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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 (NO_x) 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

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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), NO_x, Carbon monOxide (CO), Carbon DiOxide (CO_2), HydroCarbon (HC) and Oxygen (O_2) 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:

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

$$\mathrm{MSE} = \frac{\left[\sum_{i=1}^{n}(t_i - o_i)^2\right]}{n}, \tag{2}$$

$$\mathrm{MAPE} = \left[\sum_{i=1}^{n}\left|\frac{(t_i - o_i)}{t_i}\right|\right] x \frac{1}{n}. \tag{3}$$

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 (LEARNGDM) 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	C_8H_{18}–C_7H_{16}	CH_3COCH_3
Octane number ([RON + MON]/2)	95	117
Density (g/cm^3)	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 (mm^2/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	CO_2	0–10.000 ppm vol.	0.001%
3	HC	0–10.0% vol.	1 ppm
4	O_2	0–20.0% vol.	0.1%
5	NO	0–100%	1 ppm

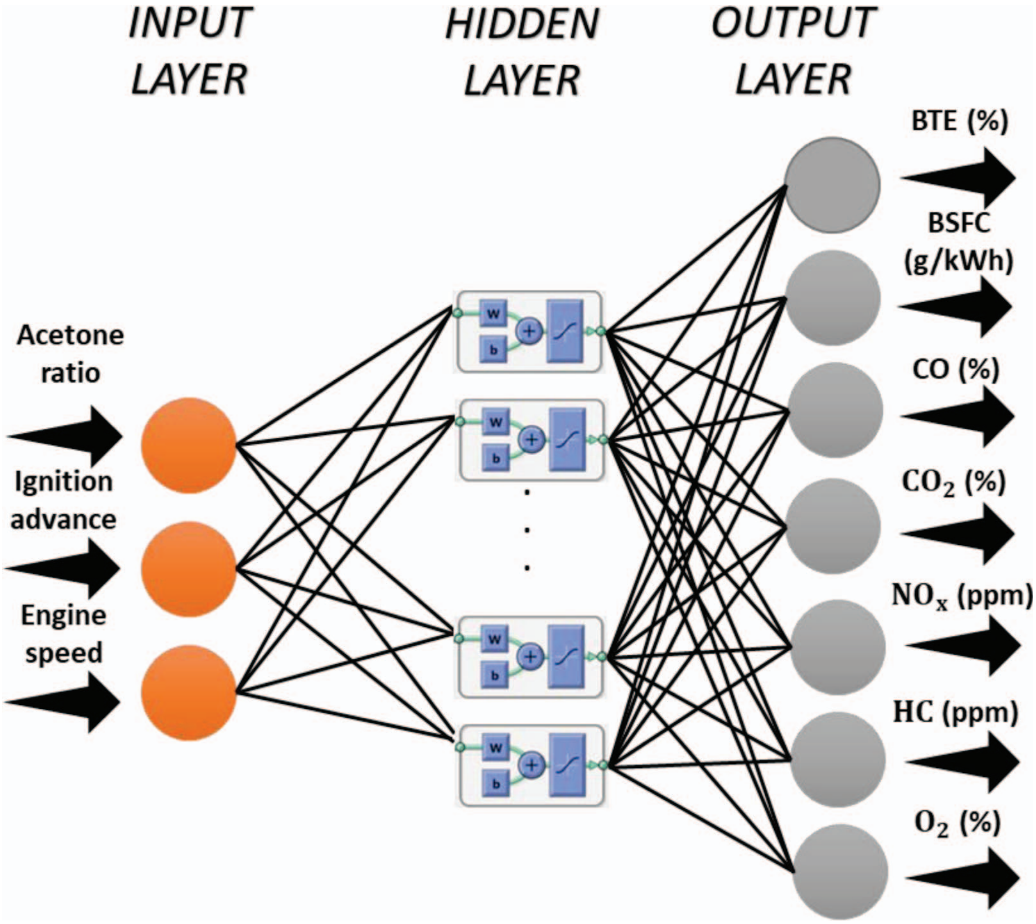

Fig. 2. The topology configuration of the developed ANN model.

