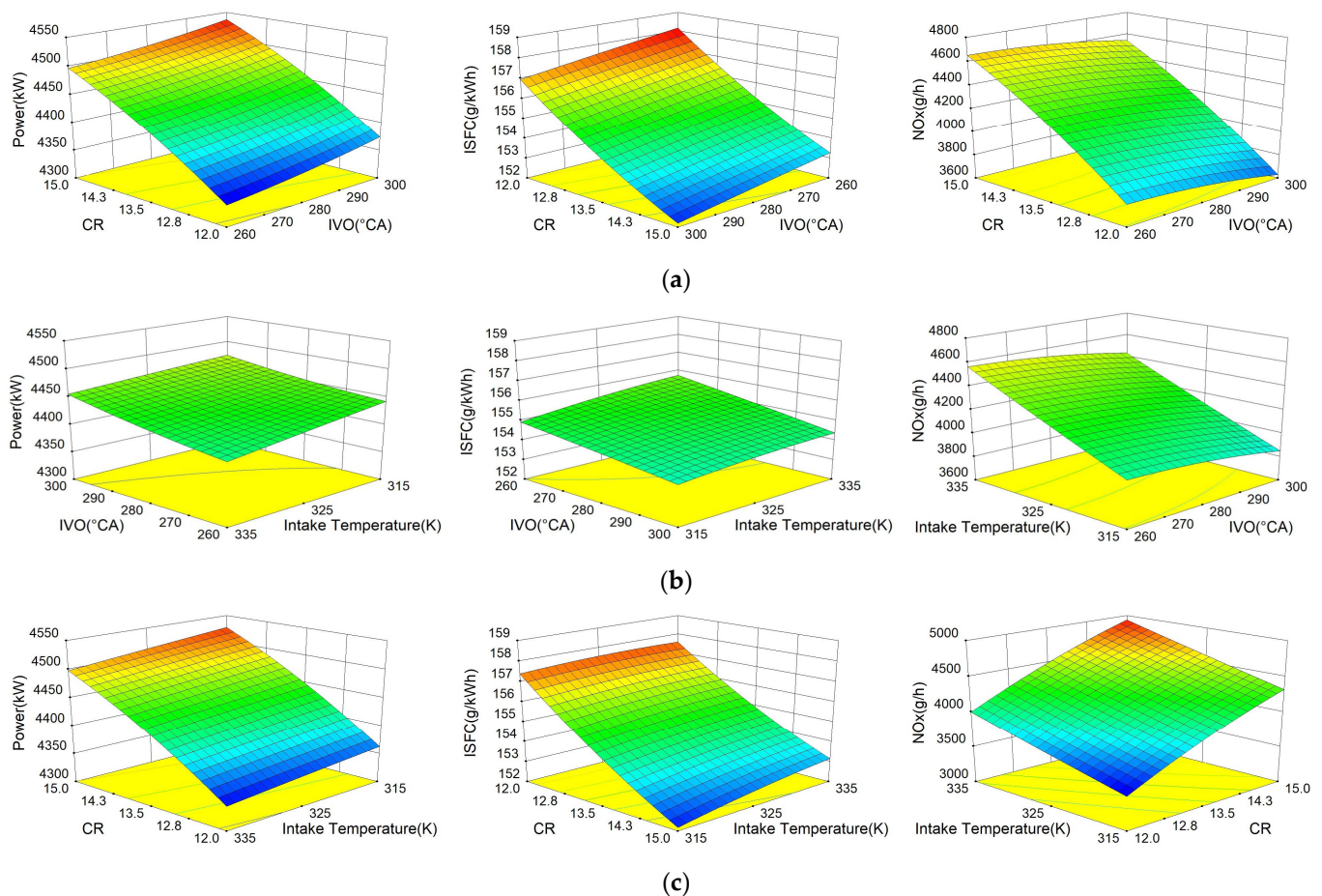


Figure 10. Response surface plots of power, ISFC and NO_x for Case2 conditions: (a) intake temperature = 325K; (b) CR = 13.5; (c) IVO = 280° CA.

