Optimization of Performance and Emission Responses for a CIE Run by Meoh/Biodiesel/Diesel Blends Utilizing Response Surface Methodology

Duraid F Maki¹, Ahmed Sh Yasiry² and Haroun A K Shahad¹
¹ Mechanical Engineering Department, College of Engineering, University of Babylon, Hilla, Babylon, Iraq
² Mechanical Engineering Department, College of Engineering- Almussaib, University of Babylon, Hilla, Babylon, Iraq
E-mail: eng.duraid.f@uobabylon.edu.iq

Abstract. The response surface methodology - central composite design matrix (RSM-CCD) is applied to make experiment design and response optimization for CIE engine fueled by different methanol-biodiesel-diesel blending ratios. The 5% biodiesel has enhanced methanol-diesel miscibility by about twelve folds. A full factorial design is employed to build the experimental tests of the performance and exhaust emissions for CIE run by methanol/biodiesel/diesel fuel. The statistical tests are used to check the significance of models by p-value test, adeq. Precision test, Predicted R², and adjusted R². With a maximum error of 6%, models of the BTE, CO, UHC, CO₂, and NOₓ are showed a good agreement between predicted and experimental results. The optimization indicated that engine load is a master input factor affecting the responses.

Keywords. Methanol miscibility, Response surface methodology, Central composite design, Compression ignition engine.

1. Introduction
For more than one century and still, the compression ignition engine (CIE) occupies a prominent place in the world of power generation, transportation, agriculture, and others. This privileged position derives its strength from identifying factors such as the fuel economy, high torque production, longer engine life span, and immense strength and durability. Thus, the (CIE) is quite reassuring and has an increasing demand [1]. The threats facing fossil fuels from the expected depletion of its sources, the pessimistic outlook for its future production, and the strict emissions conditions set by countries obliged the experts and decision-makers to reconsider CIE's fossil diesel and searching for viable alternatives to it. The most effective and influential solution is to utilize fuel with little damage to the environment and more sustainability. Many alternatives to fossil diesel are studied and tried, such as hydrogen, biodiesel, biogas, and alcohol. Methanol is one of these alternatives, and is a renewable, clean, and promising biofuel. Methanol is qualified as CIE fuel due to its low C/H ratio, high oxygen content, and other properties. The methyl alcohol, carbinol, wood's alcohol, and MeOH are names of a chemical component with a formula of CH₃OH. Nowadays, MeOH is manufactured by treating
the CO with hydrogen or natural gas for commercial purposes [2]. The simplest and lowest alcohol has multilateral, light, volatile, no color, combustible, toxin, antifreeze, polar solvent, and it smells like liquor. Furthermore, methanol is a very versatile material used as a raw material for the manufacture of other widely used chemicals, such as methanal, ethanoic acid, methyl tertiary butyl ether, as well as a group of particular chemical materials [2–4]. The methanol (methyl alcohol) and ethanol (ethyl alcohol) are high comparable but have some differences. They belong to the same alcoholic family where ethanol is mainly prepared for fermenting sugary and starchy materials. Meanwhile, methanol is produced from methane gas, coal, and biomass. Methanol differs from ethanol in the number of atoms, and this difference leads to slight variations in their properties, such as a low air-fuel ratio [5-6]. Table 1 gives the characteristics of methanol and other fuels subjected to this study. From table 1, methanol has useful features as promising fuel for auto mobilization, such as higher octane number, a good conversion efficiency comparing to other fuels because of the anti-knock part, and higher vaporization heat.

| Property                        | Diesel[1,7]                  | Methanol[1,7]                 | Biodiesel [8]       |
|---------------------------------|------------------------------|------------------------------|---------------------|
| Chemical formula                | C_{14}H_{28} (average)       | CH_{3}OH                      | -                   |
| Density (g/cm³) at 20 °C        | 0.840                        | 0.792                        | 897                 |
| Molecular weight (g.mol⁻¹)      | 170                          | 32.04                        | N/A                 |
| Kinetic Viscosity at 40 °C (mm²/s) | 2.72                      | 0.58                         | 4.68                |
| Solubility (g/L)                | Immiscible                   | Miscible                     | Immiscible         |
| Flame speed rate (cm/s)         | 33                           | 34                           | N/A                 |
| Flash point (°C)                | >55                          | 11                           | 50.9                |
| Boiling temperature (°C)        | 170-340                      | 64.5                         | 200                 |
| Auto ignition temperature (°C)  | 180-240                      | 464                          | 270                 |
| Calorific value (MJ/kg)         | 44.5                         | 23.8                         | 33.75               |
| Cetane number                   | 50-55                        | 3                            | 54                  |
| Octane number                   | N/A                          | 92                           | N/A                 |
| Stoichiometric AFR              | 14.6 / 1                     | 6.4 / 1                      | N/A                 |
| Carbon content (wt%)            | 87.4                         | 37.5                         | N/A                 |
| Oxygen content (wt%)            | 0                            | 49.93                        | N/A                 |
| Hydrogen content (wt%)          | 14                           | 12.5                         | N/A                 |

