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Review article

Response surface methodology (RSM) for optimizing engine performance and emissions fueled with biofuel: Review of RSM for sustainability energy transition

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ABSTRACT

Response Surface Methodology (RSM) is a statistical method to design experiments and optimize the effect of process variables. RSM is based on the principles of design of experiments or DOE. Design of experiments or DOE is a field of applied statistics that plans, conducts, analyses, and interprets controlled tests to assess factors that affect parameter values. Response surface methodology or RSM uses a statistical method for designing experiments and optimization. Despite the potential of response surface methodology to predict and optimize engine performance and emissions characteristics, a comprehensive review on RSM for biofuels, particularly for internal combustion engines (ICEs), is difficult to find. The review of response surface methodology is sometimes included together with other machine learning approaches such as ANN. Therefore, a review article that is exclusively written to address the specific of RSM for biofuel and ICE is required. This review article offers a fresh perspective on the application of RSM for biofuel in ICE. This article aims to critically review the RSM to optimize engine performance and emissions using biofuel. The study concludes with several possible research gaps for future works of RSM biofuel application. Although response surface methodology or RSM has drawbacks such as extrapolation inaccuracy outside the investigational ranges and discrete variables error, RSM has numerous advantages to design, model, estimate, and optimize biofuel for ICE with satisfactory accuracy. With its prediction and optimization capability, response surface methodology has the potential to assist the development of ICE optimization powered by biofuel for sustainability energy transition.

1. Introduction

As the global community increasingly aims to achieve net zero emissions and meet the Sustainable Development Goals or SDGs, biofuels have emerged as a favorable substitute to fossil fuels. Biofuels are produced from renewable energy sources such as from animal waste or plant materials, thus having the capability to substantially decrease greenhouse gas emissions. The utilization of biofuels can assist many countries shift to a more sustainable and low-carbon society, whilst also offering economic and social advantages. Yet, it is important to cautiously take into account the effects of biofuels on many aspects including food security, land use, and water resources, and to ensure that biofuel production and utilization is sustainably managed.

With all the pros and cons of biofuels, many modern and industrialized societies still rely on the continuous supply of energy due to its vital role in many vital sectors, including manufacturing [1], transportation [2], and power generation [3]. Fossil fuels, such as natural gas, coal, gasoline, and diesel, are still currently the main resources to meet the world's energy demand [4]. However, concern over its sustainability has led to the utilization of alternative fuels owing to their potential to decrease environmental pollution and reduce the reliance on depleting and non-renewable fossil fuels [5]. Numerous efforts have been attempted to explore alternative fuels such as liquefied petroleum gas (LPG) [6], dimethyl ether (DME) [7], biodiesel [8], and alcohol fuels [9]. Of all alternative fuels, biodiesel and bioalcohol have attracted

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List of acronyms

ANN	Artificial Neural Network
BBD	Box-Behnken Design
BSFC	Brake-Specific Fuel Consumption
BTE	Brake Thermal Efficiency
CA	Crank Angles
CCD	Central Composite Design
CCRD	Central Composite Rotating Design
CI	Compression Ignition
CO	Carbon Monoxide
DME	Dimethyl Ether
DOE	Design of Experiment
DTBP	Di-Tertiary-Butyl Peroxide
EGR	Exhaust Gas Circulation
EGT	Exhaust Gas Temperature
EHN	2-Ethylhexyl Nitrate
FFD	Full Factorial Design
GHG	Greenhouse Gas
HC	Hydrocarbon
HVO	Hydrotreated Vegetable Oil
ICE	Internal Combustion Engine
LGO	Lemon Grass Oil
LPG	Liquefied Petroleum Gas
MSW	Municipal Solid Waste
NO_x	Nitrogen Oxide
PM	Particulate Matter
PO	Pyrolysis Oil
RSM	Response Surface Methodology
SDG	Sustainable Development Goal
TDC	Top Dead Center
VCR	Variable Compression Ratio
WPO	Waste Plastic Oil
WPPO	Waste Plastic Pyrolysis Oil
WTW	Well-to-Wheels

considerable attention [10,11].

Biodiesels provide several benefits compared to fossil fuels as they are non-toxic, renewable, and environmental-friendly [12]. Moreover, biodiesel can be mixed with conventional diesel fuels owing to their comparable physicochemical properties [13]. Numerous potential substrates have been identified for biodiesel production in the last ten years. Several traditional biodiesel crops are palm [14–16], soybean [15,17], jatropha [18,19], sunflower [20,21], rapeseed, karanja [22–25], moringa [26,27], and mahua oil [28]. Many of these feedstocks are first-generation biodiesel produced from edible oils, thus having the potential to compete with the human food supply. In order to solve this dilemma, the use of second-generation feedstocks from non-edible vegetable oils and fats has attracted substantial interest and is now considered an effective way to reduce well-to-wheels (WTW) greenhouse gas (GHG) emissions. The second-generation biodiesel encompasses numerous biomass sources from agriculture to forestry and waste materials [29]. Note that the source of biodiesel feedstock should be produced locally to help the regional economy.

It is essential, while analysing the sustainability of second-generation feedstocks, to include the resources necessary for their production, such as land and water consumption. Second-generation feedstocks, also known as non-food feedstocks or biomass, primarily consist of waste materials such as agricultural residues, forest residues, and algae. Because they do not compete with the human food supply for resources, it is commonly believed that these materials are more sustainable than food crops. Nonetheless, it is essential to consider the land and water required for their production and processing, as well as any potential environmental repercussions. Depending on the precise manufacturing techniques and feedstocks employed, some second-generation feedstocks may demand more resources than others. It is essential to analyse a feedstock's entire lifecycle in order to determine its overall sustainability.

Alcohol can be blended with gasoline and diesel fuels. A number of studies have investigated the effects of alcohol fuel on both gasoline and diesel engines. The low cetane number of alcohol fuel is known to provide a homogeneous lean mixture that can reduce nitrogen oxide (NO_x) and smoke emissions and achieve good thermal efficiency in an engine running at high loads [30,31]. However, the use of pure alcohol (very low cetane number) cannot be operated in diesel engines. Therefore, to be run without any modification in the compression ignition (CI) engine fuel system, alcohol should be mixed with diesel fuel. Short-chain alcohols, such as methanol and ethanol, can be blended with diesel fuel. However, longer-chain alcohols, like butanol, are more favorable due to their higher energy content, stability in the blend, low corrosiveness, and lower miscibility in water [32–34].

Note that although alcohol can be blended with gasoline and diesel fuels, the blending ratio is constrained by the phase stability of the blend. With gasoline, blending ratios are high for most alcohols, but with diesel, blending ratios are extremely limited, especially for methanol and ethanol. Furthermore, even a stable blend may not fulfill other requirements set by quality standards, such as EN 590 or EN 228. When blended with diesel, the alcohol content prolongs the ignition delay, which results in a more homogeneous mixture at the onset of combustion. However, it is important to note that this mixture is not entirely homogeneous throughout the combustion process.

There are some internal combustion engine parameters that conflict with each other. For instance, an improvement in a brake thermal efficiency (BTE) will potentially increase NO_x emissions [35]. BTE is a measure of the efficiency with which a heat-generating engine converts fuel energy into useable work. It is computed by dividing the engine's work output by the fuel's energy input. The resulting percentage shows the proportion of fuel energy that is turned into useable work, as opposed to being wasted as waste heat. Therefore, it is important to optimize engine characteristics so that ICE performance, such as BTE, can be increased while at the same time, harmful emissions, such as carbon monoxide (CO), hydrocarbon (HC), particulate matter (PM), and NO_x, can be reduced. Furthermore, more specifically in diesel engines, a trade-off between PM and NO_x exists [36,37]. Also, note that the optimum engine operating conditions are dependent on the biofuel type. This is where response surface methodology (RSM) can be beneficial in overcoming such problems. RSM can be a useful method for optimizing engine variables when multiple factors need to be improved simultaneously, as well as for testing biofuels. However, it is important to note that RSM is just one of many methods that can be applied in these situations, and its advantages should be carefully considered in the context of the specific research objectives and requirements. Some researchers have evaluated several combination method by using general or meta-heuristic optimization, such as particle swarm optimization (RPSO) and dragon fly algorithm (RMODA) to optimize the response of the RSM equations [38–40].

Although the application of artificial neural networks (ANNs) has been extensively studied for biofuel and ICE purposes [41–43], ANN needs a relatively huge number of data obtained from experiments to train the networks [44]. Training the network with a small number of data may result in poor prediction results. Alternatively, a set of engine experiments, such as the number of experiments and critical operating conditions, can be designed beforehand using a statistical design of experiments (DOE) tool. The results from experiment can then be used for prediction and optimization. This is where a DOE method, such as RSM, can play a big role in biofuel research and development.

