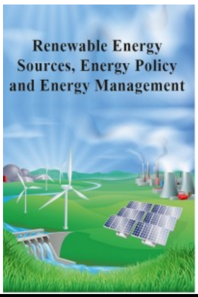
e-ISSN: 2717-9583

Renewable Energy Sources Energy Policy and Energy Management

journal homepage: https://dergipark.org.tr/en/pub/resepem



hosted by Turkish JournalPark ACADEMIC

Review Article

Optimization of Internal Combustion Engine Tests with Response Surface Methodology: A Review

Mehmet Selman Gökmen[1,*], Mehmet Bilban[1].

[1] *Necmettin Erbakan University, Seydişehir Vocational School, Seydişehir, Konya, Turkey*

ARTICLE INFO

* Corresponding author
msgokmen@erbakan.edu.tr

Received 16 August 2020
Received in revised form
1 September 2020
Accepted 2 September 2020

Published by Editorial Board
Members of RESEPEM

ABSTRACT

Experimental design is an important technique to reduce cost, determine optimum parameters and obtain scientifically meaningful results. Response surface methodology is a useful method for the design and optimization of experiments. In this review, theoretical information about the method, calculations and stages of designing are clearly stated. Apart from this, in this study, the applications in the literature are summarized for the researchers who will carry out optimization studies in internal combustion engines.

Keywords: Internal combustion engines, response surface methodology, optimization, design of experiments

1. Introduction

Statistical experimental design was implemented in the agricultural field in the 1920s under the leadership of Sir Ronald A. Fisher [1]. Fisher observed that there are constant errors in the statistical data due to errors in production. Errors concentrate on three parameters called randomness, inhibition, and replication. In addition, Fisher played a major role in the development of the factorial design concept and analysis of variance. With the following developments, the Response Surface Methodology (RSM) was developed by Box and Wilson in 1951 [2]. Optimization of test process including data acquisition, process and evaluation is ensured with this method [3].

Optimization of test process is done to determine the effect of all factors among themselves and on response variables, and it is the process of obtaining the most accurate results with the least number of tests possible by establishing the relationship between them as a mathematical function. [4].

In most test procedures, the type of mathematical function (linear or non-linear) between factors and response variables is not clearly known. In this review, it is aimed to give information about design of the experiment, determination of the function type and evaluation of the results using the RSM, and also the applications of this method to internal combustion engine tests.

2. Response Surface Methodology

RSM is an optimization technique that includes statistical and mathematical techniques that are used in order to model and analyze problems in which a response variable is affected by various factors. Thanks to this technique, it is possible to obtain mathematical expressions for interpolation between data points. In this way, a mathematical model of test conditions is obtained [5]. Given that X_1 and X_2 are independent variables, $\in$, represents the margin of error and Y is the response variable, the effect of the independent variables on the Y dependent variable is expressed as in equation 1 [6].

$$y = f(X_1, X_2) + \in \qquad \textbf{Eq.1}$$

If the response variable can be modeled with a linear function while being statistically significant, the function is defined as a "*first order model*". An example notation is given in equation 2. Here, β is constant coefficient, k represents the number of factors and x is factor [6].

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_k X_k + \in \qquad \textbf{Eq.2}$$

Polynomial functions are used for non-linear responses. The relationship between the response and the factors can be represented by polynomial that provides the highest value of coefficient of determination (R^2). The highest power in polynomial shows its order. If the number of exponents of the function is higher than necessary for the model, it increases the number of points in the polynomial curve and curvature cannot be observed. If the number of exponents is insufficient, the probability value (P-value) of the relevant factor will be greater than 0.05, because it would not give a polynomial curve. So the correlation would be statistically insignificant. Therefore the ideal exponent number is determined in such a way that it does not make the curve linear, but also does not make the P-value value statistically insignificant. This function is a quadratic function defined as a "*second order model*" and it is expressed at equation 3. β_{ii} denotes the *ith* observation or level of variable β_i [6].