Studies showed that methanol could be used in spark-ignition engines (SIE) and compression ignition engines (CIE). Methanol is suitable for SIE engines and gained successful results as substitution fuel due to its properties (i.e., high octane number, high flame speed, solubility, etc.). Consequently, there were strong tendencies toward using the methanol as a supplementary fuel in the CIE. Although there are some drawbacks, the Methanol-diesel blend has double profits as; reduces the emissions of fossil carbons and replacing conventional fuel with sustainable biofuel. However, researchers and experts focused on the auto-ignitability problem of methanol due to its low cetane number. The summarization of the proposed solutions of a methanol-diesel self-ignitable obstacle is listed [7]:

1. Add a substance as an ignition enhancer to the mixture of methanol and diesel.
2. Add spark plug (spark-assisted ignition).
3. Inject the methanol (liquid) directly into the combustion chamber.
4. Inject the fumigate methanol (gas) in the engine intake.
5. More recently, use homogeneous charge compression ignition (HCCI) mode and partially premixed combustion mode.

Many ignition improvers and co-solvents are utilized as additives to prevent the self-ignition and solve another drawback represented by the methanol-diesel blend miscibility. These enhancers are n-butanol, biodiesel, iso-
butanol, dimethyl ether (DME), and dimethoxymethane (DMM) [7–12]. Numerous researchers investigated methanol in different ways in SIE and CIE with different alternatives fuels. In these experiments different experimental parameters have been tested to study the performance and/or the emission of engines such as methanol-gasoline [13–15], methanol-hydrogen [16–18], methanol-diesel [19–22], methanol-biodiesel [23–25], methanol-DME (dimethyl ether) [26, 27], methanol-LPG [28–30], methanol-water [31, 32], methanol-ethanol-gasoline [33, 34], methanol-ethanol-diesel [35] and the final blending is the methanol -diesel- biodiesel. As far as this work, there is no research indicating the use of biodiesel made from cooking oil used as a co-solvent with methanol-diesel blends. Adding methanol to diesel at different blending ratios caused a sensible change in engine performance and emissions. Therefore, it is imperative to use optimization techniques to find the optimal methanol-diesel blend values that give the maximum engine efficiency and minimum emissions. Typically, the optimization techniques are applied to find the maximum and minimum values of experimental test output. The combustion process in the CIE is a complex detailed assessment. However, the optimization techniques are useful in building models. Those models can sufficiently initiate the regression equation of how output responses take out, as a result, to change the input factors by depending on experimental results. Different techniques are used to find optimization. Some of these optimization techniques adopted the statistical analysis. The response surface method (RSM) and the Taguchi method are used.

Apurba Pathak at el. [15] adopted Taguchi’s technique as an optimizer to find the best value for five output parameters. It is a multi-objective optimization process to obtain the minimum of brake specific fuel consumption (BSFC), carbon monoxide (CO), and unburned hydrocarbons (UHC). This experimental research considers the compression ratio, spark timing, engine load, and air/fuel ratio as control variables. The analysis of variance (ANOVA) was carried out to find significant and contributing governor parameters. The models had consistent results in predicting the output/input relation. Omar I. Awad at el. [16] used the response surface methodology in the form of multi-objective to find the maximum brake power (BP), Brake thermal efficiency (BTE). Consequently, minimize the brake specific fuel consumption (BSFC), nitrogen oxides (NOx), unburned hydrocarbon (UHC), and monoxide of carbon (CO) in a spark-ignition engine (SIE). The model considered the variation in oil/gasoline mixture ratio, throttle valve opening timing, and engine speed to control the output. This experimental study gave high compatible results in optimization. C. Esonye et al.[17] carried out experimental work to find the optimization of biodiesel production from the sweet almond. The response surface method (RSM) depends on the central composite design (CCD) was selected as an optimizer. Another optimization model is built by an artificial neural network (ANN) technique. Considerably, the temperature, catalyst concentration, reaction time, and oil/methanol molar ratio as input. The results showed that optimized biodiesel of 94.36% from the RSM and 95.45% from the artificial neural network models.

The response surface methodology (RSM) technique used the central composite design (CCD) aggregation by k. N. Krishnamurthy at el. [18] to estimate the gathering of catalyst concentration, methanol molar ratio, temperature, and reaction time that produced the highest biodiesel. The predicated models proved high compatibility with the experimental works for two types of raw oils. Nadir Yilmaz at el. [19] utilized the RSM and least-squares support vector machine (LSSVM) for modeling the relations between engine performance and exhaust emission parameters. The model considered the BP, BSFC, BTE, exhaust temperature, NOx, CO, CO2, and smoke opacity as responses. A marginal difference found between the RSM technique model result and the LSSVM technique model result, where the LSSVM showed good results. T.Ganapathy et al. [20] proposed Taguchi’s optimization method to find the best of the output parameters. This methodology predicted Weibe's heat release constants, combustion zone duration, and the CIE compression ratio fulled by jatropha biodiesel. The critical parameters that affect the performance of the engine compared to other parameters. Vezir Ayhan et al. [21] used the Taguchi method to predict the output parameters for direct injection diesel engine fueled corn oil methyl ester (COME) and diesel along with exhaust gas recirculation different ratios. The analysis of variation occurred for the model results. The optimum values of engine performance and exhaust emissions responses depend on this technique
were calculated. On the other hand, programmatic techniques that rely on programming algorithms are concerned with optimization. The statistical methods have proven their ease and simplicity in treating the optimization issue compared to programming optimization techniques. However, the mathematical programming techniques depend upon algorithms such as fuzzy theorem, artificial neural network, and genetic algorithm to optimize design response parameters. They need many experiments to provide much data to learning or training the networks of inputs and outputs. Furthermore, high computational resources, storage, and computational time are required. In 1951, Box and Wilson introduced the RSM as a statistical technique to optimize responses (outputs). This methodology took a sequence of studied experiments to obtain optimal responses and built a mathematical equation using a second-degree polynomial model. The model settles for a limited experiment number, which leads to saving the time and the cost, and it works even when a little knowledge about the type of relation between factors and responses.