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
CO_2	0.88590	0.00012	0.99379
NO_x	9.01427	0.71549	0.91202
O_2	6.58011	0.12334	0.97575

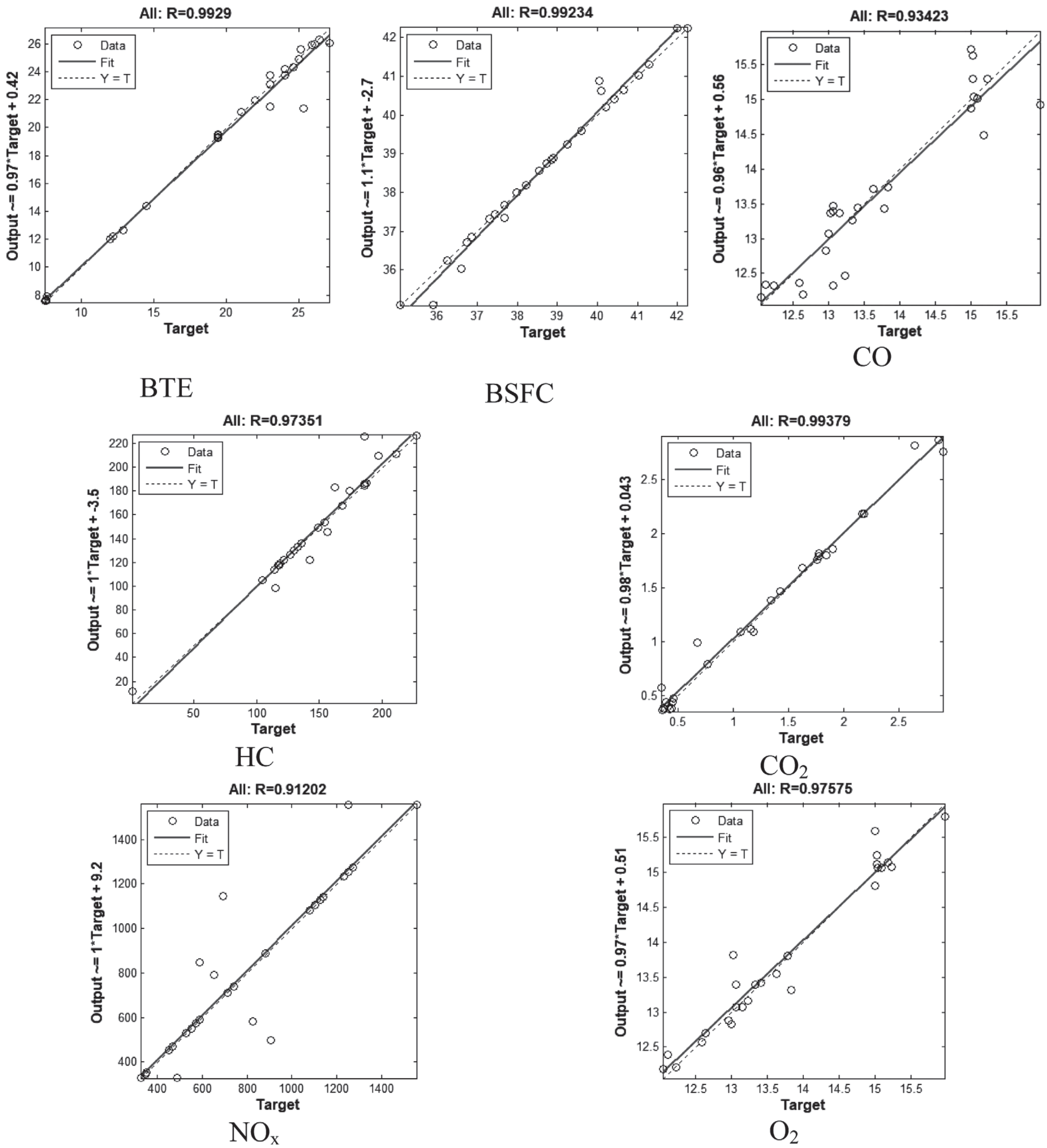

Fig. 3. ANN-regression model of responses.

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:

$$y = \beta_0 + \sum_{i}^{k} \beta_i x_i + \mathcal{E}, \tag{4}$$

$$y = \beta_0 + \sum_{i}^{k} \beta_i x_i + \sum_{i=1}^{k} \sum_{j \geq i}^{k} \beta_{ij} x_i x_j + \mathcal{E}, \tag{5}$$

where β_0 is the constant, β_i is the linear coefficient and β_{ij} collaborative coefficient, i and j are the linear and

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.

	p-values								
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 × Acetone ratio, AC: Engine speed × Ignition advance, BC: Acetone ratio × Ignition advance, A^2: Engine speed × Engine speed, B^2: Acetone ratio × Acetone ratio, C^2: Ignition advance × Ignition advance.

quadratic coefficient, respectively. $\mathcal{E}$ 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 CO_2 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

Table 7. Regression equations for each response.

