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SHORT ORIGINAL PAPER

Optimizing performance in spark ignition engines with simulation metamodels

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Abstract

This work develops a systematic methodology able to identify the desired work points, the metamodels were evaluated varying air–fuel ratio, ignition timing, compression ratio, and combustion duration using design of computer experiments and RSM. It provide the possibility to determine optimal control parameters, according to selected objectives and operating constraints. This methodology is able to automatically identify the optimal engine calibration with less computational effort. Only in this way, the reliability of an integrated metamodel/optimizer approach can be included in a general-purpose that is to identify the engine calibration that minimizes motor vehicle emissions according to European emission standards (European Union in Off J Eur Union 50, 2007). As long as it improves mean effective pressure and reduces exergy destruction due to heat transfer and combustion process. Since, in internal combustion engines, more than 30–40 % of fuel energy wastes through the exhaust and just 12–25 % of the fuel energy converts to useful work. So, researchers are motivated to recover the heat from the waste sources in engines using the ways which not only reduce the demand of fossil fuels, but also reduce the harmful greenhouse gases and help to energy saving (Hatami et al. in Neural Comput Appl 25(7–8):2079–2090, 2014). The advantages of this contribution include the ability to study a wide range of parametric space and to independently evaluate physical and chemical processes, and detailed in-cylinder information, which is normally not available or is inaccessible in experiments. The uncertainty of the information in this unexplored design region can be quantified. Finally, the problem of optimizing involves three optimization fronts, energetic, economic and ecological (Chica and Torres in Int J Interact Des Manuf 12(1):355–392, 2018).

Keywords Central composite design (CCD) · Response surface methodology (RSM) · Spark-ignition engine · Exhaust emissions · Engine performance

1 Introduction

Despite being the dominant power source for road vehicles, internal combustion engines are one of the major contributors to air pollution in the world. Besides, numerous official cautionary statements on insufficient fossil fuels and global warming have been issued [4]. Hence, attention on improving engine efficiency, reducing exhaust emissions and meeting the customers expectations has increased.

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Overall control of internal combustion engines is currently premised on the reading of various engine operating parameters such as engine speed, coolant temperature, exhaust oxygen concentration, throttle position and intake manifold pressure. All those engine functions are managed by an electronic control unit (ECU). ECU, which is an integrated computing device, is commonly used on engines to provide control signals to the actuators based on the feedback signals measured by the sensors. It mainly contains sets of look-up tables that store the control parameters for each actuator over the operating range of the engine, in which each cell represents an engine operating point [5]. Traditionally, the control parameters of the actuators are obtained through huge amount of trial-and-error experiments. However, using traditional approach to calibrate these parameters becomes more challenging with the increasing incorporation of new technologies into advanced engines [5].

Practically, by analyzing the signals acquired from the sensors, engineers are able to calibrate the actuator parameters stored in the ECU so as to optimize the engine performance (e.g., minimizing the amount of undesirable engine emissions and maximizing engine performance). However, due to the large number of sensors and actuators, calibration of a modern engine is time-consuming and expensive, creating a highly challenging environment for engineers [6]. A huge amount of resources, in terms of labor, fuel and time, are required before an optimal parameter setting can be determined [7].

Optimization is of particular importance in control law process design. Optimization algorithms include an optimization loop that tunes the controller parameters (e.g., gains, time constants) so as to minimize the cost functions to ensure that control laws meet the desired system requirements and specifications. Accordingly, a good potential for emission reduction is dependent on a well optimized set of calibration maps, tables and constants, contained in the ECU [7,8]. The time to evaluate an optimum data design strongly depends on the number of these calibration parameters. With an increasing number of such parameters, there is a need for sophisticated test systems which automatically initiate parameter variations, perform necessary measurements and search for an optimized engine calibration [9,10]. In the light of these considerations, a new and improved engine calibration method is required [4,11].

Another area of research in engine design is modelling. Modelling is performed for different reasons. One example is the design and optimisation of a controller system. Designing a controller by using the real engine in the design process is an expensive and time consuming task [8]. Thus many researchers first build a model of the engine and then design, test and optimise their controller on this model. One other application of the models is for prediction, where the model of the engine is built and used to predict different behaviours of the engine in different environments. Optimising different parts of an engine is yet another use of models. Thus, the automotive industry has turned to model-based calibration for a solution. Model-based calibration is a method that uses modern design of experiments (DoE), statistical modeling and optimization techniques to efficiently produce high quality calibrations for engines [12]. In addition, coupling the model to an optimizer, a more systematic and accurate exploration of each control parameter can be carried out, thus allowing to identify more precisely the optimal calibration.

Table 1 Metamodels to predict the performance and exhaust emission parameters of a spark ignition engine

Output variable	Model	Multiple R-squared (R^2)
Y_6	$\widehat{Y_6} \sim 367.036-1.074X_1-17.61X_2+4.43X_3+72.817X_4-1.307X_2X_3-5.685X_2X_4-0.608X_4^2$	0.99994
Y_5	$\widehat{Y_5} \sim 3695228.782-20223.82X_1-138680.42X_2+84206.95X_3+324371.757X_4-6884.132X_1X_4-43325.87X_2X_4-16438.85X_2X_3+10420.72X_3X_4+6880.395X_2^2-22401.019X_4^2$	0.9998
Y_7	$\widehat{Y_7} \sim 332.514-1.541X_1+6.859X_2-0.065X_3+4.039X_4+0.265X_2X_3+0.449X_2X_4+0.539X_3X_4+0.143X_1^2-0.823X_2^2+1.421X_4^2$	0.99969
Y_4	$\widehat{Y_4} \sim 1536.279+246.351X_1-66.510X_2+207.922X_3-431.817X_4-11.98X_1X_2+32.027X_1X_3-65.454X_1X_4-15.786X_2X_4-57.676X_3X_4+36.044X_2^2+98.996X_4^2$	0.99601
Y_1	$\widehat{Y_1} \sim 4158.788-146.037X_1-860.989X_2+458.138X_3-758.495X_4-99.303X_1X_2+87.512X_1X_4-166.21X_2X_3+361.318X_2X_4-75.487X_3X_4-67.297X_4^2$	0.98617
Y_2	$\widehat{Y_2} \sim 3.376+0.396X_1+0.461X_2+0.339X_3-2.017X_4-0.448X_1X_2-0.527X_1X_4+1.06X_4^2$	0.90853
Y_3	$\sqrt{\widehat{Y_3}} \sim 60.552+7.725X_1+1.166X_2+4.646X_3-11.635X_4+0.518X_1X_3-1.053X_1X_4-1.399X_2X_4-0.891X_3X_4+1.147X_2^2+2.493X_4^2$	0.99397