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum\sum_{i<j}^{k} \beta_{ij} X_i X_j + \in \qquad \textbf{Eq.3}$$

RSM is an optimization technique that is carried out in stages. While trying to determine the optimum points in the first stage, the determined points are analyzed in the second stage. In the first stage of optimization, it is assumed that the functions are linear and a first order model is used. The first stage ends when the effect of factor changes on response is statistically insignificant. With this stage, it is aimed to reach the closest of the optimum point. In the second stage, it is determined whether the point obtained in the first stage is a quadratic function and what it expresses on the test set. Quadratic functions should be evaluated to clearly explain the minimum, maximum, or saddle points of the response variable [7].

Figure 1a shows the response graph for the Y response function corresponding to the maximum point of the factors X_1 and X_2. In 1b, the relationships between the factors are shown with contour curves. The -1,0 and 1 points on the graph are called coded values, and the lowest, highest, and middle levels of a factor are denoted as -1, +1, and 0, respectively [6].

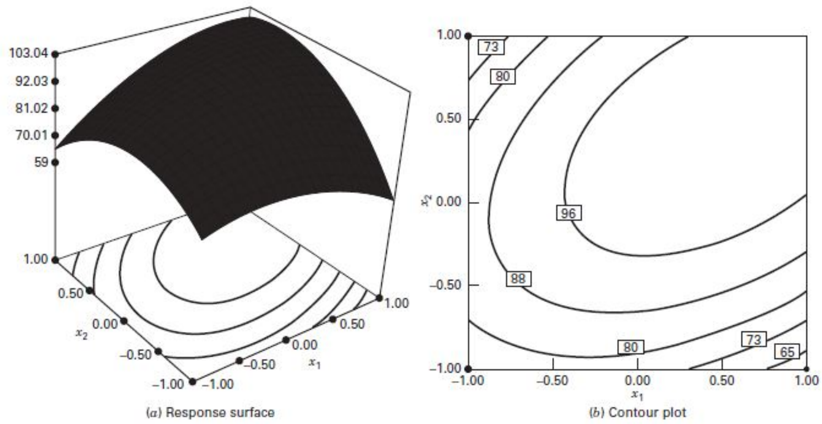


Figure 1. (a) Response Surface for Max. Point (b) Contour plot for Max. Point [6].

Figure 2a shows the response graph for the Y response function corresponding to the minimum point of the factors X_1 and X_2. In 2b, the relationships between the factors are shown with contour curves [6].

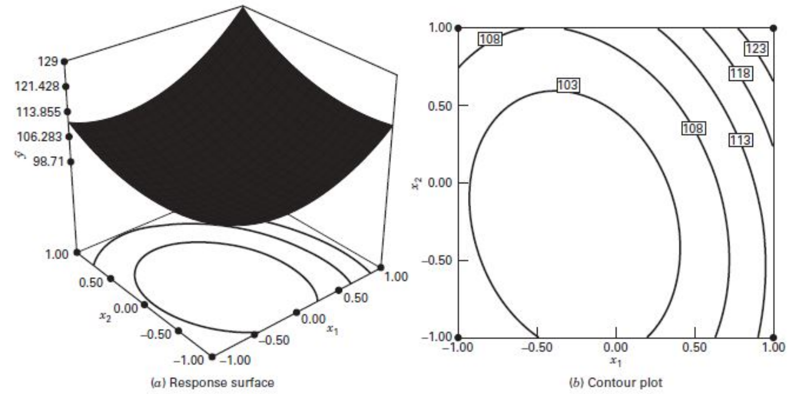


Figure 2. (a) Response Surface for Min. Point (b) Contour plot for Min. Point [6].

Figure 3a shows the response graph for the y response function corresponding to the saddle (minimax) point of the factors X_1 and X_2. In 3b, the relationships between the factors are shown with contour curves [6].

