Impact prediction model of acetone at various ignition advance by artificial neural network and response surface methodology techniques for spark ignition engine

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Abstract. In this study, it was aimed to predict and optimize the effects of acetone/gasoline mixtures on spark ignition engine responses at different engine speeds and ignition advance values with artificial neural network and response surface methodology. The regression results obtained from response surface methodology show that absolute variance ratio values for all answers are greater than 0.96. Correlation coefficient values obtained from artificial neural network were obtained higher than 0.91. Mean absolute percentage error values were between 0.8859% and 9.01427% for artificial neural network, while it was between 1.146% and 8.957% for response surface methodology. Optimization study with response surface methodology revealed that the optimum results are 1700 rpm engine speed, 2% acetone ratio and 11° before top dead center ignition advance with a combined desirability factor of 0.76523%. Additionally, in accordance with the confirmation analysis among the optimal outcomes and the estimation outcomes, it was stated that there is a great harmony with a maximum error percentage of 7.662%. As a result, it is concluded that the applied response surface methodology and artificial neural network models can perfectly provide the impact of acetone percentage on spark ignition engine responses at different engine speeds and ignition advance values.

Keywords: Artificial neural network, Response surface methodology, Acetone, Optimization, Spark ignition engine.

1 Introduction

Today, the negative effects of vehicles with internal combustion engines on the environment have reached remarkable levels by the whole world [1–3]. Based on this, many countries have decided to ban fossil fuel-powered vehicles in the coming years. Many countries are also in search of environment friendly and renewable fuels [4, 5]. Not only the environmental pollution, but also the decrease in fossil fuel resources have accelerated the search for alternative fuels [6–10].

In recent years, alcohol-based fuels are mostly preferred as an environment friendly alternative fuel to gasoline in spark ignition engines. As is known, alcohols are liquid substances of biological origin that can be obtained from renewable sources [11]. Alcohols are a suitable fuel type for spark ignition engines due to their high oxygen content, latent heat of vaporization and octane number [12, 13]. The high-octane number of alcohols allows the engine to operate at higher compression ratios and thus, the risk of knock decreases, and Brake Thermal Efficiency (BTE) increases [14]. In addition, the fact that alcohols have high latent heat of vaporization creates a cooling effect in the cylinder and reduces the Nitrogen Oxide (NOx) emission, which occurs especially at high temperatures. In recent years, many types of alcohol such as ethanol [15], methanol [16, 17], butanol [18], and isoamyl alcohol [19] have been used in spark ignition engines by researchers. Another type of alcohol that can be used in spark ignition engines is acetone. Acetone helps prevent the tendency to knock, thanks to its high latent heat of vaporization and octane number [20]. Also, the oxygenated structure of acetone can improve combustion [21]. Acetone’s high-octane number, auto-ignition temperature and low boiling temperature are the reasons why it was chosen as the ignition improver. Several studies have been conducted in recent years regarding the use of acetone in spark ignition engines. Elfasakhany [22], examining the effects on performance and emission by adding bio-acetone...
and bioethanol in volumes of 3, 7 and 10%, concluded that adding 10% bio-acetone and bioethanol to gasoline is the ideal in terms of performance and emission. In another study on the use of acetone as a fuel in spark ignition engines, Calam [23] investigated the effects of acetone use in a homogeneously charged ignition engine. He stated that acetone improved the compression ratio range and that the highest in-cylinder pressure was achieved with acetone use.

In search of alternative fuels, researchers are experimenting with a large number of fuel types. Efforts, time, and money are spent separately for each of these trials. With the developing technology, it has become extremely important to be able to simulate experiments with computer applications instead of traditional experimental methods. Although there are many applications used for this purpose, the most preferred applications in recent years are Response Surface Methodology (RSM) and Artificial Neural Network (ANN). RSM is an application that finds the ideal combination of inputs to obtain optimum outputs and to determine the effect of each input parameter on output responses [24, 25]. On the other hand, ANN is a type of application that tries to predict outputs using a small number of experimental data [26, 27]. Although there is no study on modeling with ANN and RSM considering the application of acetone in spark ignition engines, there are studies using different alternative fuels [28–30].

In this study, it is aimed to investigate the effects of acetone use on different ignition advances and engine speeds in spark ignition engines, to predict and optimize them with ANN and RSM. There are two main objectives in this study. First, contributing to the elimination of the deficiency in the scientific field considering the application of ANN and RSM in acetone used spark ignition engine. Second, by determining the optimum spark ignition engine operating conditions for the use of acetone, it contributes to saving time and money by shedding light on subsequent investigations.

2 Materials and methods

Essential tests to establish ANN and RSM simulations were performed in one cylinder spark ignition engine utilizing fuel mixtures containing various ratios of acetone (0, 5 and 10% by vol.) at several engine speeds (1200, 1500 and 1800 rpm) and different ignition advances (10, 14 and 18 Before Top Dead Center [°bTDC]). The properties of the fuels used are shown in Table 1, the picture of the test setup in Figure 1, and the properties of the test engine in Table 2. In addition, the measurement scale, and precision of particular outcomes are shown in Table 3. Since the maximum speed of the engine used in the experiments was 1800 rpm and the minimum engine speed that could be measured was 1200 rpm, the engine speed levels were determined as 1200, 1500 and 1800 rpm.