X_1: Air–fuel ratio

X_2: Ignition timing (°CAD)

X_3: Compression ratio

X_4: Combustion duration (°)

Y_1: Carbon dioxide emissions (mg/m^3)

Y_2: Carbon monoxide emissions (mg/m^3)

Y_3: Hydrocarbons emissions (mg/m^3)

Y_4: Oxides of nitrogen emissions (mg/m^3)

Y_5: Mean effective pressure (Pa)

Y_6: Exergy destruction due to heat transfer/ (J)

Y_7: Exergy destruction due to combustion Process/ (J)

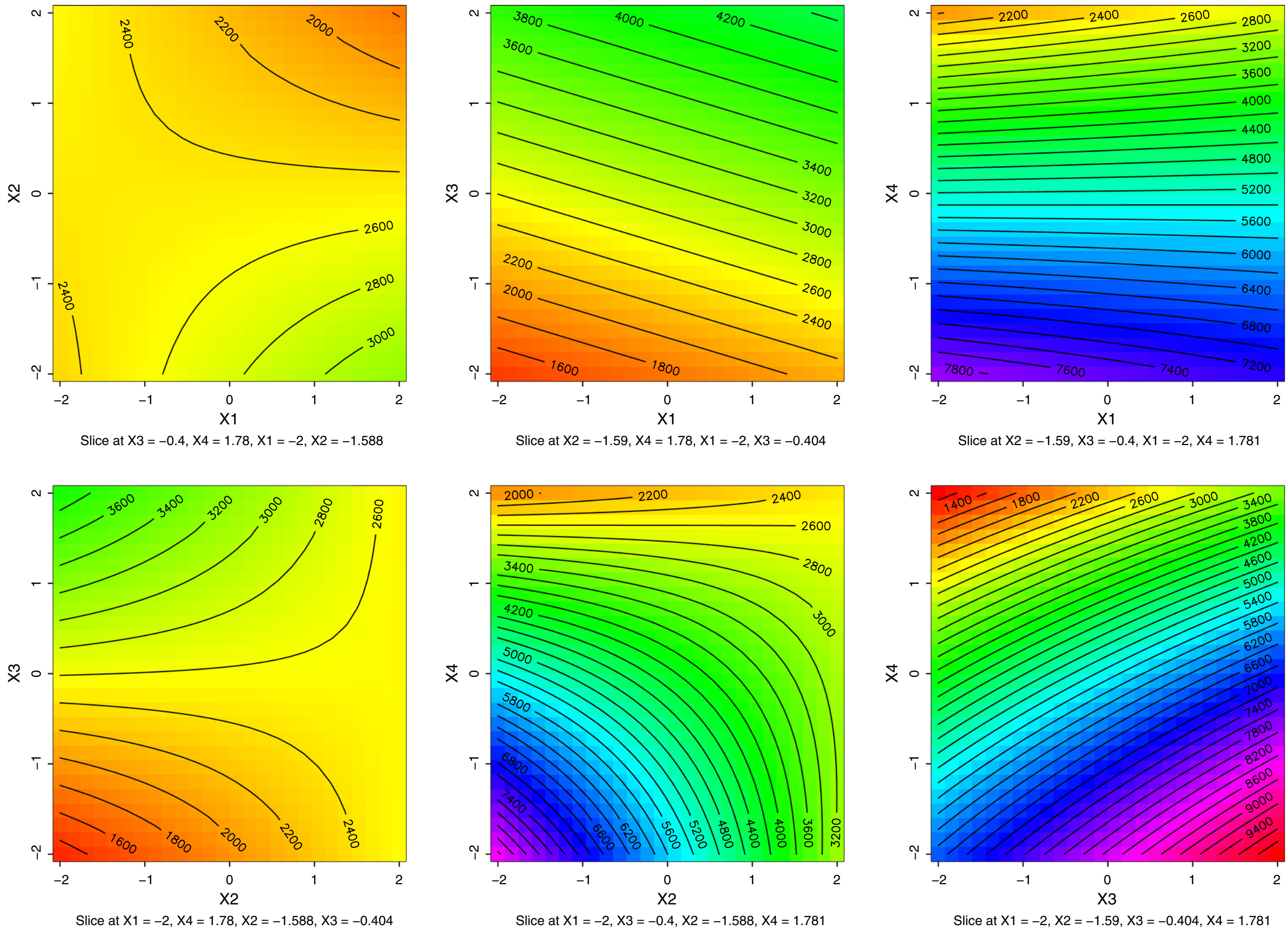

Fig. 1 Contour plots for central composite of CO_2 emissions (Y_1)

Response surface methodology (RSM) is most effective and economical solutions for the modeling and analysis of problems in which a output response of interest is influenced by single and combined factors and the objective is to optimize this output response. RSM is a set of mathematical and statistical techniques seeking to optimize an objective function (or output response) that is affected by multiple factors using DoE methods and statistical analysis. Instead of seeking the optimal solution within a large number of randomly generated candidates, RSM utilizes fewer tests to gain a thorough understanding of the system as well as optimizes the effects of various factors and the interaction between the variables to achieve best system performance.