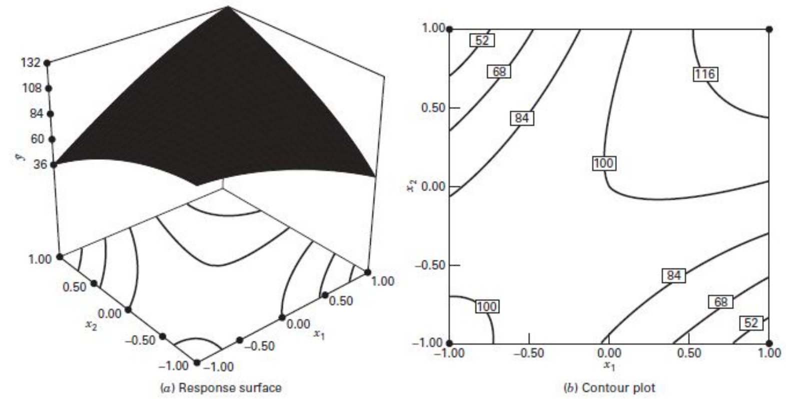


Figure 3. (a) Response Surface for Saddle Point (b) Contour plot for Saddle Point [6].

As can be seen from the graphs in Figures 1, 2 and 3, point 0 is one of the most important parameters in interpreting the answer. The lines are drawn at 0 points perpendicular to the axes where the factors are located and if these lines intersect on the graph, the maximum, minimum and saddle points are reached according to the response type represented. However, point 0 is not the optimum point for factors, even the optimum point of factors generally does not coincide with point 0. In the study conducted by Elkeway et al.[8], -1 point of the mixing speed was determined as 400, point 0 as 550 and +1 point as 700 rpm, but the optimum speed was obtained as 530 rpm. Since point 0 is equidistant to +1 and -1 points, it provides a clearer understanding of the function and is therefore important for interpretation of the answer.

2.1. Screening Design

In many experiments there are multiple factors affecting a response function. When the number of factors is high, determining the factors with high effects is one of the most important stages of the design. Some statistical calculation techniques (screening design) used to determine the factors to be examined in RSM are given in Table 1. Thanks to the correlation matrices obtained using these techniques, the interactions between factors can be determined as percentages. Determination of these effects is used to reduce factor interactions in a limited area before RSM modeling [9,10]. Screening design focuses on determining which factors are more influential on the response. After this stage, the experimenter can choose the factors according to their effect rates and remove the factors whose effects are insignificant.

Table 1. Screening Design Methods

Methods	Working Principle
Full 2 level factorials	It is used to examine all effects of all factors among themselves and on response.
Fractional factorials 1. Resolution V 2. Resolution IV 3. Resolution III	It contains 3 subsets of full 2 level factorials. 1. Resolution V: It is used to explain the effects of all factors both as a result and among each other. 2. Resolution IV: It is useful for explaining the effects of factors on the outcome, but is insufficient for explaining the effects on each other. 3. Resolution III: It is useful for explaining the effects of factors on outcome. It does not give an idea about their interactions with each other.
Irregular Fractions	It contains a non-orthogonal subset of the Full 2 level factorial technique. Used for approximate estimates.
Mixed-level Fractions	It examines the effect of -1.0 and +1 levels of any factor on any two levels of another factor.
Placket-Burman Designs	Unlike Fractional factorials, it works with subsets that are not power of 2. It is useful for examining the interplay of factors with minimal test combination.

2.2 Creating the design with RSM

After determining the important factors affecting a response, different design methods are used to achieve optimum values. There are different sub-methods according to the test conditions in optimization studies using RSM. These sub methods contain different Before starting the design, the factors planned to be used in the model and the number of response variables are determined. There are many computer software that can be used in RSM designs. Since advanced mathematical operations are carried out, in most software, the number of Response variables is limited to between 1 and 16, and the number of factors is limited to 2 to 8. This limitation is necessary to reduce the margin of error and speed up the process. Otherwise, it is not possible to examine the effect of infinite number of factors on infinite number of response variables in terms of time, and its accuracy will be scientifically insignificant. Another important factor for determining the factors is the determination of the lower and upper limit values. At the same time, depending on the number of factors (k), the Star point ($\pm \alpha$), which is equidistant from the maximum and minimum points, is calculated with the $\pm\sqrt{k}$ operation in CCD technique. [7]. The $\pm \alpha$ value is calculated separately for each factor at a point below the specified minimum point and above the maximum point, and its effect on the response variable is evaluated. In this way, when the minimum and maximum points are selected very close to each other, the margin of error in the test process and statistical calculations is reduced and the curvature of the response function is evaluated on a larger scale. To further reduce the margin of error, center points corresponding to the 0-coded values of all factors are usually added to the test combination. The number of center points can be planned to be approximately 20% of the total number of test combinations.