RSM has the potential to maximize the engine performance and combustion characteristics fueled with biofuels, while significantly reducing their exhaust emissions. A sizeable number of works have been published on the application of RSM for biofuel [45–49]. Selemani & Kombe used RSM to model and optimize a CaO catalysed glycerolysis reaction under the influence variables [50]. Simbi et al. evaluated the characteristic of operation considerations on the yield of the produced biodiesel (sunflower) using RSM [51]. Etim et al. optimized transesterification using Taguchi design of RSM to investigate the impact of catalyst loading, methanol-to-oil ratio, reaction time and temperature [52].

However, there has been no detailed review on the use of RSM for alternative fuels, especially for the ICE purpose. The application of RSM is often addressed as part of the discussion of machine learning. Therefore, a review article dedicated to explaining the specific application of RSM for biofuel is required. This review article aims to discuss the application of RSM for biofuel in ICEs critically. A number of important aspects, such as the selection of RSM design and validation results, are compared. To conclude this review article, several points to consider and possible research gaps for future works are presented. Note that in this review article, the application of RSM for biofuel production optimization lies beyond the scope of this study.

2. Points to consider in RSM

RSM is a mathematical and statistical method for designing a set of experiments. The goal is to optimize the response that is affected by a number of independent variables. Eq. (1) shows a second-order polynomial equation used to predict the output response by taking the input factors into account.

Here, S is a response, a_0 is responses average, and a_i, a_{ii}, and a_{ij} are response coefficients.

$$S = a_0 + \sum_i^k a_i x_i + \sum_i^k a_{ii} x_i^2 + \sum_{i,j=1,j\neq i}^k a_{ij} x_i x_j \tag{1}$$

Although it was initially developed for chemical applications, the application of RSM has now been expanded to other fields, such as mechanical engineering and automotive sector. In ICE, the RSM method is predominantly used to optimize the performance and emissions of gasoline and diesel engines. However, due to the increasing concern over diminishing fossil fuels and their environmental issues, the use of RSM to optimize engine performance and emissions is becoming a growing trend in biofuels research.

2.1. Experimental data required to determine range for parameters in RSM

Experimental design will determine the range of RSM parameters. It should be chosen based on the number of optimization variables and the required level of precision. For example, in a two-variable design, the quadratic model must be approximated by at least four runs. Minimum of seven runs are necessary for a three-variable design. For a more precise model and to account for any potential inaccuracy, it is customarily advised to conduct more simulations. Consequently, it is essential to meticulously arrange the range of the variables to guarantee that the ideal portion of the response surface is adequately tested.

2.2. RSM software

Numerous computer software packages are available that are either specifically dedicated to experimental design or are of a general statistical category. Design-Expert (State-Ease Inc.) and Minitab (Minitab Inc.) are the two commercial software packages commonly used to perform RSM. Alternatively, R studio is a free and open-source software for non-commercial purposes. Moreover, Chemoface and Develve are other alternative packages to perform RSM besides Statistica (Stat Soft) and MATLAB (Mathworks).

2.3. Factors (input) and responses (output) in RSM

The first and most important stage in any use of RSM is choosing the input or the independent factors, as these will significantly affect the whole process, including the desired responses as the outputs. By studying previous works on the use of RSM in ICEs fueled with alternative fuels, it is clear that the inputs are usually the operating conditions, such as engine speed, load, compression ratio, and blending ratio. Note that the ranges of the selected factors should be chosen wisely. They are normally based on previous experiments. If the independent factors and their ranges are not reasonably selected, the results will be inaccurate and unhelpful. As for the outputs, it is critically important to select desirable responses that have profound impacts on the engine performance, combustion, and emission characteristics. Therefore, the first thing that should be carefully determined before applying the RSM method is selecting the independent factors and desired responses in a reasonable manner.

2.4. Single vs. multiple responses in RSM

RSM can be performed for single or multiple responses. It is worth noting that there may be some drawbacks for multiple responses as it will be more difficult to obtain a combination of factors and levels that suits the model's optimization requirement. Convergence issues may arise if the response number is higher than that of the constraints. Therefore, it is necessary to compromise and ensure that the objectives are reasonable to obtain by prioritizing the most important responses. Generally, the factorial analysis should be initially performed before testing the effect of curvature. If all the examined data can be fitted to a linear model, the process will stop. However, if the model is nonlinear due to the presence of the curvature effect, the analysis then proceeds to RSM.

In order to decrease the trial and experiment cost, RSM can be used directly as the linear and the second-order polynomial. To check whether the model is adequate, the lack of fit value should be evaluated to assess the significance of the model which describe the discrepancy between the experimental data and the fitted model. Lack of fit is significant when the pure error (measurement error) is considerably low compared to the residual error, thus indicating several issues in the model. In this case, a number of methods can be utilized, including repeating the central points (the experimental runs at the center of the design space in RSM), selecting higher-grade models, using the transfer function (mathematical representation of the relationship between the input variables and the response), removing the outliers, and using the limited range of input variables.

In response surface approach, the selection of the model to fit the data depends on the number of variables and the complexity of the examined system. A second-order model, which is a polynomial equation with terms up to the second degree, is usually adequate for the majority of two- or three-variable optimization problems. In certain instances, a higher-order model may be required to accurately characterise the system's response.

Comparing the fit of the second-order model with a higher-order model is one method for determining whether a higher-order model is required, as indicated above. This can be accomplished by comparing the two models' goodness-of-fit statistics, such as the coefficient of determination (R^2) or the adjusted R^2. If the higher-order model fits the data far better than the second-order model, the higher-order model may need to be used. Plotting the response surface and examining the data for any curvature or nonlinear patterns is another method for determining the right model complexity. If the response surface looks to be very nonlinear and highly curved, a model of higher order may be required to adequately characterise the system's reaction.

It is also essential to consider the practicability of implementing a higher-order model in the optimization process. Complexity and the need for additional experimental runs to estimate higher-order models can make the optimization process more time-consuming and expensive. Consequently, it is often recommended to begin with a second-order model and only expand the model's complexity if necessary.

Additionally, RSM can definitely be applied to optimize multiple responses simultaneously. When dealing with multiple responses, the goal is to find a combination of factor settings that optimize all responses simultaneously or achieve a trade-off among them. The experimental design is carefully planned to gather data points covering the entire design space. The design matrix includes different factor settings, and the corresponding responses are measured. By fitting a regression model to the experimental data, relationships between the factors and the responses can be established. To address multiple responses, different approaches can be employed, such as multi-objective or response optimization and Pareto optimization. It is important to note that when optimizing multiple responses, the objectives should be prioritized based on their importance and relevance to the problem.

2.5. Response surface design for RSM

A response surface design is a series of advanced DOE methods to optimize the response. After the factors and the responses have been determined, the next critical stage is designing the experiments by choosing the points in which the desired responses could be successfully predicted and evaluated. Once the number of factors has been identified, several DOEs can be developed to achieve a response surface. These response surface designs are designated based on their key attributes (e.g., variance and number of experiments). For that reason, selecting a suitable design strategy has an important role in the overall process. However, note that in most previous published papers, reasons for choosing response surface design are not properly addressed, but with only a brief explanation. Three major classes of response surface design are full factorial design (FFD), central composite design (CCD), and Box-Behnken design (BBD).

In experimental design, a factor represents a variable that can influence the response of a system or process. The levels of a factor refer to the different values or settings at which the factor is set during the experiment. The concept of levels is important because it allows researchers to systematically explore the relationship between factors and responses across a range of conditions. The choice of levels for a factor depends on the specific goals of the experiment and the range over which the factor is expected to have an effect on the response. By choosing these specific levels, the experiment can investigate the effect of temperature on the response variable at different points within the range of interest. It is important to select appropriate levels for each factor to ensure that the experiment captures the relevant information and provides meaningful insights. The levels should span a range that is representative of the practical operating conditions or the region of interest. Additionally, the number of levels chosen for each factor can impact the precision and accuracy of the experimental results. A sufficient number of levels should be selected to adequately capture the behavior of the response variable across the range of the factors.

2.5.1. Full factorial design (FFD) RSM

An experiment with FFD considers each potential level combination of all factors. This response surface design results in experimental work in which at least one trial should be included for the entire potential combinations of factors and levels. Such a comprehensive method ensures that every interaction is included with all factor interactions being counted in.