This research has different aims. The first aim is to solve the problem of miscibility of methanol - diesel by adding 5% biodiesel to the blends and measuring the time of blend stability. Biodiesel can be served as an ignition improver and improves the miscibility of methanol in diesel. The biodiesel is produced in the Mechanical Engineering Department laboratories at the University of Babylon from local Iraqi waste cooking oil. Table (2) gives the methanol-biodiesel-diesel volume fractions based on one liter of fuel used for testing. The second aim is to investigate experimentally CIE thermal performance and exhaust emissions fueled by neat diesel and different methanol-diesel blends. The experiments designed to assist the third part of this research in assigning the optimum response. Finally, the third aim to utilize the RSM technique for optimizing thermal performance and exhaust emissions. The factors or the input parameters that affected the engine's response are the loads and the methanol ratio in blends. The BTE, CO, UHC, CO2, and NOX presented the engine responses or output parameters.

2. Work methodology and experimental setup

The experimental work is divided into three parts; the first part studies – experimentally – the enhancement of methanol solubility in diesel fuel to form a homogenous blend. The second part investigates the methanol influence on the CIE's thermal performance and exhaust gas constituents, while the third part addresses the optimum modeling procedures.

2.1. Miscibility of methanol-diesel blends

Numerous researchers mentioned that the MeOH/diesel mixing phase's instability is profoundly affected by the temperature of the mixture, the water content in methanol, and the aromatic methanol chain [25-28]. Experiments have investigated the stability of the methanol-diesel mixture alone and 5% by volume biodiesel. The test is carried out by stirring 900 ml of diesel with 100 ml of methanol (purity is 99.5%). Table (2) gives the methanol-biodiesel-diesel volume fractions based on one liter of fuel used for testing. Keep the mixture in a glass tube and watch the time taken for the complete separation of methanol and the diesel. The time is recorded using a stopwatch. The same experiment is then repeated by mixing 850 ml of diesel with 100 ml methanol and 50 ml of biodiesel and recording the time of diesel methanol separation. Table 3 shows the periods of stability for methanol-diesel and methanol-biodiesel-diesel blends, respectively, before the split. For abbreviation, methanol/biodiesel/diesel symbolled as MBD.

2.2. Methanol influence on thermal performance and exhaust gas emissions

A naturally aspirated CIE was nominated to achieve all experimental tests to investigate the MeOH/Biodiesel/Diesel effects on the combustion characteristics represented by the engine's thermal performance and its exhaust constituents. Table 4. illustrates the experimental setup details and specifications. The machine is coupled with an eddy current dynamometer to measure the engine's torque and rotational speed. Both CIE and dynamometer are fixed on a rigid chassis frame with suitable water-cooling and wiring systems. A digital fuel flow transmitter is applied to read the fuel consumption
rate. The digital airflow sensor and thermometer type PT-100 introduced to measure the quantity of airflow rate passing through the engine intake manifold and measure the exhaust temperature. The data acquisition system built to gather and transfer all digital signals to the computer. The computer presents the data in the form of excel file tables. Finally, the exhaust gas emissions are collected and analyzed by the BOSCH gas analyzer. However, CO, UHC, CO₂, and NOₓ are measured. Figure 1 illustrates the experimental setup contains.

Table 2. Fuel fractional ratios and name of each blend.

| Diesel (vol.%) | Methanol (vol.%) | Biodiesel (vol.%) | Name of blend* |
|---------------|-----------------|------------------|----------------|
| 1             | 100             | 0                | M0B0D100       |
| 2             | 85              | 10               | M10B5D85       |
| 3             | 75              | 20               | M20B5D75       |
| 4             | 65              | 30               | M30B5D65       |

*M: methanol, D: diesel, B: biodiesel.

Table 3. Results of methanol-diesel mixture miscibility.

| Type of blend* | Stability time (hr) |
|----------------|---------------------|
| M10D90         | 24                  |
| M20D80         | 10                  |
| M30D70         | 3                   |
| M10 B5D85      | 295                 |
| M20 B5D75      | 128                 |
| M30 B5D65      | 38                  |

*M: methanol, D: diesel, B: biodiesel.