statistical and mathematical approaches. It is necessary to choose the appropriate sub method according to the work to be done. These methods can be examined in 4 groups as Central Composite Designs (CCD), 3-level factorial Designs (3LFD), Box-Behnken Designs (BBD) and Draper-Lin Designs (DLD) [11].

Central Composite Designs, depending on k, 2^k test combinations are created and the combinations of factors including $\pm \alpha$ values and the number of center points determined by the experimenter are also included in the number of tests. Combinations of $\pm \alpha$ values allow it to be more clearly stated whether the optimum point of the response function is close to the lower or upper limit values.[12–14].

3-level Factorial Designs, depending on k, 3^k test combinations are created. In addition to the combinations created, only the number of center points is added. Since the test combination is determined as 3^k, the number of tests is higher than CCD [11,12,15].

Box-Behnken Designs, while creating test combinations, any factor is kept constant at 0 and combinations are created with the +1 and -1 values of the other factors. If the number of center points determined by the user is neglected, the same number of factors contains less number of tests than CCD and 3LFD [11,12,16].

Draper-Lin Designs, In case of high test costs, the number of tests should be reduced with a statistical approach. While creating test combinations with this design, either Plackett-Burmann or fractional factorial design is used at Resolution IV or Resolution III level. Similar to CCD, $\pm \alpha$ values are calculated depending on the number of factors but are used without repetition for each test combination [17,18].

3. Internal Combustion Engine Tests optimized with RSM

Optimization studies using RSM for internal combustion engine tests in recent years are summarized in Table 2. In this table, number of factor variables, number of response variables, type of response function, RSM design method and fuel types used in the study are also given. Optimization studies in tests conducted with alternative fuels enable a wide investigation such as fuel production processes, determination of engine test conditions, and the effect of fuel parameters on emission values within a certain mathematical relationship. Of course, optimization with RSM should not be limited to fuel tests and exhaust emission tests.

Table 2. Summary of studies using RSM.

Year	Factors	Responses	Response Function	Design Method	Fuel	Optimum values of factors	Ref.
2020	4	3	Polynomial	BBD/ CCD	Sunflower/Soybean Biodiesel Blends	Methanol/Oil Ratio: 203.5/1 Catalyst concentration: 0,57 wt% Reaction time: 52 min. Mixing speed: 530 rpm	[8]
2020	3	5	Polynomial	CCD	Canola, Safflower, Waste Vegetable Oil Biodiesel Blends	Engine load: 1484,85 W Injection pressure: 215.56 bar Blend Ratio: %25.79	[19]
2020	3	6	Polynomial	BBD	Biodiesel/2-ethylexyl Nitrate(EHN) Blends	Engine load: 1515 W EHN Percentage: %1.1 Biodiesel Percentage: %100	[20]
2020	3	6	Polynomial	CCD	Palm Oil Biodiesel Blends	Engine load:780 W Palm oil percentage:%17.88 Injection advance: 35 °CA	[21]
2019	4	4	Polynomial	CCD	Jojoba Biodiesel/Diesel Blends	Injection timing: 25°bTDC Injection pressure: 21.52 MPa Jojoba oil percentage:%24 Engine load:%80	[22]
2019	4	3	Polynomial	CCD	Cassia Tora Methyl Ester/Diesel Blends	Injection timing: 15°bTDC Injection pressure: 221 bar Cassia Tora oil percentage:%40 Engine load:%47	[23]
2018	4	4	Polynomial	CCD	Pongamia Biodiesel/Diesel Blends	Injection timing: 15°bTDC Injection pressure: 196.36 bar Pongamia oil percentage:%40 Engine load:%53	[24]
2017	3	5	Polynomial	3LFD	Iso-butanol/Diesel Blends	Injection timing: 23 °CA Injection pressure: 240 bar EGR:%30	[25]
2015	2	7	Polynomial	CCD	Gasoline/Ethanol Blends	Engine Speed:3000 rpm Bioethanol: %10	[26]