The quantity of trials or repetitions is a critical consideration. The number of repetitions depends on a number of factors, including the desired precision of results, variability, and available resources, such as time and resources. Increasing the number of repetitions reduces the influence of random variation and yields a more precise estimate of the actual effects of the factors. It is essential to include the number of repetitions used in the study to indicate the reliability and robustness of the experimental results. It may not be possible to conduct a huge number of repetitions due to practical constraints. In such circumstances, it is essential to recognise the limitations and potential effects on the precision and generalizability of the findings.

As a result, FFD is relatively expensive and time-consuming for multi-factor experimental work. It increases exponentially as the number of factors and levels increases. Concise notes on FFD are given in Fig. 1.

A more common FFD is the three-level FFD, where the factors can handle three values: low, center, and high. Therefore, the total number of experiments for examining k factors at 3-levels will be 3^k. However, one major drawback of three-level FFD is the requirement for numerous experimental runs that often generate unnecessary high-order interactions [53]. Sakkas et al. [54] reported that the three-level FFD is more advantageous when the number of factors is not more than five. Furthermore, note that the second-order models can substantially enhance the optimization process, particularly in the three-level FFD. Nevertheless, to avoid the difficulties in fitting the model of second or higher-order polynomial in conventional FFD, Box and Wilson [55] introduced CCD in 1951..

2.5.2. Central composite design (CCD) RSM

A CCD is the most frequently utilized response surface design. CCD is particularly useful in chronological experimental work as it can be used to build on earlier factorial experiments with the addition of axial and center points. A CCD can be used to (i) effectively approximate first- and second-order terms; and (ii) to model a response variable using curvature with the addition of center and axial points to a factorial design, as shown in Fig. 3.

The response surface curvature can be estimated due to the points at the midpoint of the experiment domain and the "star" located outside such domain. The points levels of a factorial design are ±1, while those on a "star" design are $\pm\alpha$ in which $|\alpha| \geq 1$ [57]. CCD can be divided into three categories, as illustrated in Fig. 4. The α parameter value is established based on the calculation possibilities and the required precision of the surface response estimation. The prediction performance depends on the points' position. It is important to note that the α value setting and the trial number located at the center of the domain affect the estimation precision.

2.5.3. Box-Behnken design (BBD) RSM

Another type of response surface design is known as BBD. A BBD is a category of response surface design that does not encompass a factorial design. Therefore, BBD is not established on full or fractional factorial designs. However, Box-Behnken facilitates an efficient prediction of the first- and second-order coefficients as it frequently has a smaller number of design points. As a result, BBD can be less time-consuming and more affordable. However, since BBD does not possess an embedded factorial design like CCD, a BBD is not appropriate for chronological experimental work.

Although BBD has poor coverage of the nonlinear design space corner, BBD is believed to be more capable and effective than other response surface designs, such as the three-level FFD and CCD. BBD is used to produce a higher-order response with fewer runs than a typical factorial method. BBD, along with CCD, represses chosen runs in order to sustain the higher-order surface.

BBD is rotatable and requires three levels per factor. Similar to CCD, the BBD can adapt to the full quadratic model of the response surface design [58]. In the BBD, the treatment combinations are located at the cube edges midpoints and the center, as shown in Fig. 5. This response surface design should be taken into account for experimental works having more than two factors and when the optimum is expected to be in

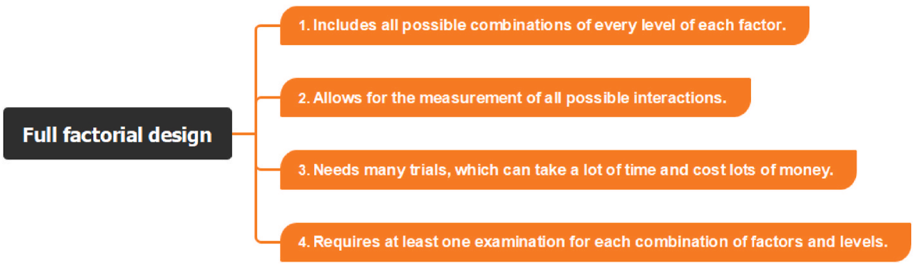

Fig. 1. A brief summary of FFD. Note that the entire input factors in an FFD are arranged at two or three levels. For example, the total number of experiments for examining k factors at 2-levels is 2^k, in which k is the number of factors. The two-level FFD is beneficial in the initial phase of the experiment, particularly when the number of factors is ≤ 4. One assumption for 2-levels factors is that the response is almost linear with low and one high value for each factor. A graphical representation of FFD is shown in Fig. 2.

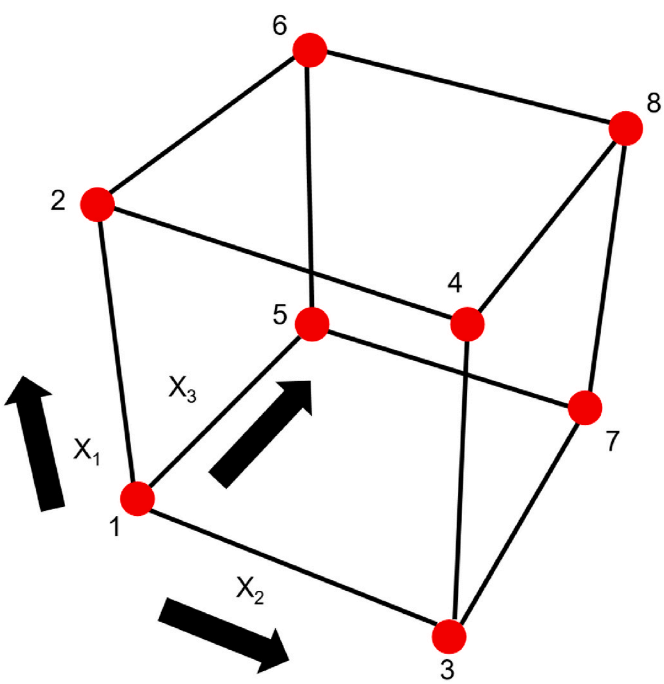

Fig. 2. FFD graphical representation, reproduced from Ref. [56].

the middle of the factor ranges.

Sharma et al. [59] used machine learning and BBD to optimize dual-fuel engine fueled with algal biodiesel as well as waste-derived biogas. The ANN model was developed to predict engine characteristics. It was found that the proposed equations was able to predict engine characteristics with a high-level of accuracy. Uludamar and Özgür [60] also used BBD to forecast and optimize exhaust emissions, noise and vibration of diesel engine fueled with diesel-biodiesel-hydrogen. The flow rate of hydrogen, ratio of biodiesel, and the engine speed were counted as the input factors. The optimum desirability was reported as 0.862 with H_2 addition of around 4.60 L/min using fuel blend of 26% with engine speed of 1500 rpm. Said et al. [61] also used Box-Behnken design combined with desirability technique for ternary blends in a diesel engine. The desirability showed the optimum engine operating parameters was at 76% engine load, 22.92° crank angles (CA) advance, and 0.92 L/min oxyhydrogen.

2.5.4. Validation criteria in RSM

Designed experiments are normally performed in four steps: planning, screening (process characterization), optimization, and verification, as shown in Fig. 6. To validate the results, validation tests need to be conducted. One issue with the application of RSM in ICE is that no studies have confidently explained why the errors are within the permissible range and considered the acceptable values. Most studies claim that their predicted results show good agreement with the confirmatory tests without giving proper references on how much percentage error is actually acceptable.

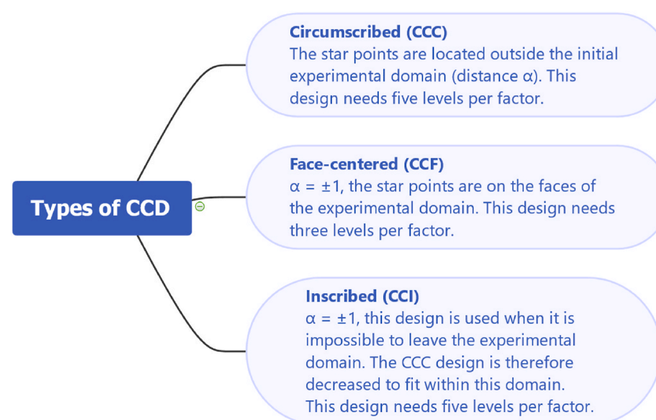

Fig. 4. Three types of CCD, adapted from Ref. [57].