Table 4. Engine details and specifications.

| Details            | Specifications                                           |
|--------------------|---------------------------------------------------------|
| Engine type        | Kirloskar AV-1                                         |
| General specification | single cylinder, four strokes, compression ignition,     |
| CR* range          | 12.5-18.5                                              |
| Engine power (hp / kW) | 5 / 3.7 at 1500 r.p.m                                   |
| Cylinder diameter (mm) | 80                                                  |
| Swept volume (cm³)  | 553                                                    |
| Cooling media      | Water                                                  |
| Fuel               | diesel                                                 |
| Rated speed (rpm)  | 1500                                                   |
| Injection timing   | 0 – 15 degree BTDC                                    |
| Method of Starting | Cold starting with the help of handle or electric      |
| Lubricating fluid  | 5W-30                                                   |

*C.R.: compression ratio
2.3. Utilizing the response surface method (RSM)

When the research compass indicates an action like optimization of experiments responses with an easiest and simple precise method, the RSM technique comes to the selection process interface. Since discovering the response surface method, it occupies a prominent place in the optimization field because it uses the minimum number of experiments based on the combination of mathematical and statistical techniques. Hence it is an optimizing tool saving effort, time, and money. Central composite design (CCD) is employed as a nonlinear statistical method with one variable or more, and its independent variables impact the sorption process. The central composite design included $2^n$ factorial runs and $2n$ axial runs where $n$ is the experiment input factors and $n_c$ center runs. The center points determine the experimental error and how well the data can be reproduced. The axial points are taken to assure the ratability, and the model prediction variance is constant at every point equidistant from the center of the design. Table (5). gives the factors (input) and their levels.

**Table 5.** Experimental factors and their levels.

| Factors             | Code | Levels of experiments |
|---------------------|------|-----------------------|
| Engine load (W)     | A    | -alpha    | -1     | 0  | +1    | + alpha |
| Engine load (W)     | A    | 512.75    | 875    | 1750 | 2625  | 2987.25 |
| Methanol ratio (%)  | B    | 6         | 10     | 20  | 30    | 34      |
| Methanol ratio (%)  | B    | 6         | 10     | 20  | 30    | 34      |

*Alpha $= \sqrt{2}$

In this work, a full factorial approach is used to build the test model where a thirteen experiments trail is selected for this purpose. The experiments aimed to improve the engine thermal performance, i.e., maximize the BTE and minimize engine emissions CO, UHC, CO$_2$, and NO$_X$. Therefore, the RSM model target is to find an approximate mathematical relationship (function) between the responses (output) and independent variables called the experiment input or factors. The fitting of the relation between the input variable named engine load and methanol blending ratio with the experiment responses represented by BTE, CO, UHC, CO$_2$, and NO$_X$ is achieved by using a second-order polynomial equation, as shown in the
equation below:

\[ Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_i^t X_i^t + \sum_{j=1}^{k} \beta_j X_j + \epsilon \]  \hspace{1cm} (1)

After that, the models are subjected to a test of validation. The analysis of variance (ANOVA) gives a vital tool to assess the models and determine whether it is sufficient or not. Finally, the tested and valid models are utilized for further analysis, prognosing, and optimization. Design Expert 12 is software that was developed commercially to estimate the optimization based on response surface methodology, including analysis of variance ANOVA and validation test and optimization.

After complete building of the models using RSM, the tests of validation are compulsory. The calculation of ANOVA gives a sophisticated tool to test the sufficiency and precision of the model. The p-value is the first crucial test. According to ANOVA, p-value of the model coefficients has to be less than 0.05. Table (6) gives the values of p for each coefficient and each model. The p-value of any model coefficient above 0.1 is highlighted to indicate the insignificant in the model. The second test is adequate precision (adeq. precision). It means the measure of signal to noise ratio, and any rate greater than 4 is desirable, or the model has high prediction accuracy. The R², adjusted R² and predicted R² is the third test. The precision index is presented by R², adjusted R², and predicted R². The precision index test (fit statistics), whose results are shown in Table (7), is used to verify the model’s validity and reliability by knowing how close the model estimated results from the experimental results.

Table 6. The p-value test of models coefficients.

| Model coefficient | P-value |
|-------------------|---------|
|                   | BTE     | CO     | UHC    | CO2    | NOX    |
| The model         | < 0.0001| 0.0029 | < 0.0001| < 0.0001| < 0.0001|
| A-engine load     | < 0.0001| 0.0002 | < 0.0001| < 0.0001| < 0.0001|
| B-methanol ratio  | < 0.0001| 0.5309 | 0.0001  | 0.0065  | 0.5737  |
| A B               | 0.6908  | 0.9918 | 1.0000  | 0.2077  | 0.9780  |
| A2                | 0.0112  | 0.0251 | 0.0157  | 0.0001  | 0.0023  |
| B2                | < 0.0001| 0.4697 | 0.2256  | 0.4372  | 0.3418  |

Table 7. The precision index values of models coefficients.

| Model | Precision index values |
|-------|------------------------|
|       | R² | Adj. R² | Pred. R² | Adeq precision |
| BTE   | 0.9879 | 0.9792 | 0.9136 | 33.2323 |
| CO    | 0.8909 | 0.8129 | 0.2238 | 10.9895 |
| UHC   | 0.9951 | 0.9916 | 0.9651 | 54.1024 |
| CO2   | 0.9906 | 0.9839 | 0.9334 | 38.0612 |
| NOX   | 0.9781 | 0.9625 | 0.8446 | 25.1000 |