2.1 ANN

ANN is one of the software computing approaches developed inspired by the human brain, which are connected to each other through weighted connections, each consisting of processing elements with its own memory and imitating biological neural networks [34–36]. ANN is an application that collects information about the data introduced to it and then decides about that data using the information it has learned when compared with the data it has never seen [37]. Because of this ability to learn, ANN finds wide application opportunities in many scientific fields and reveals the ability to successfully solve complex problems [26, 38]. The topology configuration of the developed ANN model for this study is shown in Figure 2. For the ANN model, acetone ratio, engine speed and ignition advance are used as input parameters, while BTE, Brake Specific Fuel Consumption (BSFC), NOx, Carbon monOxide (CO), Carbon DiOxide (CO2), HydroCarbon (HC) and Oxygen (O2) were used as engine responses. Principles such as correlation coefficient ($R$) that provides the difference among the test and the estimation, the Mean Square Error (MSE), which indicates the difference between test results and prediction results, the Root Mean Square Error (RMSE), which describes the relative success of any modeling application, and the Mean Absolute Percentage Error (MAPE) that measures the accuracy of the prediction results have been taken into account to evaluate the ANN’s predictive performance [39, 40]. $R$, MSE and MAPE calculations were performed with equations (1)–(3), respectively:

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n} (t_i - o_i)^2}{\sum_{i=1}^{n} (o_i)^2}},$$

$$\text{MSE} = \frac{\sum_{i=1}^{n} (t_i - o_i)^2}{n},$$

$$\text{MAPE} = \left[ \frac{\sum_{i=1}^{n} \left| \frac{(t_i - o_i)}{t_i} \right|}{n} \right] \cdot \frac{1}{n}.$$ 

In here, $t$ is calculated data by test, $n$ is complete data and $o$ is estimated value by ANN.

In the ANN simulation, the Levenberg–Marquardt backpropagation (TRAINLM) with one hidden layer is analyzed by varying quantity of neurons between 2 and 30 for Gradient Descent with Momentum weight and bias LEARNing function (LEARNGD) and LOG-SIGmoid transfer function (LOGSIG). Minimum MSE/MAPE and maximum $R$ values are achieved by a 14-neurons hidden layer network. Hence, (3–14–7) topology is noticed to be the perfect for guessing the inlet factors and output responses wherein 3 neurons for input layer, 14 neurons for hidden layer and 7 neurons for output layer. Fault percentages and $R$ values achieved for each response for ANN model utilizing best topology are demonstrated in Table 4. Furthermore, the overall $R$ value charts achieved for each response are provided in Figure 3. The maximum $R$ value and the minimum MSE value emerged as 0.99379 and
Table 1. Properties of fuels [23, 31–33].

|                     | Gasoline        | Acetone         |
|---------------------|-----------------|-----------------|
| Chemical formula    | C₈H₁₈–C₇H₁₆    | CH₃COCH₃        |
| Octane number       | 95              | 117             |
| Density (g/cm³)      | 0.720–0.775     | 0.791           |
| Boiling point (°C)  | 210             | 56.1            |
| Oxygen content (wt. %) | 0              | 27.6            |
| Calorific value (MJ/kg) | 44.0          | 29.60           |
| Latent heat of vaporization (kJ/kg) | 440            | 518             |
| Kinematic viscosity at 40 °C (mm²/s) | 0.49           | 0.35            |

RON, Research Octane Number; MON, Motor Octane Number.

Fig. 1. Pictorial view of the experimental rig.

Table 2. Technical characteristics of engine.

| S. No. | Item                          | Specification          |
|--------|-------------------------------|------------------------|
| 1      | Trademark                     | Kirloskar VCR engine/TV 1 |
| 2      | Cylinder/Stroke               | One/Four               |
| 3      | Power                         | 6.5 kW                 |
| 4      | Max. engine speed             | 1800 rpm               |
| 5      | Cylinder bore/Stroke length   | 87.5 mm/110 mm         |
| 6      | Compression ratio             | 6–10                   |
| 7      | Cooling style                 | Water-cooled           |
| 8      | Idling speed                  | 750 rpm                |
Table 3. Range and accuracy of measurements.

| S. No. | Item | Measurement scale | Accuracy |
|--------|------|-------------------|----------|
| 1      | CO   | 0–5000            | 0.001%   |
| 2      | CO₂  | 0–10.000 ppm vol. | 0.001%   |
| 3      | HC   | 0–10.0% vol.      | 1 ppm    |
| 4      | O₂   | 0–20.0% vol.      | 0.1%     |
| 5      | NO   | 0–100%            | 1 ppm    |

Fig. 2. The topology configuration of the developed ANN model.

Table 4. Error percentages and $R$ values for each response for ANN model.

| Responses | MAPE (%) | MSE       | $R$     |
|-----------|----------|-----------|---------|
| BTE       | 2.00397  | 0.01008   | 0.9929  |
| BSFC      | 3.39062  | 0.02692   | 0.99234 |
| CO        | 8.97446  | 0.34101   | 0.93423 |
| HC        | 6.85214  | 0.22182   | 0.97351 |
| CO₂       | 0.88590  | 0.00012   | 0.99379 |
| NOₓ       | 9.01427  | 0.71549   | 0.91202 |
| O₂        | 6.58011  | 0.12334   | 0.97575 |
0.00012 in CO$_2$, respectively. Conversely, the minimum $R$ value and the highest MSE were defined in NO$_x$ as 0.91202 and 0.71549, respectively. It was decided that all mistake levels and $R$ values were within satisfactory boundaries and ANN could estimate spark ignition engine outputs by acceptable error levels.