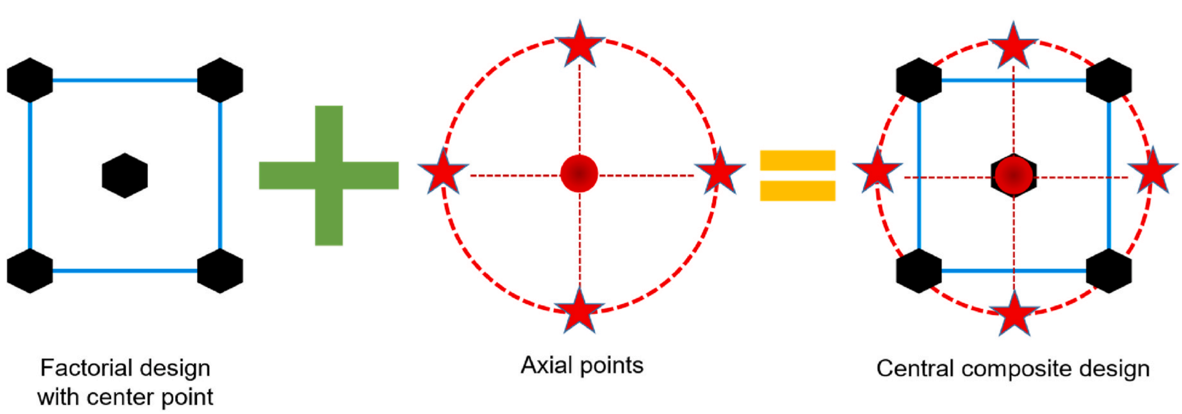

Fig. 3. CCD graphical representation, reproduced from Ref. [56].

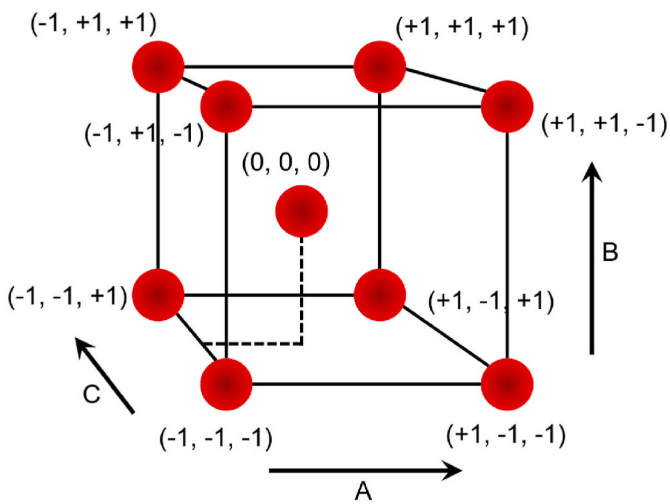

Fig. 5. BBD graphical representation, reproduced from Ref. [56].

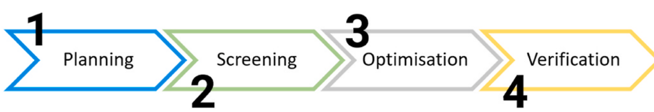

Fig. 6. Four steps in designing an experiment.

When comparing Response Surface Methodology (RSM) results to actual data, it is critical to assess the model's precision, accuracy, and reliability using a variety of statistical indicators. Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Coefficient of Determination (R-squared), Adjusted R-squared, and Residual Analysis are some of the most significant metrics to evaluate.

The MAE calculates the average absolute difference between the RSM's predicted and actual values, with lower values suggesting a better model fit. MSE, on the other hand, calculates the average squared difference between anticipated and actual values, with higher mistakes being prioritized and demonstrating sensitivity to deviations. Lower MSE values indicate a better model fit. The square root of MSE, RMSE, gives a measurement of prediction error in the same units as the response variable, making it easier to read. Lower RMSE values indicate better model fit.

R-squared represents the proportion of the variance in the dependent variable that the RSM model explains, with values ranging from 0 to 1. Greater R-squared values indicate a better model fit. Adjusted R-squared takes the sample size and amount of predictors in the RSM model into account, penalising the R-squared value when unneeded predictors are included. A better model fit is indicated by higher adjusted R-squared values.

Residual Analysis is another useful approach for assessing the performance of the RSM model. The residuals (the disparities between the anticipated and actual values) can be analysed to provide insight into the model's effectiveness. In an ideal world, residuals would be randomly distributed around zero, with no discernible pattern. Furthermore, model validation, which entails testing the RSM model's performance on a second dataset that was not used to develop the model, can provide a more accurate assessment of its generalizability and predictive potential. Note that several statistical measures must be considered to acquire a thorough knowledge of the RSM model's performance. Metrics should be chosen with the study's specific aims and context in mind.

Despite the limitations mentioned above, RSM can provide a valuable approximation. In the RSM application to optimize the output of ICEs fueled with alternative fuels, it can be seen that there are two types of biofuels that are frequently investigated by numerous researchers throughout the world. They are bioalcohol and biodiesel. It is important to compare the optimized values obtained from bioalcohol and biodiesel with the baseline fuel (gasoline or diesel fuel). The idea of any addition of biofuel is to replace the petroleum-based fuel; thus, how much improvement the biofuel can obtain should be presented in comparison with the fossil fuel as the benchmark [62–65].

3. RSM for ICE-powered with biofuel

Biodiesel is arguably the most well-known biofuel in the world. Biodiesel research has a long story [66]. Compared to bioalcohol, biodiesel has a relatively higher cetane number, viscosity, flash point, and lubricity, making it more suitable for CI engines [67]. Simsek and Uslu [68] used RSM to optimize diesel engine parameters fueled with a combination of canola, safflower, and waste vegetable oil biodiesel. Results revealed that 1484.85 kW engine load and 215.56 bar injection pressure operated with 25.79% biodiesel ratio gave the optimum responses, which were 20.54% for BTE, 199.88 °C for EGT, 0.26% for smoke, 558.44 ppm for NO_x, and 4.52% for CO_2. Other recent studies employing RSM for biodiesel in ICEs can be found in Refs. [69–73].

Biodiesel may have been considered the most promising biofuel, but its application is limited to diesel engines. Alcohol fuels, such as ethanol and n-butanol, are more versatile and offer significant emission reduction in real driving conditions [74]. Giakoumis et al. [63] reported that alcohol-diesel blends could reduce the exhaust smokiness than biodiesel during transient operation even with the same oxygen concentration. Note that in order to be used in CI engines, cetane improvers or glow plugs are sometimes required, along with the increase in compression ratio to promote ignition.

Compared to shorter-chain alcohols, such as methanol and ethanol, longer-chain alcohol fuels have better calorific values, flash points, lubricity, cetane number, and solubility in diesel fuel. Yet, their relatively lower cetane number compared to diesel fuels requires the fuels to be blended with the fuel having a comparable cetane number of diesel fuel. Adding hydrotreated vegetable oil (HVO) [75,76] or di-tertiary-butyl peroxide (DTBP) could be, therefore, one promising approach.

Unlike n-butanol, the use of iso-butanol is rarely investigated in diesel engines. Saravanan et al. [77] used RSM to optimize diesel engine parameters fueled with iso-butanol-diesel blends. Such a study aimed to minimize NO_x and smoke emissions with the highest possible BTE and minimum brake-specific fuel consumption (BSFC). Fig. 7 shows the influence of injection timing and exhaust gas recirculation on NO_x emissions for three different injection pressures. The RSM results suggested that iso-butanol-diesel blends injected at 240 bar pressure, 23°CA before top dead center (TDC) with 30% exhaust gas circulation (EGR) were found to be the optimum engine parameters. The results were validated by an experimental test. The prediction error was within 4%.

However, Fig. 7 (a), (b) and (c) show the effect of EGR and injection timing are really close and NOx emissions are more or less the same in the three graphs. Even little changes in injection pressure can affect engine combustion parameters and, as a result, emissions. While the NOx emissions in the three graphs may appear comparable, it is critical to thoroughly analyse the numerical numbers and determine any potential trends or patterns. Although the differences may not be visible, there may be minor variations in NOx emissions that are important from a quantitative perspective.

In addition, the experimental limitation and sensitivity of measuring shall be considered. The precision and accuracy of the measurement instrumentation used to quantify NOx emissions may cause uncertainties, and slight changes in emissions may not be caught with enough resolution.