Moreover, RSM has been shown to be an effective and powerful tool for optimizing engine operating parameters [13–20]. Onawumi et al. [21] used RSM as optimization technique to predict the performance and exhaust gas emissions of 4-stroke spark ignition engine. The results obtained from HC, CO and NO_X emission models showed that the engine speed (rpm), loading condition (%) and time (seconds) were found to have significant influence on the emission. The HC, CO and NO_X emission models proved positive response from the regression analysis of actual and predicted responses. Thus, the response surface methodology provides useful information required for the experiment and also useful in predicting the response of engine parameters to engine emissions. Lee et al. [22] demonstrates the emission reduction capability of exhaust gas recirculation (EGR) and other parameters on a high-speed direct-injection (HSDI) diesel engine equipped with a common rail injection system using an RSM optimization method. The variables used in the optimization process included injection pressure, boost pressure, injection timing, and EGR rate. RSM optimization led engine operating parameters to reach a low-temperature and premixed combustion regime called the modulated kinetics (MK) combustion region, and resulted in simultaneous reductions in NO_X and particulate emissions without sacrificing fuel efficiency. RSM and central composite design (CCD) were used to systematically investigate the effects over hydrogen-fuelled internal combustion engines [23]. Three types of inert gases were injected in the intake manifold to vary the gas properties compared to air. Furthermore,

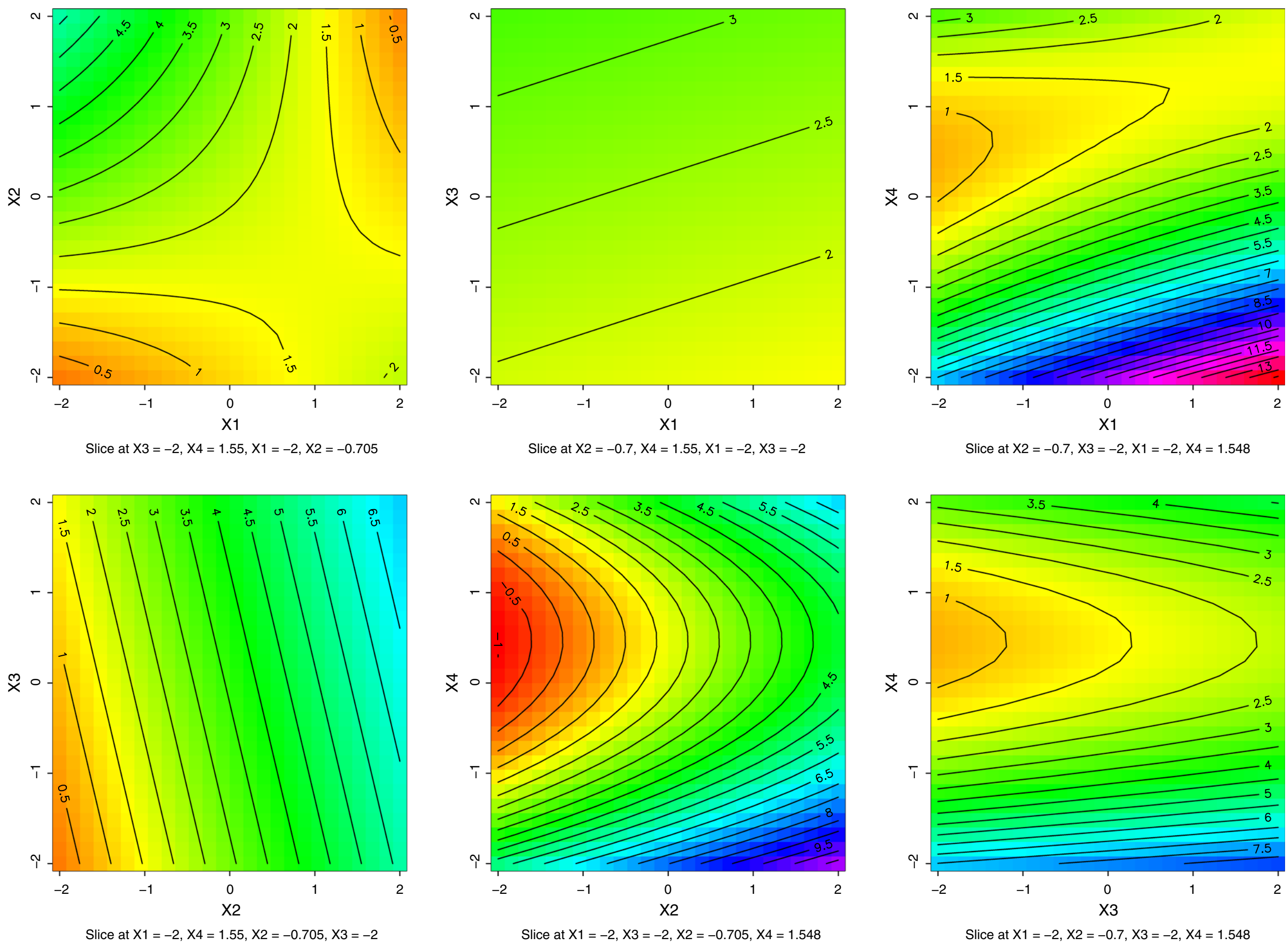

Fig. 2 Contour plots for central composite CO emissions (Y_2)

the type and quantity of the gas, the compression ratio and throttle position were varied. Similarly, the use of a response surface approach based on Radial Basis Functions to simulate a flexible fuel engine running with distinct blends of iso-octane, n-heptane, toluene and ethanol was presented in [24]. Performance, energetic efficiency and pollutant emissions are predicted in different operating conditions. In [20] was studied the use of RSM to optimize the performance parameters and exhaust emissions of a SI engine which operates with ethanol-gasoline blends. Operating parameters, engine speed and the added volume of bio-ethanol to gasoline fuel were considered as effective factors on the engine performance parameters (Power, Torque and Brake-specific fuel consumption BSFC) and exhaust emissions (CO, CO_2, HC and NO_X) as responses.