### 2.2 RSM

RSM is one of the statistical methods that produce and form a model according to the correlation among an output and some under control factors, which be capable of multivariate estimate and optimization [41–44]. The basic model according to a first-degree polynomial and quadratic model which can be applied in RSM are presented along with the equations (4) and (5), respectively:

\[ y = \beta_0 + \sum_i \beta_i x_i + \xi, \]  \hspace{1cm} (4)

\[ y = \beta_0 + \sum_i \beta_i x_i + \sum_{i=1}^{k} \sum_{j>i} \beta_{ij} x_i x_j + \xi, \]  \hspace{1cm} (5)

where $\beta_0$ is the constant, $\beta_i$ is the linear coefficient and $\beta_{ij}$ collaborative coefficient, $i$ and $j$ are the linear and
quadratic coefficient, respectively. \( e \) is random analysis mistake, \( k \) is the quantity of variables, \( y \) is the anticipated output, \( x_i \) and \( x_j \) are independent variables [45].

ANOVA was used to determine the importance of each operating parameter on the responses separately, and it can be stated that the results are reasonable considering the absolute variance ratio (\( R^2 \)) values presented in Table 5. Table 6 displays \( p \)-values that express whether a parameter has significant effects on the responses. \( P \)-values bigger than 0.05 mean that the factor is unimportant or has no influence on the response. When the table is analyzed in linear terms, engine speed appears as an effective parameter on all responses except BSFC. It can be clearly seen that the acetone ratio has an effect on all responses except BTE. Ignition advance played an active role in all responses except for CO and CO2 emissions. On the other hand, developed regression equations for all responses are tabulated in Table 7. Generally, RSM-based regression analysis shows that the behavior of the acetone percentage at various ignition advances and engine speeds on spark ignition engines is well estimated according to test conditions.

3 Findings and discussion

3.1 3-D graphs of responses

Surface graphs of BTE are shown in Figure 4 according to different acetone ratio, ignition advance and engine speed. While BTE values remained almost constant as the acetone ratio increased, it increased with increasing engine speed. On the other hand, there was a slight decrease in BTE values with the increasing ignition advance. With the increasing engine speed, BTE increased to a certain point and started to decrease after a certain engine speed due to heat losses and gas leaks at high engine speeds. While acetone ratio is expected to increase BTE with its high oxygen content and octane number, it is thought that it causes spraying difficulty due to its high density and therefore the BTE graph is horizontal. On the other hand, it is thought that the reason for the slight decrease in BTE with the increased ignition advance is that the maximum pressure cannot be achieved at the upper dead point. The change of BSFC, another response taken into consideration as a performance parameter, according to engine operating parameters is shown in Figure 5. BSFC is defined as the amount of fuel consumed to produce 1 kW of power per hour. The amount of fuel consumed is also directly related to the lower calorific value of the fuel used. In order to give the same output power, more fuel with lower calorific value should be consumed. According to the fuel properties shown in Table 1, the lower calorific value of gasoline is 44 MJ/kg, while that of acetone is 29.60 MJ/kg. Appropriately, it is expected that BSFC will increase with the use of acetone. When Figure 5 is examined, it can be clearly seen that BSFC increases with the application of acetone as expected. In addition, the BSFC value increased with increasing engine speed.

### Table 5. ANOVA outcomes.

| Responses | \( R^2 \) | Adjusted \( R^2 \) | Predicted \( R^2 \) |
|-----------|-----------|------------------|------------------|
| BTE       | 0.9913    | 0.9764           | 0.9530           |
| BSFC      | 0.9740    | 0.9505           | 0.9178           |
| CO        | 0.9674    | 0.9380           | 0.8976           |
| HC        | 0.9692    | 0.9425           | 0.9042           |
| CO\(_2\)  | 0.9934    | 0.9785           | 0.9661           |
| NO\(_x\)  | 0.9846    | 0.9529           | 0.9274           |
| O\(_2\)   | 0.9726    | 0.9479           | 0.9075           |

### Table 6. Important influence on response model terms and its coefficients.

| Inputs  | A  | B  | C  | AB | AC | BC | A\(^2\) | B\(^2\) | C\(^2\) |
|---------|----|----|----|----|----|----|---------|---------|---------|
| BTE     | 0.000 | 0.760 | 0.001 | 0.909 | 0.804 | 0.137 | 0.149 | 0.903 | 0.027 |
| BSFC    | 0.238 | 0.045 | 0.045 | 0.770 | 0.441 | 0.611 | 0.037 | 0.206 | 0.121 |
| CO      | 0.000 | 0.000 | 0.214 | 0.002 | 0.068 | 0.334 | 0.787 | 0.028 | 0.839 |
| HC      | 0.001 | 0.035 | 0.042 | 0.104 | 0.996 | 0.015 | 0.660 | 0.835 | 0.173 |
| CO\(_2\) | 0.000 | 0.014 | 0.646 | 0.009 | 0.903 | 0.486 | 0.005 | 0.654 | 0.521 |
| NO\(_x\) | 0.000 | 0.002 | 0.021 | 0.025 | 0.006 | 0.049 | 0.024 | 0.043 | 0.012 |
| O\(_2\)   | 0.000 | 0.031 | 0.044 | 0.645 | 0.796 | 0.919 | 0.022 | 0.293 | 0.532 |