In the image on IVO in Figure 10, it can be seen that delayed IVO increases the output power, but the increase is limited. Delayed IVO improves the in-cylinder excess air mass, which allows the natural gas to be burned under lean conditions and improves the fuel combustion conditions to some extent [35]. Therefore, delayed IVO can increase the power output while ISFC is reduced by a small amount. NO_x production depends on the temperature of the combustion process and the oxygen concentration in the combustion chamber. The delayed IVO increases the oxygen concentration in the combustion chamber, but the total heat capacity of the cylinder increases at the same time. In this case, the increased total heat capacity of the cylinder reduces the temperature of the cylinder. At this time, the degree of influence of the in-cylinder temperature on NO_x generation is higher

than the degree of influence of oxygen concentration on NOx generation [36]. Therefore, the delayed IVO reduces NOx emissions.

From Figure 10 it can be seen that the output power varies inversely with the intake air temperature. High intake temperature leads to lower output power, which increases ISFC and reduces fuel economy. For NOx emissions, the increase in intake air temperature raises the in-cylinder temperature and promotes NOx production. Therefore, NOx emissions are proportional to the intake air temperature.

The extent of the effects of EVO, IVO, CR, engine speed, intake temperature and intake pressure on power, ISFC and NOx emissions in Figures 9 and 10 are consistent with the conclusions obtained in the sensitivity analysis. The feasibility of the Sobol sensitivity analysis method is verified.

3.3. Optimization Results

Based on the Case1 and Case2 response functions obtained in RSM, the optimization was performed using the MOPSO algorithm. The MOPSO algorithm developed in the Matlab environment minimizes the optimization objectives of ISFC and NOx emissions. The optimization objective power function is solved for the maximum value. The number of individuals for the population is set to 100 and the number of iterations is 100.

The Case1 optimization results based on engine speed, EVO and intake pressure decision variables are shown in Figure 11a. The optimization results of Case2 based on IVO, CR and intake temperature decision variables are shown in Figure 11b. The optimized solution sets of Case1 have good diversity and are evenly distributed. The distribution ranges of the optimized solution sets of Case1 and Case2 are shown in Table 5. The optimized solution sets of Case1 have a better breadth and a larger coverage of the solution sets compared to Case2. The optimization results of Case2, on the other hand, more clearly reflect the trade-off relationship between the optimization objectives, but lack diversity and have a poor degree of uniform distribution. There is a linear relationship between power and ISFC, with a decrease in ISFC, an increase in fuel economy and an increase in fuel work capacity. The trade-off relationship between ISFC and NOx is in line with the results of Liu et al. [37].

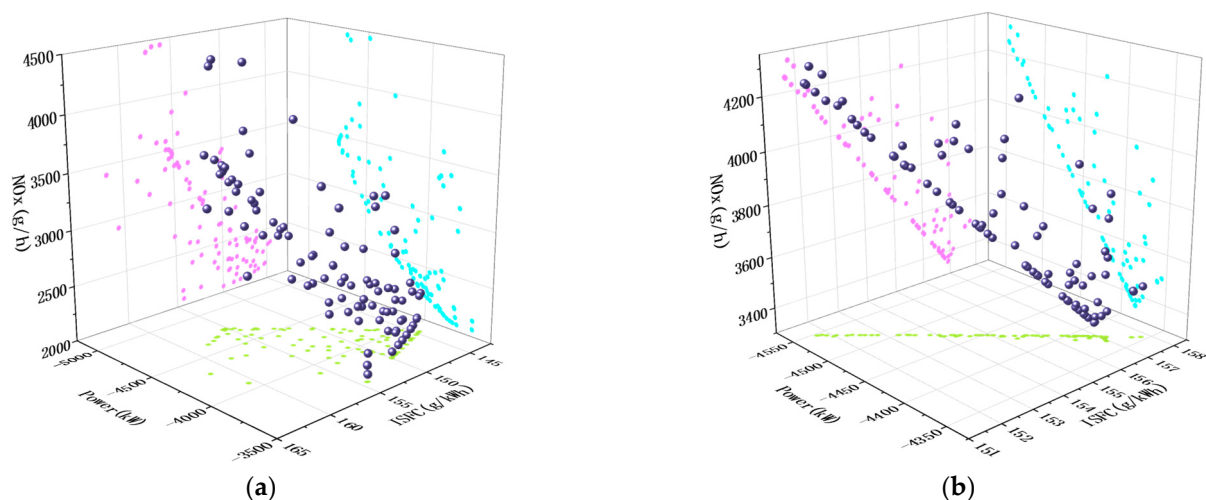


Figure 11. Optimization results: (a) Case1; (b) Case2.