In order to develop a systematic methodology able to identify the desired work points, the metamodels [Zutta et al. Development of simulation metamodels to predict the performance and exhaust emission parameters of a spark ignition engine] were evaluated varying air–fuel ratio (AFR), ignition timing, compression ratio, and combustion duration using design of computer experiments (DoCE) and RSM. It provide the possibility to determine optimal control parameters, according to selected objectives and operating constraints. This methodology is able to automatically identify the optimal engine calibration with less computational effort. Only in this way, the reliability of an integrated metamodel/optimizer approach can be included in a general purpose that is to identify the engine calibration that minimizes motor vehicle emissions according to European emission standards [1]. As long as it improves mean effective pressure (MEP) and reduces exergy destruction due to heat transfer and combustion process. Since, in internal combustion engines (ICEs), more than 30–40 % of fuel energy wastes through the exhaust and just 12–25 % of the fuel energy converts to useful work. So, researchers are motivated to recover the heat from the waste sources in engines using the ways which not only reduce the demand of fossil fuels, but also reduce the harmful greenhouse gases (GHG) and help to energy saving [2]. The advantages of this contribution include the ability to study a wide range of parametric space and to independently evaluate physical and chemical processes, and detailed in-cylinder

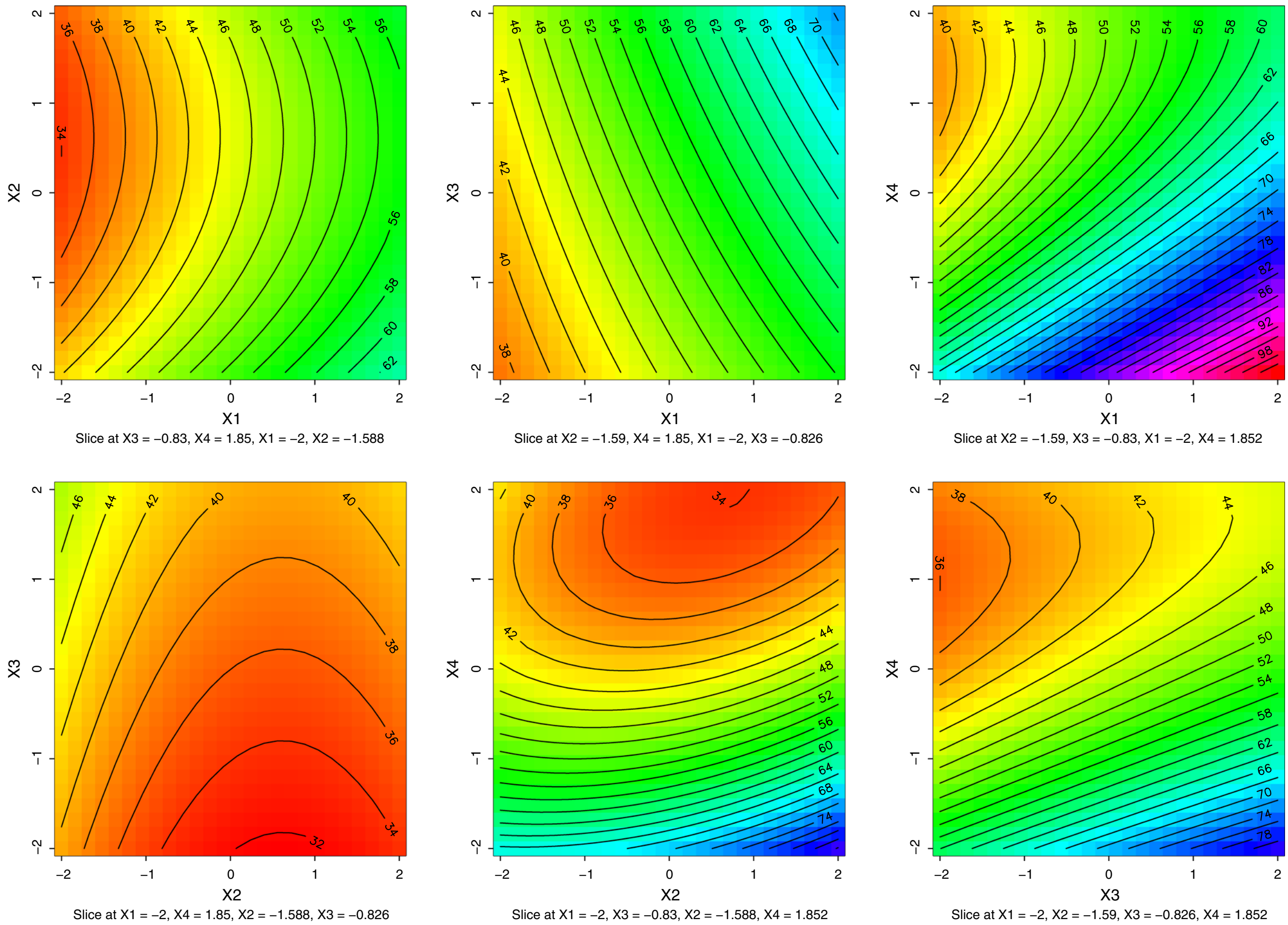

Fig. 3 Contour plots for central composite of HC emissions (Y_3)

information, which is normally not available or is inaccessible in experiments. The uncertainty of the information in this unexplored design region can be quantified. Finally, the problem of optimizing involves three optimization fronts, energetic, economic and ecological [3].