**Important** (bold values): \((0.000 < p \leq 0.05)\).

**Notes:** A: Engine speed, B: Acetone ratio, C: Ignition advance, AB: Engine speed \(\times\) Acetone ratio, AC: Engine speed \(\times\) Ignition advance, BC: Acetone ratio \(\times\) Ignition advance, A\(^2\): Engine speed \(\times\) Engine speed, B\(^2\): Acetone ratio \(\times\) Acetone ratio, C\(^2\): Ignition advance \(\times\) Ignition advance.
speed and ignition delay. Increasing fuel consumption at high engine speeds is already an expected situation and a result as expected has been achieved.

Simultaneous effects of operating parameters on emissions are shown in Figures 6–10 for NOx, CO2, O2, CO and HC emissions, respectively. Alcohol fuels generally act in the direction of cooling inside the cylinder due to their high evaporation latent heat values. While NOx emissions arising due to high temperatures are expected to decrease due to the cooling effect of acetone, it is observed that they increase with increasing acetone ratio. This situation is thought to be caused by the increase in the temperature inside the cylinder due to more combustion in the cylinder owing to the oxygen contained in the acetone. In addition to this, NOx emissions also increased, as the increased engine speed also increased the internal temperature of the cylinder. On the other hand, NOx emissions were not greatly affected by the increased ignition advance. In the combustion process, if complete combustion occurs, CO and HC emissions do not appear, while CO2 and O2 emissions do not appear when incomplete combustion happens.

Since acetone is a type of fuel that contains oxygen, it is expected that the rate of complete combustion will increase and, on the contrary, the incomplete combustion rate will decrease with the addition of acetone into the fuel. When the graphs below are examined, CO and HC emissions have decreased, on the other hand, CO2 and O2 emissions have increased due to the increasing complete combustion rate with the addition of acetone. As the engine speed increased, full combustion occurred and while HC and CO emissions decreased, CO2 and O2 emissions increased. For HC, O2 and CO2 emissions, the best results were obtained with the mid-level ignition advance, while for the top-level ignition advance minimum values for CO emissions were achieved.

### 3.2 Difference of test, ANN and RSM findings

To evaluate the predictive ability of the applied RSM and ANN, a comparison was made with the experimental

| Table 7. Regression equations for each response. |
|-----------------------------------------------|
| Regression equation                           |
| BTE 22.3 + 0.0320 A – 0.342 B – 1.251 C – 0.000008 A² – 0.0023 B² + 0.0328 C² – 0.000024 AB – 0.000065 AC + 0.0274 BC |
| BSFC 0.437 – 0.000414 A + 0.00246 B + 0.01140 C + 0.000000015 A² – 0.000239 B² – 0.000476 C² – 0.000001 AB + 0.000002 AC + 0.000086 BC |
| CO 9.82 – 0.00608 A – 0.3088 B – 0.122 C + 0.0000003 A² + 0.00413 B² – 0.00120 C² + 0.000167 AB + 0.000014 AC – 0.00341 BC |
| HC 595 + 0.057 A – 24.8 B – 45.7 C – 0.000091 A² + 0.144 B² + 1.59 C² + 0.01351 AB – 0.00005 AC + 0.069 BC |
| CO2 19.58 – 0.01280 A + 0.415 B – 0.125 C + 0.000006 A² – 0.00262 B² + 0.00602 C² – 0.000205 AB – 0.000010 AC – 0.00381 BC |
| NOx –44 – 1.30 A + 33.2 B + 102.6 C + 0.001229 A² + 0.74 B² + 0.28 C² + 0.0048 AB – 0.0766 AC – 1.03 BC |
| O2 –6.58 + 0.01582 A – 0.133 B – 0.152 C – 0.000006 A² + 0.00845 B² + 0.0079 C² + 0.000040 AB – 0.000028 AC – 0.00074 BC |

**Fig. 4.** Simultaneous impacts of process factors on BTE.

**Fig. 5.** Simultaneous impacts of process factors on BSFC.
Fig. 6. Simultaneous impacts of process factors on NO\textsubscript{x} emission.

Fig. 7. Simultaneous impacts of process factors on CO\textsubscript{2} emission.

Fig. 8. Simultaneous impacts of process factors on O\textsubscript{2} emission.

Fig. 9. Simultaneous impacts of process factors on CO emission.
Comparison results with error rates are presented in Table 8 for BTE and BSFC, Table 9 for CO and HC emissions, and Table 10 for CO2, NOx and O2. When the comparison tables were examined, the maximum error was found to be less than 9% for all responses in general. This shows that ANN and RSM can make predictions successfully. The minimum error rate obtained from the RSM application was obtained in estimating CO2 with 1.146%, while the maximum error was 8.957% with estimated CO emission. On the other hand, in ANN application, the highest error rate appeared in the CO estimation with 8.974%, and the minimum error in the CO2 estimation with 0.886%. In general, it can be said that ANN error rates are less compared to RSM.