3. Results and discussions

3.1. The miscibility of methanol in diesel

Table 3 represents the periods of stability for methanol-diesel and methanol-biodiesel-diesel blends, respectively, before separation. It appears clearly that the addition of 5% of biodiesel to methanol-diesel blends enhanced the period of mixture stability by about twelve folds. It shows that the balance of the combination M10D90 is 24 hrs, while the balance of the blend M10 B5D85 is 295 hrs. The reasons behind it are weakly electrolytes and nonpolar molecules frequently have low methanol solubility. Thus, biodiesel worked as co-solvent, and the process is known as co solvency. The Cosolvent system works by reducing the interfacial tension between the methanol solution and diesel solute. These results are a very significant
improvement. The biodiesel worked as a co-solvent where it seems necessary because of the unideal inter-
solubility in the binary blends.

3.2. The RSM models

a. The BTE model: Table (6) presents the p-value of BTE model coefficients. The coefficients A, B, 
A^2, and B^2, are significant (p-value less than 0.05) whereas, A is the engine load, and B is the 
methanol ratio. It can be noticed that the interaction between A and B is less significant, where the 
p-value is greater than 0.1. Also, from the table (7), adeq. Precision is higher than four by many 
times (33.2323>>4). Wherefore the model is significant, and the prediction results are close to 
experimental results (the predicated R2 of 0.9136 is in reasonable agreement with adjust R2 of 
0.9792; i.e., the difference is less than 0.2). Figures 2-a and 2-b give the contour and 3D diagram 
for the variation of BTE with engine load and methanol ratio in the methanol-diesel blend 
respectively. As seen in figure 2-a, efficiency is increased with engine load. It is self-evident; the 
load increasing leads to an increase in consumption fuel, and that causes BTE to increase. The 
addition of methanol in methanol-diesel blends made the BTE increase. Methanol increment led 
to BTE increasing up to 20% methanol-80% diesel, where the maximum BTE is obtained. Then 
the BTE started reduction. The reason is that methanol has a short CV (23 kJ/kg) but has 50% 
oxygen in its content. The effect of oxygen availability enhancing the combustion till the 
methanol ratio reach 20.0% approximately. After that, the methanol caloric value appears and 
affects the BTE enhancing and starts to reduce.

Figure 2-a. The contour plot of the BTE model. Figure 2-b. The 3D surface plot of the BTE model.

b. CO model: It can be observed from table (4) that the significant CO model coefficients are the A: 
engine load and A^2. Values of p that greater than 0.1 indicate the model coefficient are not 
significant. Even though the B, B2, and interaction between A an B (AB) are not significant, the 
overall model coefficients are significant. The response surface contour and 3D plots are given in 
figures 3-a and 3-b, respectively. It can be inferred that the load engine has a minor effect on the 
CO formation. Whereas with load engine increment, the CO emission is increased due to the 
increase in fuel burning. As methanol increasing in the methanol-diesel blend, the appearance of 
CO is decreased due to methanol has low carbon content. At high load, this CO decrease is much 
than at idle load.
c. UHC model: The p-value for the UHC model shows that A, B, and $A^2$ are significant coefficients. Coefficients have values greater than 0.1 not significant. The model in overall is significant and primarily affected by the engine load factor. Table (6) represents the p-values of each model coefficients. UHC model has adeq. Precision greater than 4. Furthermore, the adjusted and predicted $R^2$ are very closed values; it indicates that model has a good prediction ability to the responses very well. Table (7) gives the precision index values. In figure (4), the contour drawing chart and 3-dimensional surface response chart are presented. Increasing engine loads led to an increase in UHC emission. Meanwhile, adding methanol caused a reduction in UHC formation, as shown in figure 4-a. At the same load, it is clearly observed that a significant decrease in the UHC emission due to decrease carbon in blending fuel, as represented in figure 4-b.
d. The CO₂ model: Table (6) shows the p-value of the CO₂ model's coefficient. The A, B, and A² are the significant coefficients in this model. Again the engine load is the primary factor influence the model. There is no desirable interface between A and B, where the p-value is 0.2077 and B² too. The model is significant and has a right response prediction, where adeq. Precision =38.06 higher than four, and the values of prediction R² and adjusted R² so close (difference less than 0.2), as shown in table (7). Figure 5 illustrates the contour drawing and 3D surface drawing of the CO2 model. Naturally, with the increment in the engine load, the CO2 emission increased. This concept is evident, as given in figure (5-a) and (5-b). The methanol addition enhances the combustion emission due to reducing the C/H ratio compared with C/H of diesel alone. This combustion enhancing emitted less CO₂ at the same engine load, as illustrated in figure (5-b).