2 Methodology

2.1 Metamodels

Metamodel-based design optimization is attractive when function evaluations are computationally expensive simulations or have significant numerical noise [25]. But, metamodels requires a full model evaluation on the entire data set to compute gradient and Hessian. Therefore, the metamodels used were the result of a previous work and can be observed in Table 1. Zutta et al. developed a metamodel by performance parameter, which are carbon dioxide (CO_2) (Y_1), carbon monoxide (CO) (Y_2), hydrocarbon (HC) (Y_3) and oxides of nitrogen (NO) (Y_4) emissions, mean effective pressure (MEP) (Y_5) and exergy destruction due to heat transfer (Y_6) and combustion process (Y_7). Each metamodel was characterized by a set of factors allowing an accurate reproduction of performance parameters in the whole-engine map. Each metamodel was evaluated varying air–fuel ratio (AFR) (X_1), ignition timing (X_2), compression ratio (X_3), and combustion duration (X_4). In addition, each iteration of the regression technique is much more faster since it operates on polynomial approximations rather than on the full model [26]. For more information about the process of obtaining the metamodels, see [Zutta et al].

For this study three optimization criteria were proposed, the first one is to maximize the mean effective pressure (Y_5) according to Eq. 1. The second one is to minimize exergy destruction due to heat transfer (Y_6) according to Eq. 2. And the third one is to minimize exergy destruction due to combustion process (Y_7) according to Eq. 3. The resulting objective functions are polynomial, with constraints, and very fast convergence can be achieved by classical optimization techniques.

Control law design process generally begins with a multiple of requirements which are often referred to as specifications or constraints. Accordingly, all these objectives

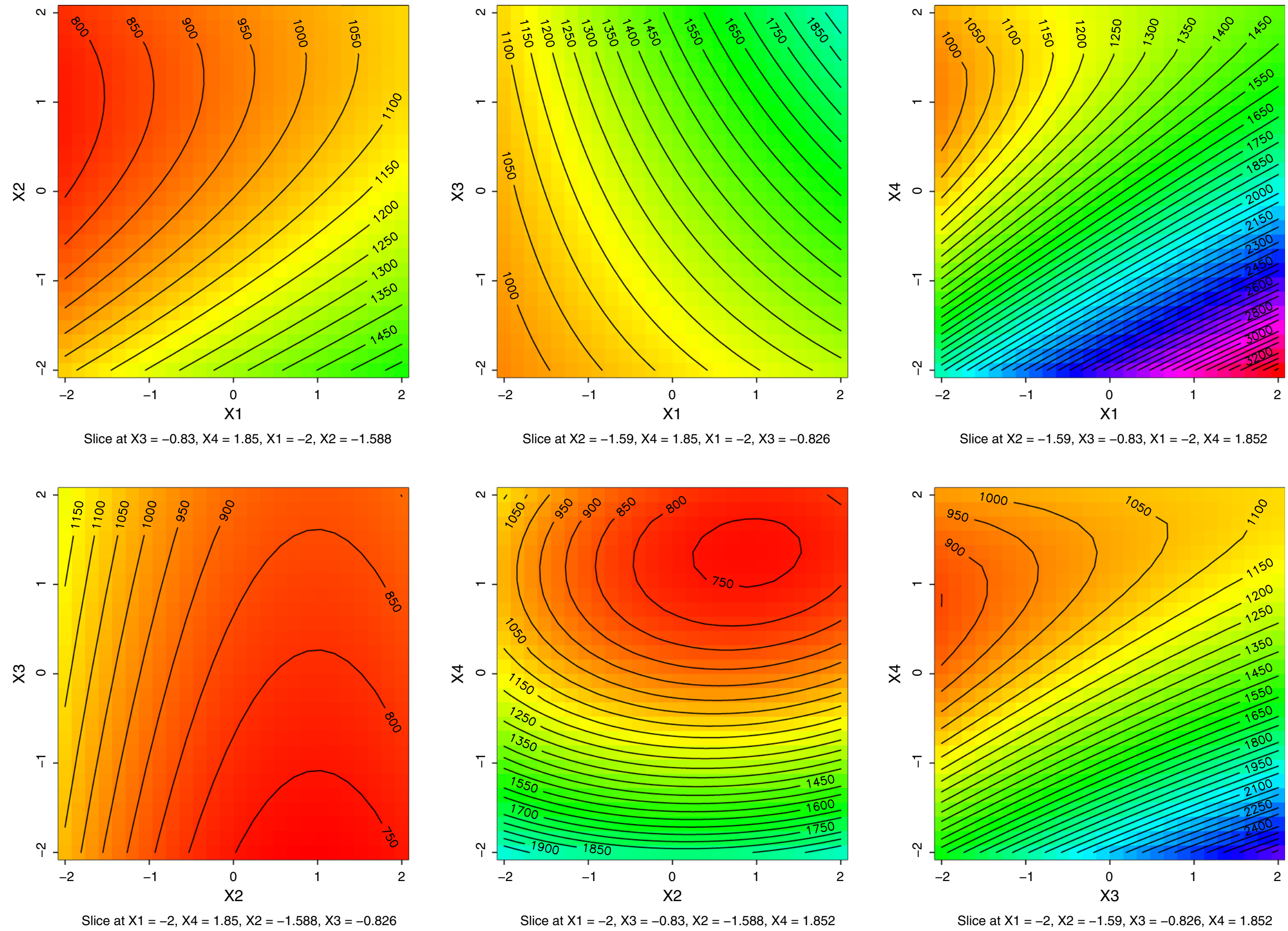

Fig. 4 Contour plots for central composite of NO_x emissions (Y_4)

must respect the gas emissions according to European Emission Standard EURO V [1]. Although currently there are no standards for limits on CO_2 emissions from vehicles, due to the prominence of CO_2 emissions in the production of greenhouse gases, it was limited to a maximum of $Y_1 \leq 2000\,(\mathrm{mg/m^3})$. It reflects the application of the metamodel to future regulations, in which exhaust emissions will be more strictly limited.