### 4 Optimality of the process factors and corresponding responses

An optimization analysis was performed by RSM to define the optimum engine speed, acetone ratio and ignition advance levels and to reach the optimal performance and emission outputs according to the optimum engine factors.
Lists of the optimization constraints for RSM are tabulated in Table 11. The objective in optimization is to reach the maximum achievable level of BTE, BSFC and the lowest level of all emissions. While the optimization aims to reach the highest possible level of BTE, on the contrary, it is aimed to reach the lowest level of BSFC and all emissions. The importance level of each answer is stated with the same weight. Lower and higher-level outputs are chosen from test results. Optimized results based on the RSM are given in Table 12.

Optimal process parameter levels were obtained as 2% acetone percentage, 1700 rpm engine speed and 11 °BTDC ignition advance. According to the optimum process parameters, optimum responses were obtained as 41.023% BTE, 0.207 kg/kWh BSFC, 0.686% CO, 116.33 ppm HC, 14.1460% CO2, 1062.3 ppm NOx and 1.569% O2. Additionally, the desirability values of each answer are presented in Figure 11. The combine desirability value was found to be 0.76523. In addition, verification tests were performed in three tests to verify the accuracy of the optimized values, and the average results are tabulated in Table 13. Highest mistake was determined as 7.662% and minimum error as 0.047%.

In addition, confirmatory tests were performed on three tests to verify the accuracy of the optimized values, and the average results are tabulated in Table 13.

5 Conclusion

In this study, it was aimed to investigate the effects of acetone/gasoline fuel mixtures containing acetone in different concentrations (5% and 10%) on spark ignition engine performance and emissions at different ignition advances and engine speeds. Additionally, RSM and ANN models were utilized to create accurate regression simulation for test outcomes and also to define optimal operating parameters. Overall investigation outcomes taken from the research are presented below:

- It was concluded that the created RSM simulation can correctly estimate and optimize the tests. Regression findings show that $R^2$ values bigger than 0.96 were obtained for all responses. This demonstrates that the created RSM has the capability to precisely provide the influence of acetone percentage on spark ignition engine outputs at different ignition advances and engine speeds. The applied ANN can estimate engine outputs between 0.8859% and 9.01427% MAPE value. MAPE values for RSM were found among 1.146% and 8.957%.
- In the RSM optimization analysis, the collective desirability was obtained to be 0.76523 in accordance with the restrictions. In addition, optimum engine
variables were obtained as 2% acetone ratio, 1700 rpm engine speed and 11°BTDC ignition advance. Additionally, in accordance with the validation analysis among the optimum outcomes and the estimation outcomes, it was determined that there is a great deal with a maximum error ratio of 7.662%.

Table 10. Difference of test, ANN and RSM findings for CO₂, NOₓ, and O₂ emission.

| Trial No. | Engine speed | Acetone ratio | Ignition advance | CO₂ (%) Test | ANN % Error | RSM % Error | NOₓ (ppm) Test | ANN % Error | RSM % Error | O₂ (%) Test | ANN % Error | RSM % Error |
|-----------|--------------|---------------|------------------|--------------|-------------|-------------|----------------|-------------|-------------|--------------|-------------|-------------|
| 1         | 1200         | 0             | 10               | 12.12        | 2.270       | 0.231       | 32.0           | 8.518       | 14.614      | 2.70         | 3.10        | 2.62        |
| 2         | 1800         | 0             | 10               | 15.23        | 1.011       | 0.512       | 15.06          | 10.836      | 1.10        | 1.10        | 1.22        | 3.765       | 15.283      |
| 3         | 1200         | 0             | 14               | 12.23        | 0.116       | 0.884       | 35.0           | 3.475       | 10.836      | 0.271       | 1.756       | 2.45        | 1.956       | 9.651       |
| 4         | 1500         | 0             | 14               | 15.09        | 0.167       | 0.450       | 117.31         | 7.850       | 8.962       | 0.114       | 0.130       | 0.117       | 10.720       | 0.068       |
| 5         | 1800         | 0             | 18               | 13.06        | 2.575       | 1.918       | 74.77          | 27.166      | 8.940       | 2.61        | 2.67        | 2.72        | 2.699        | 4.232       |
| 6         | 1500         | 0             | 18               | 15.98        | 3.902       | 1.307       | 1173.1         | 1053.6      | 2.524       | 8.863       | 1.12        | 1.54        | 1.22        | 3.765       | 15.283      |
| 7         | 1800         | 0             | 18               | 12.64        | 0.333       | 0.042       | 731.3          | 1.241       | 3.249       | 2.59        | 2.68        | 2.34        | 4.367        | 4.154       |
| 8         | 1500         | 5             | 10               | 13.78        | 0.153       | 0.022       | 583.0          | 2.942       | 6.386       | 2.35        | 2.37        | 2.31        | 1.000        | 1.734       |
| 9         | 1800         | 5             | 10               | 15.03        | 1.399       | 0.639       | 1283.6         | 2.524       | 8.636       | 1.12        | 1.49        | 1.38        | 33.076       | 23.482      |
| 10        | 1200         | 5             | 14               | 12.64        | 0.488       | 0.042       | 474.8          | 1.241       | 3.249       | 2.59        | 2.68        | 2.34        | 4.367        | 4.154       |
| 11        | 1500         | 5             | 14               | 13.63        | 2.383       | 1.918       | 731.3          | 1.173       | 3.07        | 2.84        | 3.07        | 2.71        | 7.994        | 4.437       |
| 12        | 1800         | 5             | 18               | 12.96        | 0.138       | 0.384       | 540.8          | 7.129       | 2.84        | 2.81        | 2.84        | 2.662       | 2.324        | 2.324       |
| 13        | 1500         | 5             | 18               | 13.33        | 0.822       | 0.450       | 720.8          | 1.241       | 3.249       | 2.59        | 2.68        | 2.84        | 2.662        | 2.324       |
| 14        | 1800         | 5             | 18               | 15.01        | 1.120       | 0.822       | 1108.8         | 1.241       | 3.249       | 2.59        | 2.68        | 2.84        | 2.662        | 2.324       |
| 15        | 1200         | 10            | 10               | 13.00        | 1.069       | 0.384       | 536.0          | 1.173       | 3.07        | 2.84        | 3.07        | 2.71        | 7.994        | 4.437       |
| 16        | 1500         | 10            | 10               | 15.18        | 0.390       | 0.138       | 553.9          | 7.129       | 2.84        | 2.81        | 2.84        | 2.662       | 2.324        | 2.324       |
| 17        | 1200         | 10            | 14               | 13.06        | 0.233       | 0.099       | 327.5          | 1.241       | 3.249       | 2.59        | 2.68        | 2.84        | 2.662        | 2.324       |
| 18        | 1500         | 10            | 14               | 13.41        | 0.227       | 0.035       | 797.4          | 1.241       | 3.249       | 2.59        | 2.68        | 2.84        | 2.662        | 2.324       |
| 19        | 1200         | 10            | 18               | 13.23        | 1.063       | 0.479       | 790.5          | 1.241       | 3.249       | 2.59        | 2.68        | 2.84        | 2.662        | 2.324       |
| 20        | 1800         | 10            | 18               | 15.04        | 1.139       | 0.140       | 1140.0         | 1.241       | 3.249       | 2.59        | 2.68        | 2.84        | 2.662        | 2.324       |