Furthermore, it is important to note that focusing solely on NOx emissions could lead to overlooking other crucial performance or emission characteristics. To obtain an understanding of engine's behaviour comprehensively, it should be examined the complete emissions profile, such as PM, CO, and HC. So, considering potential

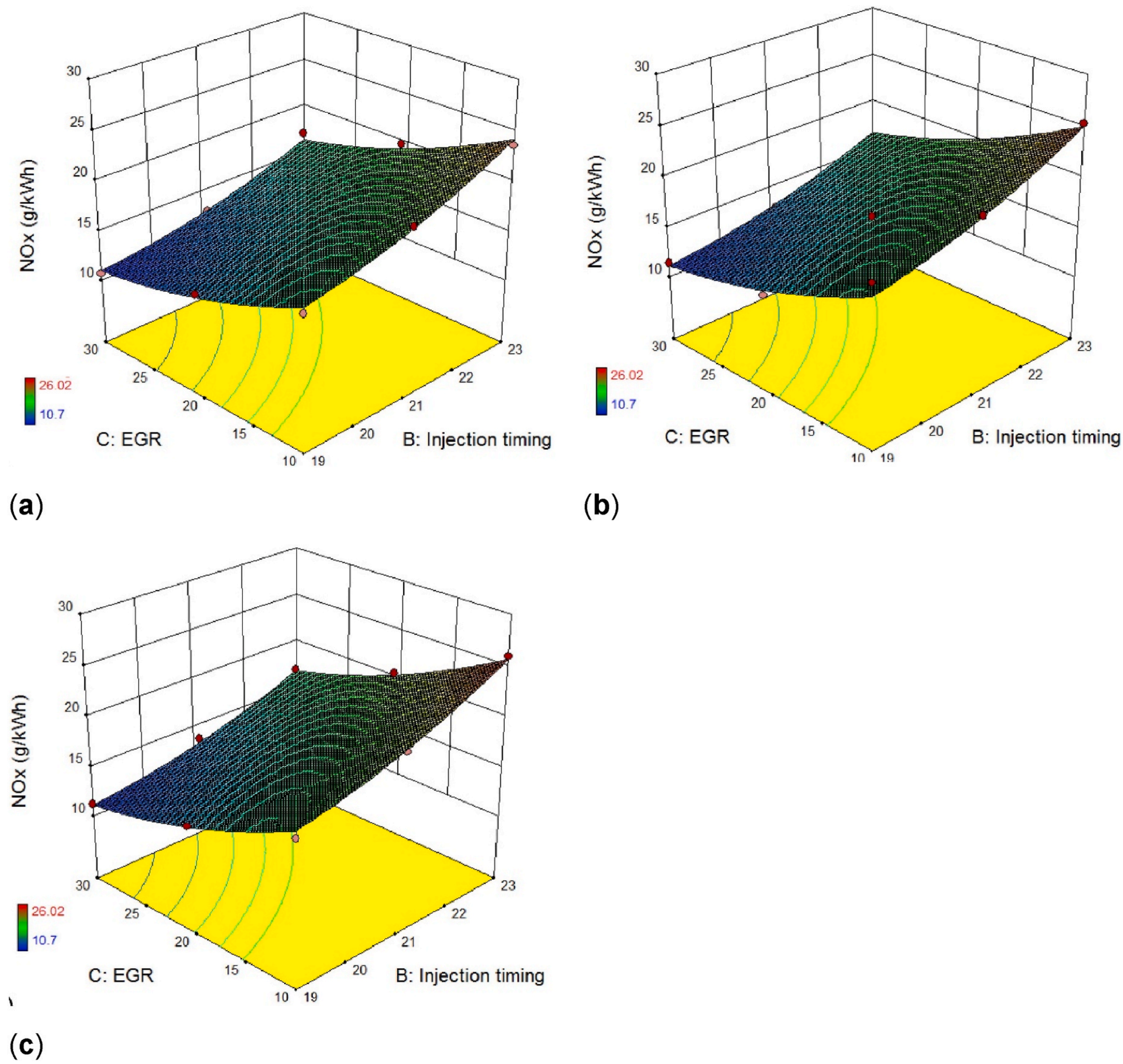

Fig. 7. Influence of injection timing and EGR on NO_x for three different injection pressure:(**a**) 200 bar; (**b**) 220 bar; and (**c**) 240 bar, reused with permission from Ref. [77].

measurement uncertainties, exploring a broader range of injection pressures, and examining the complete emissions profile will contribute to a more comprehensive and robust analysis.

Overall, the intersection plots that indicate the optimum regions of engine performance and emission characteristics are illustrated in Fig. 8.

Fusel alcohols (fuselol), known as fusel oils in Europe, are mixtures of alcohols (mainly amyl alcohol) that are formed as a by-product during alcoholic fermentation. Around 2.5 L of fusel oil can be produced per 1000 L. In Brazil, given its massive bioethanol industry, the annual fusel oil production can reach 80,000,000 L [78]. Therefore, the use of fusel oil as a gasoline additive has attracted attention [79], but the optimum responses are rarely determined to achieve maximum engine performance and minimum emissions. Abdalla et al. [80] applied the RSM method to investigate the fusel oil-gasoline blends at different engine loads and speeds. Results revealed that 4500 rpm and 60% of the wide-open throttle engine load was the optimum condition to operate F20. Moreover, the maximum percentage of absolute error was 5.6%. The error percentage was relatively higher for emissions (>4%) than that of performance characteristics (<4%). A possible explanation for these results may be the lack of combined desirability values due to a lack of experimental measurements. However, good agreement was found when comparing the confirmatory test results against the experimental data, as the maximum error percentage was less than 6%.

All in all, alcohol, which is identified by a hydroxyl group attached to the atom carbon, has been extensively used as biofuel not only in gasoline (due to their high-octane number) but also in diesel engines. Numerous alcohols have been investigated, but ethanol and n-butanol, in particular, are the two most investigated alcohol fuels. It is interesting to see the use of bioalcohol that is developed using cheaper substrates, such as agricultural and industrial wastes.

Pyrolysis oil (PO) is an attractive biofuel for diesel engines. In order to be used in the compression-ignition engine, modifications are sometimes needed due to its low energy density, high acidity, high viscosity, high water content, and low cetane number. One solution to compensate for those drawbacks is blending PO with other fuels that possess high cetane numbers. PO, however, has poor miscibility with light petrol fuel. Since butanol has better miscibility properties, the butanol/PO blend is considered one of the most suitable candidate mixtures in order to be used in diesel engines without modifications, thus improving the storage and handling properties of the PO. In other words, the properties of PO could be improved by blending butanol. Having said that, studies on RSM application for pyrolysis oil can be found in Refs. [81–83].

Trash or garbage, technically known as municipal solid waste (MSW), is a major problem all over the world. A waste management

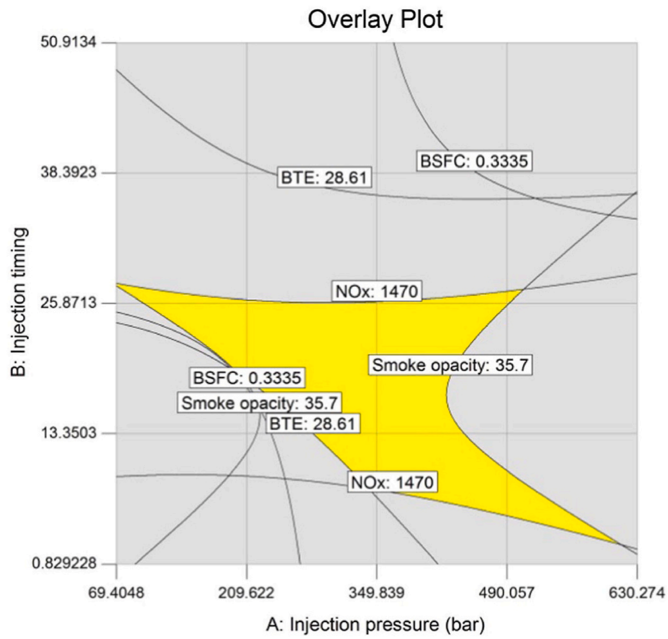

Fig. 8. Intersection plot indicating regions of optimum engine performance and emission; BTE (in %), BSFC (in kg/kWh), smoke opacity (in %) and NOx (cg/kWh), reused with permission from Ref. [77].

strategy needs to be implemented to minimize and recycle the waste. However, such a strategy alone cannot manage to process the whole MSW cycle. This leaves a huge amount of urban waste in several regions. As the main components in MSW, plastics can be used as an alternative fuel. The conversion of plastic waste into fuel can be realized using several processes, such as gasification [84], hydrocracking [85], catalytic cracking [86], and pyrolysis [87]. Of all the aforementioned processes, pyrolysis is more favorable as it can break down plastic waste into smaller molecules without causing harmful effects on the environment. In addition to that, waste plastic pyrolysis oil (WPPO) consists of 70% of carbon chains varying from C10–C15. This characteristic resembles diesel fuel, thus making it applicable to be used in compression ignition engines. Several studies have used WPPO in diesel engines [88–90]. Although there is a potential slight reduction in engine performance and a distinct increase in NO_x and smoke emissions compared to diesel fuel, the application of RSM for waste plastic pyrolysis oil in ICE is still scarce.