![Figure 5-a. The contour drawing of the CO₂ model.](image1)

![Figure 5-b. The 3D drawing of the CO₂ model.](image2)

e. The NOₓ model: The ANOVA results and precision index values for the NOₓ model and coefficients are given in tables (6) and (7). The coefficients A and A² are significant. The coefficient's values of others are not significant. The overall model coefficients are substantial to predict NOₓ accurately. The adeq. Precision is more than four, and proper closing between R² predicted and R² adjusted where the difference is less than 0.2. Figure (6) demonstrates the contour and the 3D response surface plot for the changing NOₓ with engine load and methanol ratio. It is noticed that the NOₓ formation increased with load and methanol blending ratio increasing. Methanol has 50% oxygen in its content, which leads to oxygen availability increasing in the combustion chamber. The increase of NOₓ with load increment means more fuel consumption, higher cylinder temperature, and higher NOₓ, as plotted in figure 6-a and 6-b.
In this investigation, five models have been obtained using quadratic response surface methodology, which produced five mathematical equations to predict each response, and the coefficients are estimated from models. Each equation contains two factors named engine load (A) and methanol ratio (B) as input. The equations are:

\[ BTE = 16.8 + 0.831A + 0.416B - 0.025AB - 0.136A^2 0.431B^2 \]  \hspace{1cm} (2)

\[ CO = 759 + 114.371A - 10.959B + 0.25AB - 50.625A^2 + 13.625B^2 \]  \hspace{1cm} (3)

\[ UHC = 61 + 10.480A - 2.149B + 2.395 \times 10^{-14} AB - 0.969A^2 + 0.406B^2 \]  \hspace{1cm} (4)

\[ CO_2 = 3.5 + 0.823A - 0.121B - 0.0625AB + 0.253A^2 + 0.028B^2 \]  \hspace{1cm} (5)

\[ NOX = 616 + 201.534A + 7.286B + 0.5AB + 62A^2 + 13.5B^2 \] \hspace{1cm} (6)

3.3. The optimization
The optimization criteria goal is to maximize BTE and minimize CO, UHC, CO2, and NOX. The multi-objective optimization by Design Expert shows 11 possible solutions, as shown in Table (8) where the best solution is highlighted by the word (selected) in the first row.

**Table 8. Best optimum solution.**

| No. | Engine load (W) | Methanol ratio (%) | BTE  | CO   | UHC  | CO2  | NOX  | Desirability |
|-----|----------------|--------------------|------|------|------|------|------|--------------|
| 1   | 875            | 0.540              | 15.925 | 591.926 | 48.508 | 2.906 | 475.077 | 0.661 Selected |
| 2   | 875            | 0.547              | 15.925 | 591.953 | 48.497 | 2.906 | 475.225 | 0.661 |
| 3   | 875            | 0.532              | 15.925 | 591.897 | 48.524 | 2.906 | 474.890 | 0.661 |
| 4   | 875            | 0.517              | 15.925 | 591.851 | 48.549 | 2.907 | 474.584 | 0.661 |
| 5   | 875            | 0.567              | 15.924 | 592.030 | 48.463 | 2.905 | 475.654 | 0.661 |
| 6   | 875            | 0.580              | 15.923 | 592.096 | 48.442 | 2.905 | 475.948 | 0.660 |
| 7   | 875            | 0.485              | 15.925 | 591.781 | 48.605 | 2.908 | 473.940 | 0.660 |
| 8   | 875            | 0.670              | 15.915 | 592.610 | 48.294 | 2.903 | 478.070 | 0.659 |
| 9   | 875            | 0.808              | 15.887 | 593.848 | 48.079 | 2.900 | 481.776 | 0.655 |
| 10  | 875            | 0.850              | 15.876 | 594.327 | 48.018 | 2.900 | 482.990 | 0.653 |
| 11  | 875            | 0.041              | 15.830 | 593.567 | 49.464 | 2.928 | 467.768 | 0.641 |
3.4. The Validation of model
The confirmation and validation test is compulsory to achieve the model usability for maximizing BTE and minimizing each CO, UHC, and NO\textsubscript{X} utilizing the RSM-CCD optimizer for two input parameters, namely engine load, and MeOH ratio. The desirability is 0.849, which is desired because it is remarkably adjacent to optimization conditions. For the validation process, three trails for each engine load and methanol ratio are randomly selected and re-tested in the model compared with the responses' experimental values. The comparison and estimation of error percentage give high compatibility between experimental and predicted results with a 6% maximum error. Table 9 shows the confirmation test results.

| Trail-1 | Trail-2 | Trail-3 |
|---------|---------|---------|
| Engine load | Methanol ratio | Engine load | Methanol ratio | Engine load | Methanol ratio |
| 875 W | 30% | 1750 W | 20% | 2625 W | 10% |
| Exp. | Pred. | Exp. | Pred. | Exp. | Pred. | Exp. | Pred. | Err.% | Exp. | Pred. | Exp. | Pred. | Err.% | Exp. | Pred. | Err.% |
| BTE | 16.80 | 15.82 | 5.81 | 16.80 | 16.80 | 0 | 17.12 | 16.65 | 2.75 | 16.80 | 16.80 | 0 | 17.12 | 16.65 | 2.75 |
| CO | 600.00 | 596.42 | 0.60 | 759.00 | 759.00 | 0 | 850.00 | 847.08 | 0.34 | 759.00 | 759.00 | 0 | 850.00 | 847.08 | 0.34 |
| UHC | 50.50 | 47.81 | 5.0 | 61.00 | 61.00 | 0 | 71.50 | 73.10 | 2.24 | 61.00 | 61.00 | 0 | 71.50 | 73.10 | 2.24 |
| CO\textsubscript{2} | 2.90 | 2.90 | 0.38 | 3.50 | 3.50 | 0 | 5.10 | 4.79 | 6.07 | 2.90 | 2.90 | 0.38 | 3.50 | 3.50 | 0 | 5.10 | 4.79 | 6.07 |
| NO\textsubscript{X} | 492.00 | 487.75 | 0.86 | 616.00 | 616.00 | 0 | 900.00 | 894.25 | 0.64 | 616.00 | 616.00 | 0 | 900.00 | 894.25 | 0.64 |