Overall error (%) = 0.886 1.146 9.014 6.344 6.580 8.155

Table 11. Optimization constraints for RSM.

| Response | Aim | Lower | Higher | Weight | Significance |
|----------|-----|-------|--------|--------|--------------|
| BTE      | Maximum | 35.08 | 41.990 | 1      | 1            |
| BSFC     | Minimum | 0.200 | 0.200  | 0.23   | 1            |
| CO       | Minimum | 346.000 | 346.000 | 1557.00 | 1            |
| HC       | Minimum | 12.120 | 12.120 | 15.98  | 1            |
| CO₂      | Minimum | 1.060 | 1.060  | 3.10   | 1            |
| NOₓ      | Minimum | 1.660 | 1.660  | 227.00 | 1            |
| O₂       | Minimum | 0.354 | 0.354  | 2.86   | 1            |

Table 12. Optimum process parameters and corresponding responses.

| Acetone ratio | Engine speed | Ignition advance | BTE | BSFC | CO | HC | CO₂ | NOₓ | O₂ |
|---------------|--------------|------------------|-----|------|----|----|-----|-----|----|
| 2             | 1700         | 11               | 41.023 | 0.207 | 0.686 | 116.33 | 14.460 | 1062.3 | 1.569 |
It has been observed that the addition of acetone does not have a significant effect on BTE but increases BSFC due to its low lower calorific value. On the other hand, it has increased NOx, CO2 and O2 emissions while reducing CO and HC emissions.

As a result of the research, acetone was found to have a potential capacity as an alternative fuel for spark ignition engines. In accordance with the findings of the research, it was concluded that RSM and ANN were successful in simulating the spark ignition engine according to the selected variables. Since the running of the engine is impacted by several running issues, additional investigation with such an approach is recommended to define the optimal levels of the various running variables.

### Authors’ contributions

**Samet Uslu**: Methodology, Software, Writing – Original Draft, Writing – Review & Editing. **Murat Kadir Yesilyurt**: Conceptualization, Methodology, Investigation, Writing – Review & Editing. **Hayri Yaman**: Conceptualization, Methodology, Investigation, Writing – Review & Editing.

### Table 13. Verification test with error proportion.

|          | BTE   | BSFC  | CO    | HC    | CO2   | NOx   | O2    |
|----------|-------|-------|-------|-------|-------|-------|-------|
| Optimal  | 41.023| 0.207 | 0.686 | 116.33| 14.46 | 1062.3| 1.569 |
| Test     | 41.004| 0.209 | 0.703 | 125.98| 14.53 | 1057.6| 1.565 |
| Error (%)| 0.047 | 1.130 | 2.414 | 7.662 | 0.474 | 0.443 | 0.234 |

![Desirability values](image)
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References