Note that a typical conventional diesel engine suffers from the trade-offs of thermal efficiency with energy loss and exhaust emissions [91, 92]. The NO_x-BSFC [93] and NO_x-PM trade-offs [94], for instance, are still prevalent in many diesel engines. This is where RSM can be beneficial in overcoming such problems. However, the application of RSM for ICEs is predominantly used for simple optimization methods. In most studies, emission characteristics are sometimes not reported in full, whereas some emissions such as CO and soot are sometimes excluded.

In view of all studies that have been discussed thus far, it is clear that the utilization of RSM could result in exceptional design and optimization of biofuel for ICE application. The results of the present review article provide important insights into the role of RSM for both researchers and engineers working on the use of biofuel for ICE. Fig. 9 shows the flowchart of RSM for ICE-powered with biofuels. Summing up, Table 1 summarizes the application of RSM for biofuels in ICEs. Among them, bioalcohol and biodiesel have received increased attention due to their potential to be produced from inexpensive resources and their ability to reduce harmful emissions significantly.

4. Limitation of RSM

Extensive research has revealed the effectiveness of RSM as a prediction and optimization method. However, it is important to remember that RSM is a black-box approach in which the approximation accuracy is difficult to estimate. Although it can detect the effects of independent input variables, RSM is unable to justify why an interaction occurs as there is no definite knowledge of the true relationship between an input variable and the response. However, it is worth noting that the effect of variable input combinations on the responses can be understood since the model equation will be generated to describe the behavior of the system.

A detailed explanation of the difference between black-box, grey-box, and white-box models is illustrated in Fig. 10. In statistics or mathematical modelling, a grey box model is a combination between data and a partial theoretical structure. Different from the black box

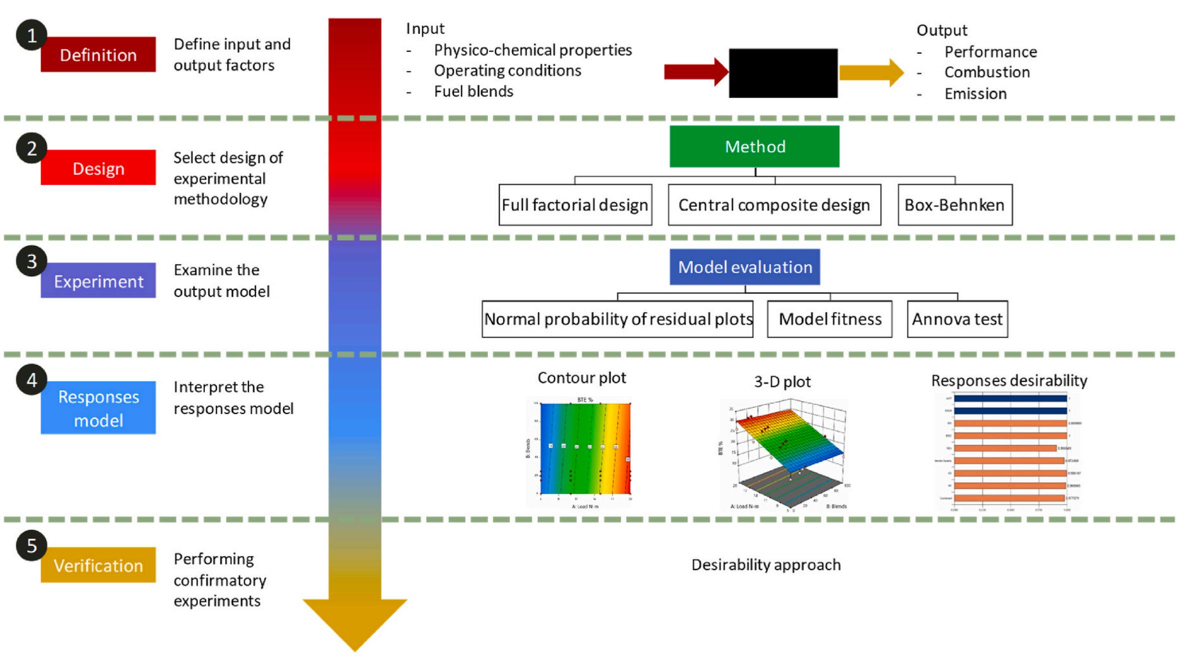

Fig. 9. RSM flowchart for ICE-powered with biofuels.

Table 1
Summary of significant recent studies of RSM for biofuel in ICE.

Fuel	Engine	RSM design	Software	Input/factor	Output/response	R^2	Validation results	Authors [Ref.]
Iso-butanol-diesel blends	Single cylinder, 17.5:1 CR, 661 cc N/A DI CI engine	3 × 3 full factorial design	Design Expert	3 - Injection pressure, injection timing, and EGR rate	5 - NO_x, smoke opacity, CO_2, BSFC, BTE	–	Error ≤3.41%	Saravanan et al. [77]
n-octanol-diesel blends	Single cylinder, water cooled 17.5:1 CR, 661 cc DI CI engine	3 × 3 full factorial design	Design Expert	3 - Blend composition, injection timing, EGR	4 - NO_x, smoke BSFC, BTE	$R^2 \geq 0.9258$	Error ≤3.59%	Gopal et al. [95]
n-propanol-diesel, n-butanol-diesel and n-pentanol-diesel blends	Single cylinder, water cooled, 17.5:1 CR, 661 cc, N/A DI CI engine	3 × 3 full factorial design	Design Expert	3 - Injection timing, EGR rate, alcohol type	6 - NO_x, smoke opacity, BSFC, BTE, HC, and CO	–	Error ≤6.01%	Krishnamoorthy et al. [96]
Fusel oil-gasoline blends	Four cylinders, 9.5:1 CR, 1.834 L, SOHC N/A PFI SI engine	–	Design Expert	3 - Load, speed, fuel %	4 - brake power, BSFC, CO, NO_x	$R^2 \geq 0.7261$	Error ≤5.60%	Abdalla et al. [80]
Fusel oil-gasoline blends	Four cylinders, 9.5:1 CR, 1.834 L, SOHC N/A PFI SI engine	–	Design Expert	3 - Load, speed, fuel %	6 - BP, BSFC, TE, NO_x, HC, and CO	–	Error ≤5.00%	Awad et al. [97]
Sunflower, soybean biodiesel blends	Single cylinder, N/A, DI water-cooled CI engine.	Box-Behnken and Central composite design	Minitab 17	2 - Engine load and blend %	3 - BTE, UHC, NO_x	–	Error ≤3.34%	Elkelawy et al. [98]
Canola, safflower, and waste vegetable biodiesel blends	Single cylinder, 296 cc, N/A DI air-cooled CI engine	Central composite design	Minitab	3 - Biodiesel ratio, injection pressure, engine load	5 - EGT, BTE, CO_2, NO_x, smoke	$R^2 \geq 98.31$	Error ≤7.26%	Simsek and Uslu [68]
2-ethylhexyl nitrate (EHN)-biodiesel (canola, safflower, and waste vegetable) blends	Single cylinder, 296 cc, N/A DI air-cooled CI engine	Box-Behnken design	Minitab	3 - Biodiesel ratio, EHN ratio, load	6 - BTE, BSFC, CO, HC, NO_x and smoke	$R^2 \geq 92.36$	Error ≤4.57%	Simsek and Uslu [99]
Iamyl alcohol (isopentanol)-gasoline blends	Single cylinder, 8.5:1 CR, 196 cc, air-cooled SI engine	–	Minitab	3 - CR, fuel ratio, engine speed	6 - BMEP, BTE, BSFC, NO_x, CO, HC	$R^2 \geq 0.906$	Error ≤7.58%	Uslu and Celik [100]
Hydrogen and Lemon Grass Oil (LGO) biodiesel blends	Single cylinder, 16.5:1 CR, 553 cc, water-cooled CI engine	Factorial design with 13 × 6 tests	Minitab	3 - Load, LGO, hydrogen %	6 - BTE, BSFC, CO, NO_x, HC, opacity	$R^2 \geq 95.72$ with an exception of 46.39 for BSFC	Error ≤4.69%	Hariharan et al. [101]
Cassia tora biodiesel-diesel blends	Single cylinder, 17.5:1 CR, 0.661 L DI CI engine	Central composite rotating design (CCRD)	Minitab	4 - Blends, load, injection timing, injection pressure	3 - BTE, UHC, NO_x	–	Error ≤4.65%	Singh et al. [102]
Pongamia biodiesel blends	Single cylinder, 17.5:1 CR, 0.661 cc DI CI engine	Central composite rotating design (CCRD)	Minitab	5 - Blends, load, injection timing, injection pressure	4 - BTE, UHC, NO_x	–	Error ≤4.95%	Singh et al. [103]
Honge biodiesel-diesel blends	Single cylinder, water cooled, CI engine	Central composite design	Minitab	4 - Engine load, Honge methyl ester blend %, CR, injection timing	2 - BTE and NO_x	–	Error ≤3.50%	Kumar et al. [35]
Waste biomass pyrolysis biodiesel (*Calophyllum inophyllum*) blends	Single cylinder, 17.5:1 CR, water-cooled DI CI engine	3 × 3 full factorial design	Minitab	3 - CR, fuel concentration, load	7 - BTE, BSFC, CO CO_2, HC, NO_x, smoke	$R^2 \geq 0.90$	Error ≤1.58%	Sakthivel et al. [104]
Karanja biodiesel–diesel blends	Single cylinder, 12:1–18:1 CR (VCR), water-cooled CI engine	3 level factor design	Design Expert	2 - CR, fuel fraction	6 - BTE, BSFC, CO, CO_2, HC, NO_x	–	Error ≤9.00%	Sivaramakrishnan [105]
Polanga-ethanol-biogas blends	Single cylinder, 17.5:1 CR, 661 cc, DI CI engine	–	Minitab	4 - Fuel mode, engine load, engine speed, air flow rate	6 - BTE, VE, EGT, NO_x, CO and HC	–	Error ≤9.50%	Sharma et al. [106]
Nicotiana Tabaccum biodiesel blends	Single cylinder, 17.5:1 CR, 661 cc, DI CI engine	Central composite rotating design	Minitab	4 - Blends, load, injection timing, injection pressure	4 - BTE, HC, EGT, Pmax	–	Error ≤5.70%	Sharma et al. [106]
Diesel, waste plastic oil (WPO), WPO-*n*-pentanol, WPO-*n*-	Single cylinder, 17.5:1 CR, 661 cc, water cooled DI CI engine	3 × 3 full factorial design	Design Expert	3 - Injection timing, EGR rate, alcohol type	3 - NO_x, smoke opacity, BSFC	–	Error ≤5.58%	Damodharan et al. [107]