4. Conclusion

With this review, the important points of an optimization study to be carried out using RSM are clearly stated and supported with case studies. According to the present literature survey, following points are detected;

- Thanks to the design and optimization of the experiments, it is possible to obtain the results in the form of mathematical functions by reducing the test costs.

- Obtaining preliminary information about the factors with Screening Design will contribute to the researcher before making a response surface design.
- Since there is no common method that works in all situations, researchers should choose the method that best suits their test conditions.
- Familiarity with statistical and mathematical concepts will help researchers who will working about experimental design and optimization to make the most appropriate choices for their test conditions.
- Optimum values of factors and response functions can be obtained with RSM.
- Mathematical functions can be obtained to explain the effects of factors on the response. Using these functions, the response can be calculated for different factor values. Thus, uncertainties are eliminated since the answer can be reached at any desired point.
- Adding center points to test combinations makes error detection easier. In tests performed at the same center point in the same conditions but at different times, the results are expected to be statistically significantly close.
- The highest R^2 expression is used for accurate interpolation.
- RSM simplifies calculations and increases the usefulness of mathematical models derived from response functions.

Using this method will provide the following benefits of internal combustion engine tests,

- In biodiesel production, fuel quality and production efficiency can be increased by optimizing production parameters,
- In tests with alternative fuel mixtures, which fuel is more effective on performance and optimum values of the mixture can be obtained,
- In studies investigating the effects of alternative fuels on exhaust emission parameters, the factors that increase and decrease the emission can be determined and their optimum values can be reached,
- Optimum spraying parameters can be determined in studies related to the spraying of fuels,
- The optimum values of the experimental conditions can be determined in studies where the effects of different fuels on performance are carried out.
- It can be used to reach optimum values when working on parameters such as compression ratio, injector pressure, ignition / spray timing, coolant temperature, engine oil temperature.

5. References

[1] M. Mäkelä, “Experimental design and response surface methodology in energy applications: A tutorial review,” Energy Convers. Manag., vol. 151, no. August, pp. 630–640, 2017.

[2] N. R. Draper, “Introduction to Box and Wilson (1951) On the Experimental Attainment of Optimum Conditions,” no. 1951, pp. 267–269, 1992.

[3] T. J. Robinson, “A discussion of ‘Response surface design evaluation and comparison,’” J. Stat. Plan. Inference, vol. 139, no. 2, pp. 669–670, 2009.

[4] B. Everitt, Introduction to Optimization Methods and Their Application in Statistics, no. 1. New York: Chapman and Hall, 1987.

[5] N. Bradley, “The Response Surface Methodology,” Indiana University of South Bend, 2007.

[6] D. C. Montgomery, Design and Analysis of Experiments, vol. 48, no. 1. 2006.

[7] R. H. Myers, D. C. Montgomery, and C. M. Anderson-Cook, Response Surface Methodology, 4., no. 1. Hoboken, New Jersey: John Wiley & Sons, 2016.

[8] M. Elkelawy et al., “Maximization of biodiesel production from sunflower and soybean oils and prediction of diesel engine performance and emission characteristics through response surface methodology,” Fuel, vol. 266, no. December 2019, p. 117072, 2020.

[9] Anonymous, “Statgraphics User Manual -Design of Experiments – Screening Designs,” StatPoint Inc. StatPoint Inc., p. 49, 2005.

[10] Anonymous, “Statgraphics User Manual -Screening Design Selection,” StatPoint Inc. StatPoint Inc., p. 7, 2005.