1 Gülüm M., Bilgin A. (2016) Two-term power models for estimating kinematic viscosities of different biodiesel-diesel fuel blends, Fuel Process. Technol. 149, 121–130.
2 Yesilyurt M.K., Eryılmaz T., Arslan M. (2018) A comparative analysis of the engine performance, exhaust emissions and combustion behaviors of a compression ignition engine fuelled with biodiesel/diesel/1-butanol (C4 alcohol) and biodiesel/diesel/n-pentanol (C5 alcohol) fuel blends, Energy 165, Part B, 1332–1351.
3 Perera F., Ashrafì A., Kinney P., Mills D. (2019) Towards a fuller assessment of benefits to children’s health of reducing air pollution and mitigating climate change due to fossil fuel combustion, Environ. Res. 172, 55–72.
4 Vignesh P., Kumar A.R.P., Ganesh N.S., Jayaseelan V., Sudhakar K. (2021) Biodiesel and green diesel generation: An overview, Oil Gas Sci. Technol. - Rev. IFP Energies nouvelles 76, 6.
5 Venkatesan B., Seenippan K., Shanmugam E., Subramanian S., Veerasundaram J. (2021) Characterization and effect of the use of safflower methyl ester and diesel blends in the compression ignition engine, Oil Gas Sci. Technol. - Rev. IFP Energies nouvelles 76, 29.
6 Yılmaz E. (2019) Investigation of the effects of diesel-fuel oil fuel blends on combustion, engine performance and exhaust emissions in a single cylinder compression ignition engine, Fuel 255, 115741.
7 Polverino P., D’Aniello F., Arsic L., Pianese C. (2019) Study of the energetic needs for the on-board production of Oxy-Hydrogen as fuel additive in internal combustion engines, Energy Convers. Manage. 179, 114–131.
8 Fayad M.A., Tsolakis A., Martos F.J. (2020) Influence of alternative fuels on combustion and characteristics of particulate matter morphology in a compression ignition diesel engine, Renew. Energy 149, 962–969.
9 Saravanan P., Mala D., Jayaseelan V., Kumar N.M. (2019) Experimental performance investigation of Partially Stabilized Zirconia coated low heat rejection diesel engine with waste plastic oil as a fuel, Energy Sources A: Recovery Util. Environ. Eff., 1–14. https://doi.org/10.1080/15567036.2019.1683647.
10 Balu P., Saravanan P., Jayaseelan V. (2021) Effect of ceramic coating on the performance, emission, and combustion characteristics of ethanol DI diesel engine, Mater. Today: Proc. 39, 4, 1259–1264.
11 Dogan B., Cakmak A., Yesilyurt M.K., Erol D. (2020) Investigation on 1-heptanol as an oxygenated additive with diesel fuel for compression-ignition engine applications: An approach in terms of energy, exergy, exergoeconomic, environ-economic, and sustainability analyses, Fuel 275, 117973.
12 Geo V.E., Godwin J., Thiagarajan S., Saravanan C.G., Aloui F. (2019) Effect of higher and lower order alcohol blending with gasoline on performance, emission and combustion characteristics of SI engine, Fuel 256, 115806.
13 Liu W., Shadlloo M.S., Tili I., Maleki A., Bach Q. (2020) The effect of alcohol-gasoline fuel blends on the engines’ performances and emissions, Fuel 276, 117977.
14 Kalwar A., Singh A.P., Agarwal A.K. (2020) Utilization of primary alcohols in dual-fuel injection mode in a gasoline direct injection engine, Fuel 276, 118068.
15 Ayad S.M.M.E., Belchior C.R.P., da Silva G.L.R., Lucena R. S., Carreira E.S., de Miranda P.E.V. (2020) Analysis of performance parameters of an ethanol fueled spark ignition engine operating with hydrogen enrichment, Int. J. Hydrogen Energy 45, 5, 5588–5606.
16 Prasad B.S.N., Pandey J.K., Kumar G.N. (2020) Impact of changing compression ratio on engine characteristics of an SI engine fueled with equi-volume blend of methanol and gasoline, Energy 191, 116005.
17 Sharudin H., Abdullah N.R., Najafi G., Mamat R., Masjuki H.H. (2017) Investigation of the effects of iso-butanol additives on spark ignition engine fuelled with methanol-gasoline blends, Appl. Therm. Eng. 114, 593–600.
18 Tang Q., Jiang P., Peng C., Chang H., Zhao Z. (2021) Comparison and analysis of the effects of spark timing and lambda on a high-speed spark ignition engine fuelled with n-butanol/gasoline blends, Fuel 287, 119505.
19 Udu S., Celik M.B. (2020) Combustion and emission characteristics of isooctyl alcohol-gasoline blends in spark ignition engine, Fuel 262, 116496.
20 Aydogan B. (2020) Combustion characteristics, performance and emissions of an acetone/n-heptane fuelled Homogenous Charge Compression Ignition (HCCI) engine, Fuel 275, 117840.
21 Rao D.C.K., Karmakar S., Som S.K. (2017) Puffing and Micro-Explosion Behavior in Combustion of Butanol/Jet A-1 and Acetone–Butanol–Ethanol (A–B–E) Jet A-1 Fuel Droplets, Combust. Sci. Technol. 189, 10, 1796–1812.
22 Elhasekhany A. (2020) Gasoline engine fueled with bioethanol-bio-acetone-gasoline blends: Performance and emissions exploration, Fuel 274, 117825.
23 Calam A. (2020) Study on the combustion characteristics of acetone/n-heptane blend and RON50 reference fuels in an HCCI engine at different compression ratios, Fuel 271, 117646.
24 Kumar A.N., Kishore P.S., Raju K.B., Ashok B., Vignesh R., Jeevanantham A.K., Nanthagopal K., Tamilselvan A. (2020) Decanol proportional effect prediction model as additive in palm biodiesel using ANN and RSM technique for diesel engine, Energy 213, 119072.
25 Inayat M., Sulaïman S.A., Kurnia J.C. (2018) Catalytic co-gasification of coconut shells and oil palm fronds blends in the presence of cement, dolomite, and limestone: Parametric optimization via Box Behnken Design, J. Energy Inst. 92, 4, 871–882.
26 Niu X., Yang C., Wang H., Wang Y. (2016) Investigation of ANN and SVM based on limited samples for performance and emissions prediction of a CRDI-assisted marine diesel engine, Appl. Therm. Eng. 111, 1353–1364.
27 Dey S., Reang N.M., Majumder A., Deb M., Das P.K. (2020) A hybrid ANN-Fuzzy approach for optimization of engine operating parameters of a CI engine fueled with diesel-palm biodiesel-ethanol blend, Energy 202, 117813.
28 Awad Omar I., Mamat R., Ali O., Azmi W.H., Kadirgama K., Yusri I.M., Leman A.M., Yusaf T. (2017) Response Surface Methodology (RSM) based multi-objective optimization of fuel oil-gasoline blends at different water content in SI engine, Energy Convers. Manage. 150, 222–241.
29 Simsek S., Uslu S. (2020) Experimental study of the performance and emissions characteristics of fusel oil/gasoline blends in spark ignited engine using response surface methodology, Fuel 277, 118182.