(*continued on next page*)

Table 1 (*continued*)

Fuel	Engine	RSM design	Software	Input/factor	Output/ response	R^2	Validation results	Authors [Ref.]
hexanol, WPO-*n*-octanol blends								
Plastic and castor oil biodiesel blends	Single cylinder water cooled N/A VCR engine	Box-Behnken design	Minitab	3 - Blend, CR, load	5 - BSFC, BTE, HC, CO, NO_x	$R^2 \geq 99.26\%$	Error ≤4.40%	Mohamed et al. [108]
Hevea brasiliensis biodiesel blends	Single cylinder, 18:1–22:1 CR (VCR) DI CI engine	Full factorial design	–	4 - CR, load, biodiesel blends %, injection pressure	6 - CO, HC, CO_2, NO_x, BTE, BSFC	$R^2 \geq 0.9873$	Error ≤16.24%	Murugapoopathi et al. [109]
Argemone Mexicana biodiesel-diesel blends	Single cylinder, multi-fuel VCR engine	D-optimal	Minitab	3 - Load, CR, blend	5 - BSFC, BTE, CO, HC, NO_x	$R^2 \geq 0.952$	Error ≤5%	Parida et al. [110]
Jatropha curcas shell biodiesel blends	Single cylinder, 661 cc, VCR engine	Central composite design	Design Expert	3 - CR, load, blend	5 - BTE, BSFC, UHC, CO and CO_2	$R^2 \geq 0.6904$	–	Patel et al. [111]

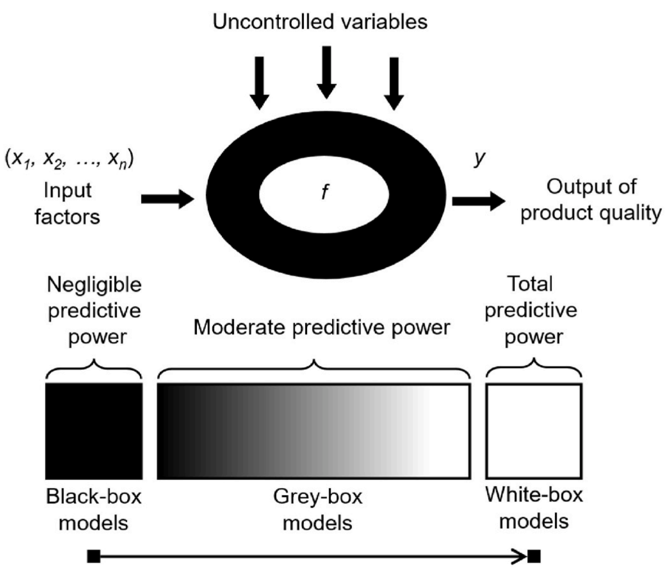

Fig. 10. Difference between black-box, grey-box, and white-box models, reproduced from Ref. [56].

model, a grey box model is correlated with several physical attributes of the systems. Note that nearly all models are grey box contrasted with a black-box model in which no model form is presumed or white box models that are totally theoretical.

One major limitation of RSM is its local analysis, meaning that the studied response surface cannot be applied to other regions outside the developed ranges of factors. RSM may give poor results in predicting the outcome of a system other than the investigated range of study. Curvature is another issue. If a system contains curvature that cannot be fitted to a second-order polynomial, the RSM will give poor results. In this case, the range of independent input variables must be reduced to improve the accuracy of the model. It is also important to remember that RSM cannot be applied to the data obtained from experiments that have been conducted before, as the regression model will not give significant results. Data point selection is, therefore, an essential stage in the RSM. Different data points will give a different approximation. Thus, in order to develop the RSM model, the experimental data need to be collected according to the DOE methods.

As far as the selection of response surface design is concerned, the majority of previously published studies did not clearly explain why certain response surface design is selected. FFD is relatively expensive and time-consuming. Therefore, in many cases, FFD is not preferable as it has numerous unnecessary runs in order to fit the model. For that reason, a fractional design could be the option. It is a design where only a certain subset (fraction of the runs) is selected from the FFD. With fewer runs, a fractional factorial design is a good option especially when resources are limited or when there are too many numbers of factors in the design. However, bear in mind that a number of important effects and two-way interactions can be confounded, thus making it impossible to be detached from the influences of other higher-order interactions. To solve this issue, higher-order effects are often assumed to be negligible, so that the information about the important effects and low-order interactions using fewer runs can be achieved.

BBD and CCD are the other two major response surface designs. CCD can incorporate data from a properly prepared factorial experiment, while Box-Behnken cannot include runs from a factorial experiment. BBD is not based on full or fractional factorial designs and needs three levels for each factor. On the other hand, the CCD can possess up to five levels per factor, unlike Box-Behnken, which always has three.

Note that the design selection relies both on the factors and the factor levels considered in the experimental design. In general, CCD has more features than BBD. However, for three or fewer input variables (factors), the BBD is more beneficial than the CCD method because fewer experiment runs are needed. However, for four or more input variables, this advantage disappears. In CCD, the values of factor levels are low and high settings for the cube portion of the design, not the design's minimum and maximum values. The axial points are typically out of the cube. If an α is not specified ≤1, this could cause axial points to be outside the region of concern or may be unfeasible to do.

Almost every published article that has been written on the application of RSM for biofuel includes a section relating to validation or confirmatory tests. However, some studies seem to forget to include the errors analysis indicating a discrepancy between the predicted optimized values and the real validated experimental results. Also, in view of all studies that have been mentioned, it seems that the application of RSM for biofuels and ICE application is mostly undertaken in Asian countries, such as India, Malaysia, and Turkey. To date, there has been very little published research on its application in European or American countries.

Thus far, much of the RSM research for ICEs has been repetitive. Although many reports have been published on the use of RSM, most are restricted to optimizing the same output response again and again, such as BTE, BSFC, CO, CO_2, HC, and NO_x. Most of the previous studies of RSM have also suffered from a paucity of standardized measures to set the acceptable error values. Within what range the errors can be accepted is not well defined and standardized.