$$\begin{aligned} &max\ Y_5(X)\\ &\quad with\ respect\ to\ x = (X_1, X_2, X_3, X4)\\ &\quad subject\ to\ Y_1, Y_2, Y_3, Y_4 \leq\ European\ emission\ standards\\ &\quad bounds\ on\ X_1, X_2, X_3\ and\ X4 \end{aligned} \tag{1}$$

$$\begin{aligned} &min\ Y_6(X)\\ &\quad with\ respect\ to\ x = (X_1, X_2, X_3, X4)\\ &\quad subject\ to\ Y_1, Y_2, Y_3, Y_4 \leq\ European\ emission\ standards\\ &\quad bounds\ on\ X_1, X_2, X_3\ and\ X4 \end{aligned} \tag{2}$$

$$\begin{aligned} &min\ Y_7(X)\\ &\quad with\ respect\ to\ x = (X_1, X_2, X_3, X4)\\ &\quad subject\ to\ Y_1, Y_2, Y_3, Y_4 \leq\ European\ emission\ standards\\ &\quad bounds\ on\ X_1, X_2, X_3\ and\ X4 \end{aligned} \tag{3}$$

2.1.1 Response surface method (RSM)

RSM as a multivariate statistical method simultaneously optimizes an objective function (or response) that is affected by multiple factors and interactions using design of experiments (DoE) methods and statistical analysis [27]. Instead of seeking the optimal solution within a large number of randomly generated candidates, RSM utilizes reduced and simplified experimental designs to gain a thorough understanding of the system as well as obtain the optimal combinations of operating parameters.

Generally, graphical analysis and simulation methods are used in modeling for design, analysis, and synthesis. The visual representation allows for a convenient interpretation of model factors and structure and provides a quick intu-

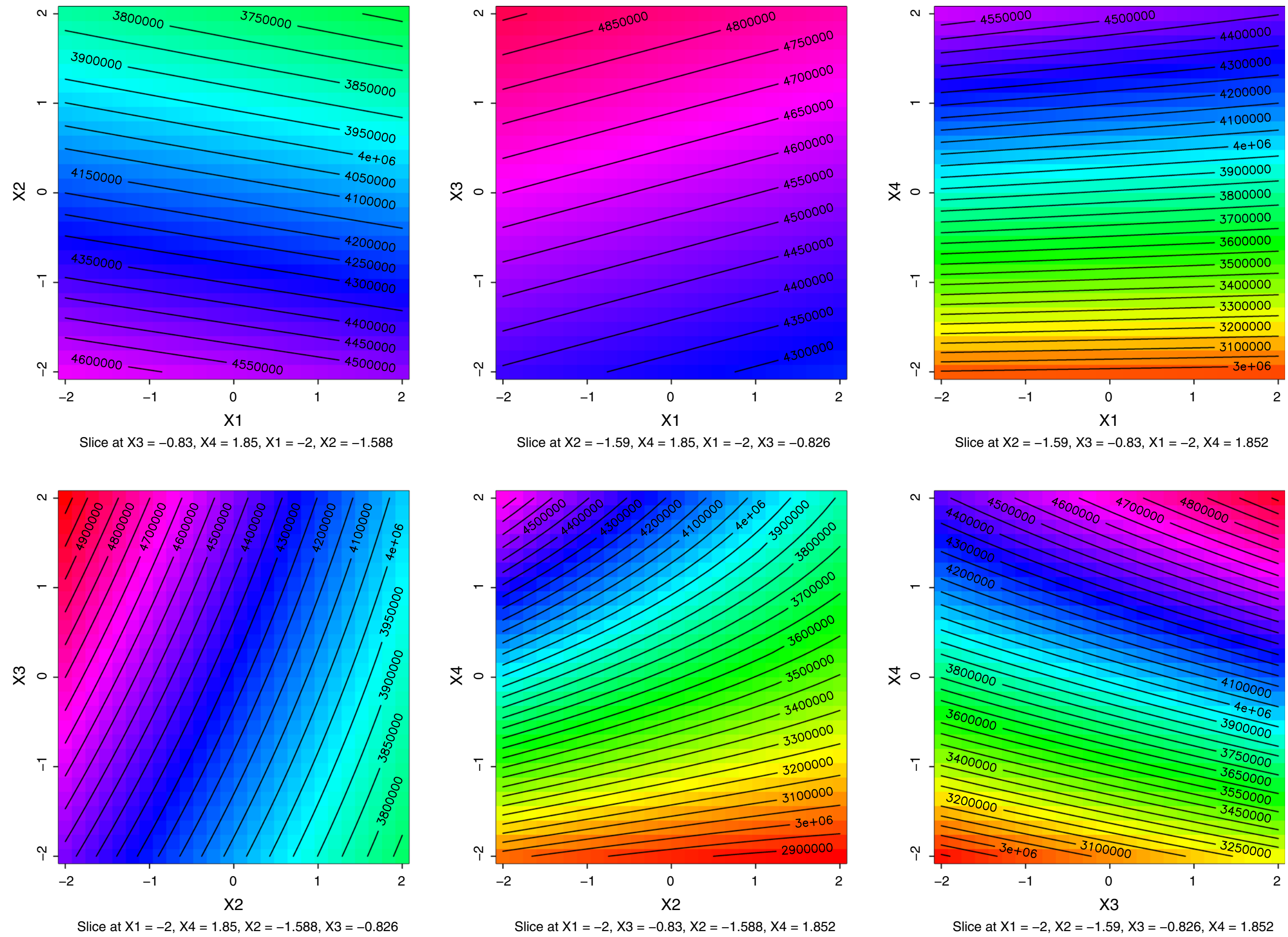

Fig. 5 Contour plots for central composite of MEP (Y_5)

itive notion of system behavior. Thus, contour plots of the response surface to explore the effect of changing factor levels on the response were used. The direction for changing the inputs through the gradient was selected. This gradient was used in the mathematical (not statistical) technique of steepest descent or steepest ascent. Finally, RSM took the derivatives of the locally fitted second-order polynomial to estimate the optimum input combination.