Table 5. The distribution range of optimized results.

Parameter	Case1	Case2
Power (kW)	3600–4800	4300–4600
ISFC (g/kWh)	144–162	151–158
NOx (g/h)	2000–4500	3300–4400

The set of optimization solutions obtained using the MOPSO algorithm demonstrates the trade-offs between the optimization objectives and provides diverse solutions. However, there is a non-dominated relationship between the solutions, so it is difficult to select the best solution from them. The solution with higher power in the non-dominated solution set is preferred due to economic considerations when sailing the ship. The optimal solution for Case1 was selected to have an EVO of 146.2° CA, a rotational speed of 800 r/min and an intake pressure of 5.5 MPa, which resulted in an engine power of 4734.4 kW, an ISFC of 155.2 g/kWh and NOx emissions of 3435 g/h. For Case2, the optimal solution had an IVO of 300° CA, a CR of 15 and an inlet temperature of 315 K. The optimal solution was selected to have a power of 4734.4 kW, an ISFC of 155.2 g/kWh and emissions of 3435 g/h. At an intake temperature of 315 K, the engine output is 4546.8 kW, ISFC is 151.7 g/kWh and NOx emissions are 4254 g/h.

As shown in Table 6, Case1 optimization resulted in a significant increase in output power and a slight decrease in ISFC, while NOx emissions were significantly reduced. Case2 optimization increased output power to some extent, but NOx emissions were significantly increased, while ISFC was reduced a little.

Table 6. Degree of optimization.

Parameter	Power	ISFC	NOx
Case1	+7.2%	−0.4%	−11.2%
Case2	+3%	−2.7%	+9.9%

Therefore, the selection of optimization parameters during engine optimization has a significant impact on the final optimization results. Selecting parameters that have a high impact on the optimization objective can lead to better performance in the final optimization results. On the other hand, the selection of parameters that have little influence on the optimization objective not only does not lead to better optimization results, but also worsens the performance and emission performance of the engine.

4. Conclusions

Six control parameters of the engine were evaluated and optimized based on Sobol sensitivity analysis and the MOPSO algorithm. The main conclusions obtained are as follows:

1. The application of the Sobol method can evaluate the degree of influence of engine control parameters on engine performance parameters. The BBD method can help to reduce the number of experiments required by the Sobol method.
2. EVO, engine speed and intake pressure are the three parameters that have the most significant effect on engine power, ISFC and NOx emissions. IVO, CR and intake temperature have a relatively small effect.
3. The relationship between the effects of the two groups of parameters on the three parameters of engine power, ISFC and NOx emissions was analyzed, and the degree of parameter influence is consistent with the results of Sobol sensitivity analysis.
4. Two groups of control parameters with high and low impact levels were optimized using RSM and MOPSO, and two sets of non-dominated solution sets were obtained. The optimized solution sets of high impact control parameters have better diversity and breadth of distribution.
5. The optimal solutions for the control parameters with a high degree of are optimized to a higher degree, and the optimization effect is better. The optimal solutions for low impact control parameters are less optimized and show deterioration in NOx emissions.
6. For the determined engine optimization objectives, the selection of control parameters has a non-negligible impact on the final optimization results. Therefore, suitable control parameters should be selected for optimization in the engine design process.

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Nomenclature

IVO	intake valve opening timing
EVO	exhaust valve opening timing
CR	compression ratio
ISFC	indicated specific fuel consumption
NO _x	nitrogen oxides
BMEP	brake mean effective pressure
BBD	Box–Behnken design
RSM	Response surface methodology
MOPSO	multi-objective particle swarm optimization
° CA	Crank angle

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