4. Conclusion
The following points are concluded from the current work:

1. The addition of 5% biodiesel to the blend of methanol–diesel enhanced its miscibility by twelve folds.
2. Adding MeOH led to sensible improvement in engine BTE up to 20% of methanol and reduced the emission of CO, UHC, and CO\textsubscript{2}.
3. NO\textsubscript{X} emissions are increased due to methanol high oxygen content.
4. Due to the CIE's problematic behavior, the RSM–CCD is an excellent tool to predict efficient engine responses. It needs fewer experimental tests, and shorter computer run time as tested in this work.
5. Five models are built by RSM optimizer at a maximum error of 6%.
6. At the optimum, the efficiency increased by 9%.
7. The CO, UHC, and CO\textsubscript{2} decreased by 8%.
8. NO\textsubscript{X} marginally increased.

5. References
[1] Saravanan S, Rajesh Kumar B, Varadharajan A, Rana, Balaji Sethuramasamyraja D, Lakshmi G and Narayana R 2017 Optimization of DI diesel engine parameters fueled with iso-butanol/diesel blends – Response surface methodology approach (Fuel) vol 203 p 658–670
[2] Fiedler, E, Grossmann, G, Burkhard Kersebohm, D, Weiss, G and Witte, C 2005 Methanol Ullmann’s Encyclopedia of Industrial Chemistry; weinheim: (Wiley-VCH . doi:10.1002/14356007.a16_465. ISBN 978-3527306732)
[3] National Institute for Occupational Safety and Health 2008 The Emergency Response Safety and Health Database: Methanol
[4] Abdulaziz Alarifi, Ali Elkamel and Eric Croiset 2013 Steady-State Simulation of a Novel Annular Multitubular Reactor for Enhanced Methanol Production (pubs.acs.org/IECR)
[5] Abdulaziz Alarifi, Saad Alsobhi, Ali Elkamel and Eric Croiset 2014 Multi-Objective Optimization of Methanol Synthesis Loop from Synthesis Gas via a Multibed adiabatic Reactor with
Additional Interstage CO$_2$ Quenching (energy and fuel; pubs.acs.org/EF)

[6] Simeon Iliiev 2018 A Comparison Of Ethanol, Methanol and Butanol Blending with Gasoline and Relationship with Engine Performances and Emissions (29th daaam international symposium on intelligent manufacturing and automation, doi: 10.2507/29th.daaam.proceedings) vol 073 pp 505–514

[7] Yusaf T, Hamawand I, Baker P And Najafi G 2013 The Effect of Methanol-Diesel Blended Ratio on CI Engine Performance (International Journal Of Automotive And Mechanical Engineering (ijame)) Issn: 2229-8649 (Print); Issn: 2180-1606 (Online) vol 8 pp 1385–1395

[8] Sebastian Verhelst, James WG Turner, Louis Silegheb and Jeroen Vancoillie 2019 Methanol as a Fuel for Internal Combustion Engines (Progress in Energy and Combustion Science) vol 70 pp 43–88

[9] Al-Hassan A Mujafeta H and Al-Shannag M 2012 An Experimental Study on the Solubility of a Diesel-Ethanol Blend and on the Performance of a Diesel Engine Fueled with Diesel-Biodiesel - Ethanol Blends (Jordan Journal of Mechanical and Industrial Engineering) vol 6 no 2 ISSN 1995-6665 pp 147–153

[10] Norhidayah Mat Taib, Mohd Radzi Abu Mansor, Wan Mohd Faizal Wan Mahmood, Fais Ahmad Shah, and Nik Rosli Nik Abdullah 2016 Investigation of Diesel-Ethanol Blended Fuel Properties with Palm Methyl Ester as Co-Solvent and Blends Enhancer (MATEC Web of conferences 90 01080, AiGEV.)

[11] Satge de Caro A, Mouloungui Z, Vaitilingom G and Ch Berge J 2001 Interest of Combining an Additive with Diesel–Ethanol Blends for use in Diesel Engines (fuel) 565–574

[12] Ashraf Elfasakhany and Abdel-Fattah Mahmrous 2016 Performance and Emissions Assessment of n-Butanol–Methanol–Gasoline Blends as a Fuel in Spark-Ignition Engines (Alexandria Engineering Journal) vol 55 3015–3024

[13] Ashraf Elfasakhany 2016 Performance and Emissions of Spark-Ignition Engine using Ethanol–Methanol–Gasoline, N-Butanol–Iso-Butanol–Gasoline and Iso-Butanol–Ethanol–Gasoline Blends: a Comparative Study (Engineering Science and Technology) vol 19 pp 2053–2059