In the application of RSM to ICEs, it is essential to recognise the potential occurrence of incomplete or insufficient data. There are a number of reasons that cause such limitation, namely empirical limitation, inaccessible or unmeasurable parameters, instrumentation errors, and safety issues. The process of conducting experiments on ICEs can incur significant expenses, require a substantial amount of time, and demand a considerable allocation of resources. The empirical limitations have the potential to constrain the quantity of experiments that can be conducted or the extent of operating conditions that can be investigated. Consequently, the experimental dataset may lack specific data points or combinations of variables.

Certain parameters or variables that are pertinent to the functioning and emissions of internal combustion engines (ICEs) may pose challenges in terms of direct measurement or accessibility, causing them either inaccessible or unmeasurable. Internal parameters such as cylinder pressure or combustion characteristics may pose difficulties in terms of precise and non-invasive measurement. The aforementioned circumstance may result in the absence of data pertaining to said variables within the experimental dataset. Experimental measurements are susceptible to a range of errors, uncertainties, and limitations associated with instrumentation. Occasionally, technical difficulties or equipment malfunctions may result in the absence or questionable validity of certain data points. In instances of this nature, it is necessary to meticulously evaluate the calibre and authenticity of the accessible data.

It is important to consider safety when conducting ICE experiments because of the use of high-pressure, high-temperature, and hazardous settings. The exploration of operating conditions may be limited by safety protocols and constraints, resulting in the absence of data points in specific areas of the parameter space. The management of absent or deficient data in response surface methodology (RSM) necessitates meticulous deliberation. A potential methodology involves the utilization of statistical methodologies, such as imputation or regression, to approximate the absent data points by leveraging the information present within the accessible dataset. An alternative approach involves formulating supplementary experiments aimed at addressing the deficiencies in the dataset, with emphasis on the areas or parameters that are absent but deemed significant.

It is essential to acknowledge that the existence of incomplete data may give rise to probable partialities or ambiguities in the RSM examination and enhancement procedure. It is imperative for researchers to exhibit transparency regarding the constraints of the dataset and the plausible ramifications of absent data on the inferences derived from the investigation. The implementation of sensitivity analyses and robustness checks can facilitate the evaluation of the impact of incomplete data on the outcomes of Response Surface Methodology (RSM). In order to effectively address the matter of absent or deficient data in ICEs for RSM, it is imperative to engage in meticulous experimental preparation, data acquisition, and analysis methodologies to guarantee dependable and precise modelling of the response surface and optimization results.

5. Concluding remarks for RSM

There are numerous factors influencing engine performance, combustion, and emission characteristics. These include fuel percentage, engine load, speed, injection timing, and pressure. Therefore, it is essential to optimize those factors in order to minimize the cost of the experimental process.

- Compared to conventional experimental methods where only a variable is examined at a time, thus requiring a huge number of experimental data and costly experimental runs, RSM can generate considerable information from a smaller number of experiments to lower the experimentation cost.
- Instead of searching for the optimum response within a sizable number of randomly generated possible solutions, RSM simplifies the experimental designs and reduces the experimental runs to obtain a comprehensive interpretation of the system and achieve the best possible solution with the least combinations of input variables. The effect of variable input combinations on the responses can be understood since the model equation will be generated to describe the behavior of the system.
- It is common in the literature to present the optimized operating conditions as a set of inputs (factors) and verify these values with a set of experiments. Modern engines aim to achieve higher engine performance and more efficient combustion with near-zero emission without expensive additional equipment such as after-treatment systems. Therefore, optimization methods, such as RSM, have become more important in automotive technology.
- Moving forward, the use of RSM in automotive technology can be improved by combining it with other optimization approaches, using the power of sophisticated computing, and exploring new experimental designs customised for RSM. This would allow researchers to overcome some of RSM's limitations while relying on its virtues. Finally, the continuing usage and improvement of RSM will lead to the creation of more efficient, ecologically friendly, and cost-effective engines and cars, assisting in addressing the automotive industry's critical difficulties.

Compared to other DOE approaches, RSM has been systematically employed for ICE fueled with biofuels in the last two decades. The present article reviews the important work on the design and optimization of biofuel in ICE using RSM. Although it has drawbacks such as extrapolation inaccuracy outside the investigational ranges and discrete variables error, RSM has numerous advantages to offer. Previous studies discussed above have shown that RSM can be utilized successfully to design, model, estimate, and optimize biofuel for ICE applications with satisfactory accuracy.

6. Challenges and opportunities of RSM

In the context of internal combustion engines (ICE) and biofuels, the application of Response Surface Methodology (RSM) presents both challenges and opportunities. The complexity of ICE and their interactions with biofuels, which may contribute to inaccuracies in the generated response surfaces, is one of the obstacles. In addition, RSM is sensitive to the experimental range within which the input variables are examined, and extrapolation beyond this range can lead to inaccurate predictions. In addition, RSM is better adapted for continuous variables, and its performance may suffer when dealing with discrete or limited-value variables. Nonlinear relationships between input variables and system responses, which are prevalent in ICE and biofuel systems, can be challenging for RSM to effectively capture.

There are numerous opportunities for RSM in ICE and biofuel applications despite these obstacles. Integration of RSM with other optimization techniques, such as genetic algorithms, particle swarm optimization, or machine learning approaches, can enhance the optimization process' precision and robustness. In addition to biofuels, RSM can be applied to a wide variety of engine types and fuels, allowing for more thorough investigations into engine performance and emissions optimization. The development of novel experimental designs tailored specifically for RSM in ICE and biofuel applications can aid in overcoming its limitations, such as discrete variable and nonlinearity issues.

Implementing RSM for real-time optimization of engine performance and emissions may become more feasible as computing power continues to increase, providing significant benefits for vehicle efficiency and emissions control. In addition, the use of RSM to optimize the performance of ICE and biofuels can contribute to the development of more environmentally favorable and sustainable transportation solutions.

While the use of RSM in ICE and biofuel applications presents challenges, the opportunities presented by this methodology, especially when combined with other optimization techniques and advances in experimental design, can significantly contribute to the comprehension and optimization of engine performance, emissions, and fuel efficiency.

7. Research gap for RSM future studies

Generally, three aspects should be evaluated comprehensively in

ICEs. They are engine performance, combustion, and emissions characteristics. However, it is not easy to find the application of RSM to optimize engine combustion parameters. Most studies tend to focus on engine performance and emission only. Several engine combustion behaviors need further investigation, such as maximum in-cylinder pressure, start of combustion, combustion noise level, knock, and misfire events. It is possible to quantify numerous characteristics utilising response surface methodology for optimization.

In RSM, variables are typically selected based on their ability to influence the system's response. The number of variables that can be incorporated in the optimization process is limited only by the examined system's complexity and the number of experimental runs that can be conducted. To quantify the variables, it is required to measure them using appropriate experimental methodologies and record the results of each experiment. The experimental runs' data are then utilized to fit the polynomial equation to the response data and determine the optimal combination of variable values. To guarantee that the ideal portion of the response surface is appropriately sampled, it is necessary to meticulously prepare the experimental design and the range of variables. This will ensure that the optimization process identifies the optimal combination of variable values in an efficient and effective manner.

Regarding engine performance, fuel economy is one of the most important engine performance parameters that need to optimize. A number of approaches have been proposed, such as engine downsizing, variable compression ratio, and lean-burn engines. However, only the optimization of the VCR engine can be found in the literature using RSM. The use of RSM tends to exploit conventional engines such as naturally aspirated SI and CI engines. Modern engines equipped with a turbocharger or advanced lean-burn combustion technology such as HCCI, PCCI, and RCCI that suffers from performance-emission trade-off are rarely investigated. This is where the RSM can play an important role in solving such a problem.

As for the emission characteristics, PM or soot emission is the major concern of CI engines. The use of bioalcohol and biodiesel, due to their oxygen content, can significantly reduce such emissions. However, PM is sometimes not reported and not taken into account as the output response. Considering the NO_x-PM trade-off in diesel engines, both emissions should be given high priority to be optimized. It is problematic to decrease NO_x and PM emissions simultaneously due to the diffusion combustion in diesel engines. In addition to regulated emissions, the effects of several other compounds, such as carbonyl compounds (formaldehyde, propionaldehyde, acetaldehyde, and acetone) or known as the unregulated emission, are worth investigating.

Author contributions

Conceptualization, I.V., and M.S.; methodology, I.M.R.F.; formal analysis, I.V.; investigation, M.I., I.M.R.F. and M.S.; resources, I.V. and M.S.; data curation, I.M.R.F. and M.I.; writing—original draft preparation, I.V., and M.I.; writing—review and editing, M.S. and M.I.; visualization, I.V., I.M.R.F. and M.I.; supervision, I.V. , and M.S.; project administration, M.I. All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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