30 Yusri I.M., Mamat R., Azmi W.H., Omar A.L., Obed M.A., Shaiful A.I.M. (2017) Application of response surface methodology in optimization of performance and exhaust emissions of secondary butyl alcohol-gasoline blends in SI engine, Energy Convers. Manage. 133, 178–195.

31 Tang Q., Jiang P., Peng C., Duan X., Zhao Z. (2021) Impact of Acetone–Butanol–Ethanol (ABE) and gasoline blends on the energy balance of a high-speed spark-ignition engine, Appl. Therm. Eng. 184, 116267.

32 Anderhofstadt B., Spinler S. (2020) Preferences for autonomous and alternative fuel-powered heavy-duty trucks in Germany, Transp. Res. Part D: Transp. Environ. 79, 102232.

33 Guo Z., Yu X., Li G., Sun Y., Zhao Z., Li D. (2020) Comparative study of different injection modes on combustion and particle emission of Acetone–Butanol–Ethanol (ABE) and gasoline in a dual-injection SI engine, Fuel 281, 118786.

34 Taghavifar H., Mardani A., Mohebbi A., Taghavifar H. (2014) Investigating the effect of combustion properties on the accumulated heat release of DI engines at rated EGR levels using the ANN approach, Fuel 137, 1–10.

35 Rehman S., Mohandes M. (2008) Artificial neural network estimation of global solar radiation using air temperature and relative humidity, Energy Policy 36, 2, 571–576.

36 Uslu S., Celik M.B. (2020) Performance and exhaust emission prediction of a SI engine fueled with 1-amylo alcohol-gasoline blends: An ANN coupled RSM Based Optimization, Fuel 265, 116922.

37 Ghabadian B., Rahimi H., Nikbakht A.M., Najafi G., Yusaf T.F. (2009) Diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an artificial neural network, Renew. Energy 34, 4, 976–982.

38 Aydin M., Uslu S., Çelik M.B. (2020) Performance and emission prediction of a compression ignition engine fueled with biodiesel-diesel blends: A combined application of ANN and RSM based optimization, Fuel 269, 117472.

39 Roy S., Banerjee R., Bose P.K. (2014) Performance and exhaust emissions prediction of a CRDI assisted single cylinder diesel engine coupled with EGR using artificial neural network, Appl. Energy 119, 330–340.

40 Bhownik S., Paul A., Panua R., Ghosh S.K., Debroy D. (2018) Performance-exhaust emission prediction of diesose-nol fueled diesel engine: An ANN coupled MORSM based optimization, Energy 153, 212–222.

41 Alrugibah M., Yagiz Y., Gu L. (2021) Use natural deep eutectic solvents as efficient green reagents to extract procyanidins and anthocyanins from cranberry pomace and predictive modeling by RSM and artificial neural networking, Sep. Purif. Technol. 255, 117720.

42 Bezerra M.A., Santelli R.E., Oliveira E.P., Villar L.S., Escaleira L.A. (2008) Response Surface Methodology (RSM) as a tool for optimization in analytical chemistry, Talanta 76, 5, 965–977.

43 Alam M.A., Ya H.H., Azeem M., Hussain P.B., Salit M.S.B., Khan R., Arif S., Ansari A.H. (2020) Modelling and optimisation of hardness behaviour of sintered Al/SiC composites using RSM and ANN: A comparative study, J. Mater. Res. Technol. 9, 6, 14036–14050.

44 Sharma V.K., Kumar V., Joshi R.S. (2020) Parametric study of aluminium-rare earth based composites with improved hydrophobicity using response surface method, J. Mater. Res. Technol. 9, 3, 4919–4932.

45 Simsek S., Uslu S. (2020) Investigation of the effects of biodiesel/2-EthylHexyl Nitrate (EHN) fuel blends on diesel engine performance and emissions by Response Surface Methodology (RSM), Fuel 275, 118005.