[14] Brânke J Deb K Miettinen K and Slowinski R 2008 Multi-objective Optimization: Interactive and Evolutionary Approaches (1–26 Springer-Verlag, Berlin, Heidelberg)

[15] Pathak A; Choudhury PK and Dutta RK 2018 Taguchi-Grey Relational Based Multi-Objective Optimization of Process Parameters on the Emission and Fuel Consumption Characteristics of a VCR Petrol Engine (Mater Today Proceedings) vol 5 pp 4702–10

[16] Awad OI, Mamat R, Ali OM, Azmi WH, Kadirgama K and Yusri IM 2017 Response Surface Methodology (RS M) Based Multi-Objective Optimization of Fusel Oil -Gasoline Blends at Different Water Content In SI. Engine (Energy Convers Manag) vol 150 pp 222–41

[17] Esono C, Onukwuli OD and Ofoefule AU 2019 Optimization of Methyl Ester Production from Prunus Amygdalus Seed Oil Using Response Surface Methodology and Artificial Neural Networks (Renew Energy) vol (130) pp 61–72

[18] Krishnamurthy K N, Sridhara SN and Ananda Kumar CS 2018 Synthesis and Optimization of Hydnocarpus Wightiana and Dairy Waste Scum as Feed Stock for Biodiesel Production by using Response Surface Methodology (Energy) vol 153 1073e86

[19] Yilmaz N, Ileri E, Atmanli A, Deniz Karaglan A, Okkan U and Sureyya Kocak M 2016 Predicting the Engine Performance and Exhaust Emissions of a Diesel Engine Fueled with Hazelnut Oil Methyl Ester: the Performance Comparison of Response Surface Methodology And LSSVM (J Energy Resour Technol; 138.052206-052206-7)

[20] Ganapathy T, Murugesan K and Gakkhar RP 2009 Performance Optimization of Jatropha Biodiesel Engine Model Using Taguchi Approach (Appl Energy) vol 86 pp 2476e86

[21] Vezir Ayhana, Çiçek Çangalb, İdris Çesura, Aslan Çobana, Gökhen Ergena, Yusuf Çaya, Ahmet Kolipa and İbrahim Özserta 2020 Optimization Of The Factors Affecting Performance And
Emissions in a Diesel Engine using Biodiesel and EGR with Taguchi Method (Fuel) vol 261 p 116371

[22] Asadi, Nooshin; Zilouei and Hamid 2017 Optimization of Organosolv Pretreatment of Rice Straw for Enhanced Biohydrogen Production using Enterobacter Aerogenes (Bioresource Technology) vol 227 pp 335–344

[23] R H Myers, D C Montgomery and C M Anderson-Cook 2016 Response Surface Methodology: Process and Product Optimization Using Designed Experiments (John Wiley & Sons)

[24] Duraid F Maki 2019 Study on Combustion Performance of Diesel Engine Fueled by Synthesized Waste Cooking Oil Biodiesel Blends (Journal of University of Babylon) vol 26 Issue 3 pp 328–339

[25] Magn Lapuerta , Octavio Armas and Reyes García-Contreras 2007 Stability of Diesel–Bioethanol Blends for use in Diesel Engines (fuel) vol 86 pp 1351–1357

[26] Bang-Quan Hea, Shi-Jin Shuaia, Jian-Xin Wang and Hong He 2003 The effect of Ethanol Blended Diesel Fuels on Emissions from a Diesel Engine (Atmospheric Environment) 37 pp 4965–4971

[27] Gerdes K R and Suppes G J 2001 Miscibility of Ethanol in Diesel Fuels (Ind. Eng. Chem. Res., vol 40 pp 949–956

[28] Hajaba L, Eller Z and Nagy E 2011 Properties of Diesel-Alcohol Blends (HANCSOK, Hungarian journal of industrial chemistry) vol 39 no 3 pp 349–352

[29] Kline S J and McClintock F A 1953 Describing the Uncertainties in Single Sample Experiments, Mech. Eng pp 75 3–8

[30] R J Moffat 1988 Describing the Uncertainties in Experimental Results (Exp. Thermal Fluid Sci.) vol 1 pp 3–17

[31] Coleman H W and Steele W G 1989 Experimentation and Uncertainty Analysis for Engineers (Wiley)

[32] Ganapathy T, Gakkhar RP and Murugesan K 2011 Optimization of Performance Parameters of Diesel Engine with Jatropha Biodiesel using Response Surface Methodology (Int J Sustain Energ; 30(sup1):S76–90. http://dx.doi.org/10.1080/14786451.2011.594889)

[33] Rao S S, Milkey K R, Samsudin A R, Dubey A K and Kidd P 2014 Comparison between Taguchi and RSM methodology in modelling CO2 laser machining (Jordan J. Mech. Ind. Eng., JJMIE) vol 8 no 1 pp 35–42

[34] Sodhi H S, Bansal G and Singh J 2014 Optimization of Machining Parameters for MRR in Boring Operation using (RSM, IJRME) vol 4 no 2

[35] Peter R Nelson, Marie Coffin and Karen A F Copeland 2016 Introductory Statistics for Engineering Experimentation (By academic press, an imprint of Elsevier science)