[11] Anonymous, “Statgraphics User Manual - Design of Experiments – Response Surface Designs,” StatPoint Inc. pp. 1–15, 2005.

[12] H. F. Wagner, J. R., Mount, E. M., & Giles, “Design of Factorial Experiments,” Extrusion, pp. 291–308, 2014.

[13] O. A. Adeleke et al., 2 -Locally Derived Activated Carbon From Domestic, Agricultural and Industrial Wastes for the Treatment of Palm Oil Mill Effluent. Elsevier Inc., 2018.

[14] B. Ait-Amir, P. Pougnet, and A. El Hami, “Meta-model development,” Embed. Mechatron. Syst., vol. 2, pp. 151–179, 2015.

[15] M. Hemmat Esfe, H. Rostamian, A. Shabani-samghabadi, and A. A. Abbasian Arani, “Application of three-level general factorial design approach for thermal conductivity of MgO/water nanofluids,” Appl. Therm. Eng., vol. 127, pp. 1194–1199, 2017.

[16] C. M. Anderson-Cook, C. M. Borror, and D. C. Montgomery, “Response surface design evaluation and comparison,” J. Stat. Plan. Inference, vol. 139,

no. 2, pp. 629–641, 2009.

[17] N. R. Draper and D. K. J. Lin, "Response surface designs," Handb. Stat., vol. 13, no. 1, pp. 343–375, 1996.

[18] L. Gámiz-Gracia, L. Cuadros-Rodríguez, E. Almansa-López, J. J. Soto-Chinchilla, and A. M. García-Campaña, "Use of highly efficient Draper-Lin small composite designs in the formal optimisation of both operational and chemical crucial variables affecting a FIA-chemiluminescence detection system," Talanta, vol. 60, no. 2–3, pp. 523–534, 2003.

[19] S. Simsek and S. Uslu, "Determination of a diesel engine operating parameters powered with canola, safflower and waste vegetable oil based biodiesel combination using response surface methodology (RSM)," Fuel, vol. 270, no. February, p. 117496, 2020.

[20] S. Simsek and S. Uslu, "Investigation of the effects of biodiesel/2-ethylhexyl nitrate (EHN) fuel blends on diesel engine performance and emissions by response surface methodology (RSM)," Fuel, vol. 275, no. April, p. 118005, 2020.

[21] S. Uslu, "Optimization of diesel engine operating parameters fueled with palm oil-diesel blend: Comparative evaluation between response surface methodology (RSM) and artificial neural network (ANN)," Fuel, vol. 276, no. April, p. 117990, 2020.

[22] A. Sharma, Y. Singh, N. K. Singh, and A. Singla, "Sustainability of jojoba biodiesel/diesel blends for DI diesel engine applications- taguchi and response surface methodology concept," Ind. Crops Prod., vol. 139, no. March, p. 111587, 2019.

[23] Y. Singh, A. Sharma, S. Tiwari, and A. Singla, "Optimization of diesel engine performance and emission parameters employing cassia tora methyl esters-response surface methodology approach," Energy, vol. 168, pp. 909–918, 2019.

[24] Y. Singh, A. Sharma, G. Kumar Singh, A. Singla, and N. Kumar Singh, "Optimization of performance and emission parameters of direct injection diesel engine fuelled with pongamia methyl esters-response surface methodology approach," Ind. Crops Prod., vol. 126, no. October, pp. 218–226, 2018.

[25] S. Saravanan, B. Rajesh Kumar, A. Varadharajan, D. Rana, B. Sethuramasamyraja, and G. Lakshmi Narayana rao, "Optimization of DI diesel engine parameters fueled with iso-butanol/diesel blends – Response surface methodology approach," Fuel, vol. 203, pp. 658–670, 2017.

[26] G. Najafi, B. Ghobadian, T. Yusaf, S. M. S. Ardebili, and R. Mamat, "Optimization of performance and exhaust emission parameters of a SI (spark ignition) engine with gasoline-ethanol blended fuels using response surface methodology," Energy, vol. 90, pp. 1815–1829, 2015.