Rsm package of R was used to generate response-surfaces. In addition, it was used to analysis of the resulting data, display an ensemble of contour plots of the fitted surface, and do follow-up analyses.

3 Results and discussion

3.1 Optimization

In order to find the most desirable nominal setting for the controllable independent parameters, second order function response surfaces were evaluated using standard optimization methodology to determine the maximum combustion desirability.

RSM package of R generated maps for all the performance parameters based on test factors X_1, X_2, X_3, X_4 using the models in Table 1. Particularly, Figs. 1, 2, 3, 4 show the CO_2, CO, HC and NO_x optimized maps for the first objective. Consequently, the responses surfaces represented in Figs. 5, 6 and 7 were obtained, which describe mean effective pressure, exergy destruction due to heat transfer and exergy destruction due to combustion process respectively.

In Table 2 the combination of factors that simultaneously satisfy the requirements placed on each of the performance parameters, factors and optimization criterion can be found using GAMS. After the optimized maps are obtained, some verification tests need be performed to check the optimization results. Therefore, in Table 3 the results for performance parameters of both the original model and the metamodel can be compared.

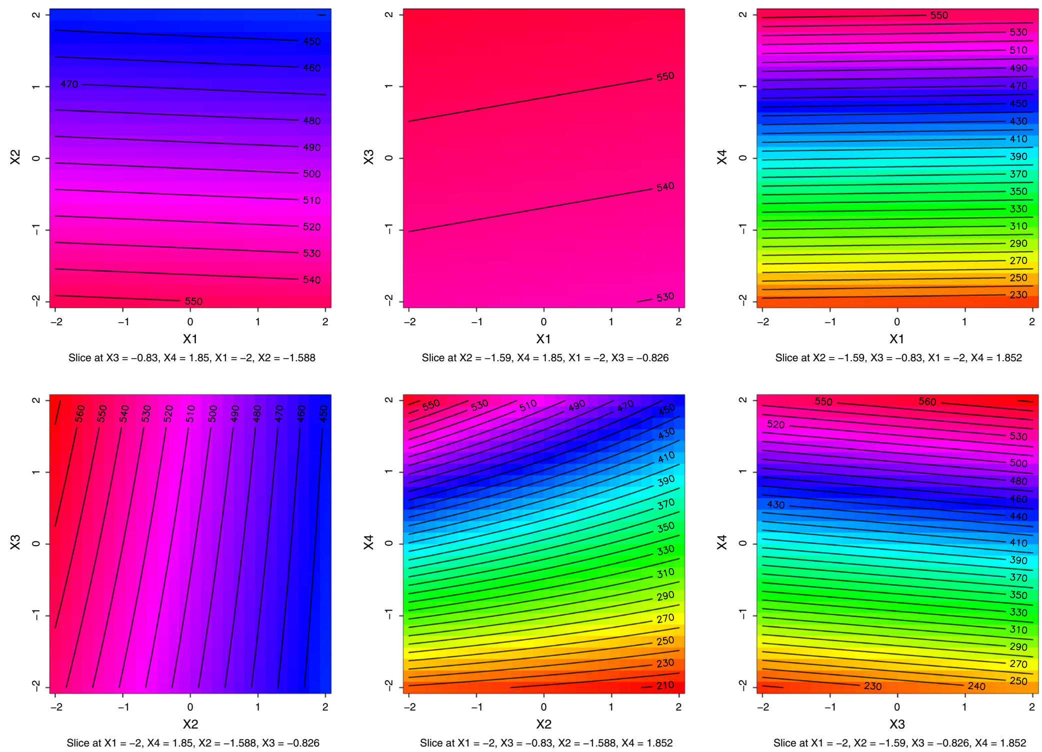

Fig. 6 Contour plots for central composite of destruction exergy due to heat transfer (Y_6)

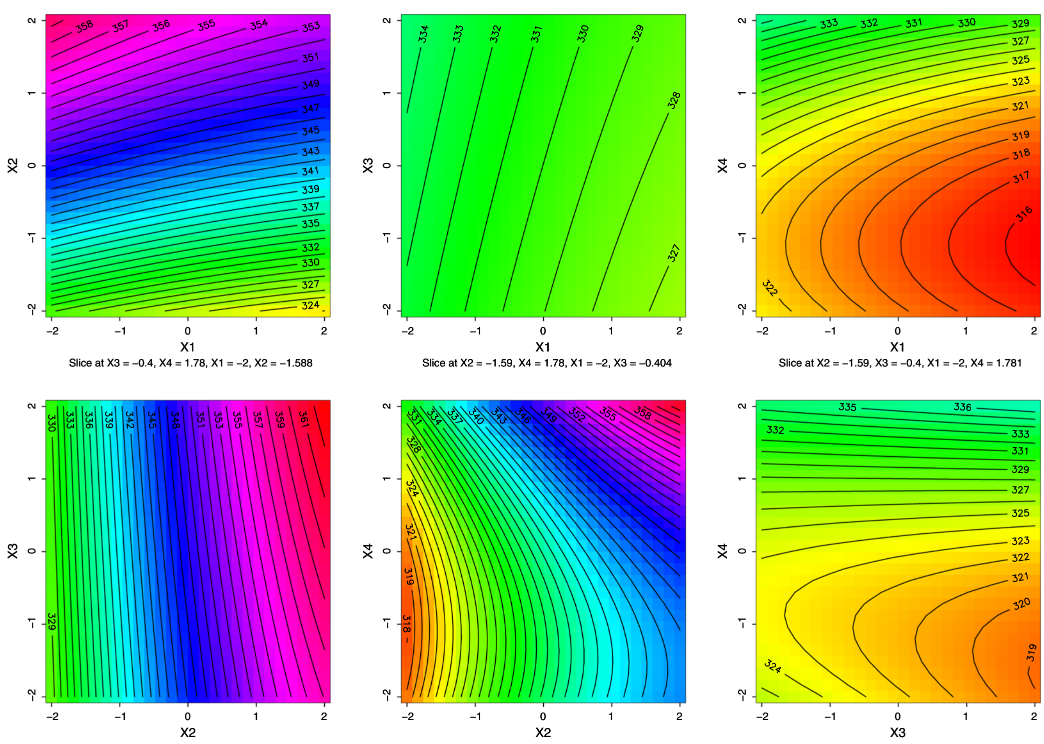

Fig. 7 Contour plots for central composite of destruction exergy due to combustion process (Y_7)

Table 2 Optimization results

Optimization criterion	X_1	X_2	X_3	X_4
Maximizing MEP	12	− 22.94	8.174	68.52
Minimizing exergy destruction due to heat transfer	12.468	− 25	7	64.06
Minimizing exergy destruction due to combustion process	12	− 18.525	7	65.48

Table 3 Performance parameters

Performance parameters	Maximizing mean effective pressure	Minimizing exergy destruction due to heat transfer	Minimizing exergy destruction due to combustion process
Y_{1Model}	1975.5	2040.7	1975.2
$Y_{1Metamodel}$	1999.42	1999.42	1999.42
Y_{2Model}	2.04	1.76	0.0824
$Y_{2Metamodel}$	1.917	1.917	0.106
Y_{3Model}	39.544	29.889	34.1467
$Y_{3Metamodel}$	39.538	33.137	39.735
Y_{4Model}	996.31	758.98	968.5
$Y_{4Metamodel}$	1000.1254	770.944	1000
Y_{5Model}	4.5935e6	4.1466e6	4.3352e6
$Y_{5Metamodel}$	4.5428e6	4.130e6	4.3207e6
Y_{6Model}	544.4624	492.3954	510.3627
$Y_{6Metamodel}$	541.219	488.374	507.148
Y_{7Model}	333.4607	339.0201	324.6995
$Y_{7Metamodel}$	333.809	338.932	325.412

4 Conclusions and future work

The aim of this study is to determine the final distribution on controllable independent parameters, when design is optimized and constraints are met. From the outcome of this research, the following conclusions are drawn:

- The best condition of engine factors to maximize MEP were 12 as air–fuel ratio (AFR), − 22.94 °CAD as ignition timing, 8.174 as compression ratio, and 68.52 °as combustion duration. In additional the optimal values were 1999.42 (mg/m^3), 1.917 (mg/m^3), 1563.25 (mg/m^3),
1000.1254 (mg/m^3) for CO_2, CO, HC and NO_x emissions respectively. MEP reached was 4.5428e6 Pa.
- The optimum factors to minimize exergy destruction due to heat transfer were 12.468 as air–fuel ratio (AFR), -25 °CAD as ignition timing, 7 as compression ratio, and 64.06 °as combustion duration. In additional the optimal values were 1999.42 (mg/m^3), 1.917 (mg/m^3), 1098.06 (mg/m^3), 770.944 (mg/m^3) for CO_2, CO, HC and NO_x emissions respectively. Exergy destruction due to heat transfer reached was 488.374 J.
- The best condition of engine factors to minimize exergy destruction due to combustion process were 12 as air–fuel ratio (AFR), − 18.525 °CAD as ignition timing, 7 as compression ratio, and 65.48 °as combustion duration. In additional the optimal values were 1999.42 (mg/m^3), 0.106 (mg/m^3), 1578.87 (mg/m^3), 1000 (mg/m^3) for CO_2, CO, HC and NO_x emissions respectively. Exergy destruction due to combustion process reached was 325.412 J.
- The complex interaction of engine variables (varying air–fuel ratio (AFR) (X_1), ignition timing (X_2), compression ratio (X_3), and combustion duration (X_4)) and their different effect on emissions and performance make it impossible to intuitively determine the direction, no less the magnitude, of changes required in all control variables simultaneously to achieve a given change in constraint level. It is because of these complex interactions that an metamodel-based design optimization framework is required.
- Response surface methodology was found to be efficient optimization technique, which provides higher flexibility and can forecast the results in-depth. By that, the available information for each generated concept is enhanced, so the human designers can make a more informed decision as to which concepts to pursue in detail design. This aims to reduce costs and iterations due to errors in later phases that are, thus, intercepted during conceptual design. Fur-

thermore, expert and novice automotive engineers may use this methodology as an assistant when calibrating an prototype.

- Metamodels can help designers explore new directions by providing a wider variety of possibilities thereby expanding the range of solutions that are normally considered and might be translated into guidance for new engine technology development.
- Optimization was done among the four-stroke spark ignition engine test conditions with no restrictions on ability to implement the results. This selects the optimum solution independent of control system limitations. However, the role of the engine control system is to manage engine functions so as to achieve as much as possible of this inherent potential performance. Of course even the best possible control system will not result in exhaust emissions-fuel performance which exceeds these fundamental limits. If complete calibration flexibility were possible, this capability could be achieved.
- It is expected that this approach will provide guidance in the development of more efficient and systematic engine calibratiion techniques. However, it is recognized that by virtue of certain approximations and limitations in the current applications of these methods that the resulting calibrations may have to be adapted and extended for other optimization tasks with special demands. Nonetheless, the results may be used as upper bounds to the performance expected and thereby be useful in evaluating hardware configurations relative to required performance levels or other legislative limits.
- The proposed methodology proved to be a valuable tool to realize a virtual engine calibration. If applied in an industrial environment, and utilizing more advanced optimization strategies, it will hence contribute to drastically reduce time and costs related to experimental activities at the test bench.
- Future work is related to design analysis for the definition of both engine optimal control maps and control system strategies.

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