	Regression equation
BTE	$22.3 + 0.0320\ A - 0.342\ B - 1.251\ C - 0.000008\ A^2 - 0.0023\ B^2 + 0.0328\ C^2 - 0.000024\ AB - 0.000065\ AC + 0.0274\ BC$
BSFC	$0.437 - 0.000414\ A + 0.00246\ B + 0.01140\ C + 0.000000015\ A^2 - 0.000239\ B^2 - 0.000476\ C^2 - 0.000001\ AB + 0.000002\ AC + 0.000086\ BC$
CO	$9.82 - 0.00608\ A - 0.3088\ B - 0.122\ C + 0.0000003\ A^2 + 0.00413\ B^2 - 0.00120\ C^2 + 0.000167\ AB + 0.000104\ AC - 0.00341\ BC$
HC	$595 + 0.057\ A - 24.8\ B - 45.7\ C - 0.000091\ A^2 + 0.144\ B^2 + 1.59\ C^2 + 0.01351\ AB - 0.00005\ AC + 0.069\ BC$
CO_2	$19.58 - 0.01280\ A + 0.415\ B - 0.125\ C + 0.000006\ A^2 - 0.00262\ B^2 + 0.00602\ C^2 - 0.000205\ AB - 0.000010\ AC - 0.00381\ BC$
NO_x	$-44 - 1.30\ A + 33.2\ B + 102.6\ C + 0.001229\ A^2 + 0.74\ B^2 + 0.28\ C^2 - 0.0048\ AB - 0.0766\ AC - 1.03\ BC$
O_2	$-6.58 + 0{,}01582\ A - 0.133\ B - 0.152\ C - 0.000006\ A^2 + 0.00845\ B^2 + 0.0079\ C^2 + 0.000040\ AB - 0.000028\ AC - 0.00074\ BC$

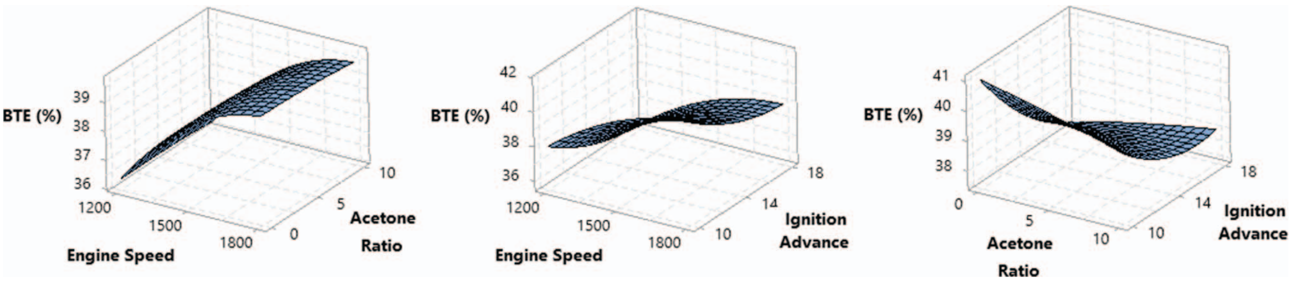

Fig. 4. Simultaneous impacts of process factors on BTE.

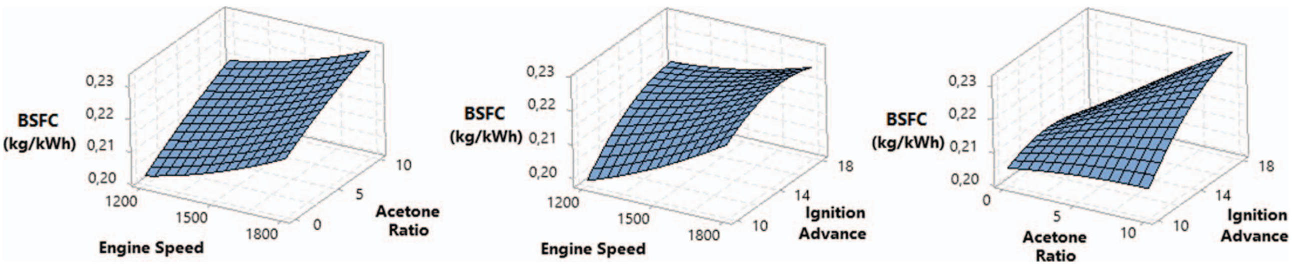

Fig. 5. Simultaneous impacts of process factors on BSFC.

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 NO_x, CO_2, O_2, 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 NO_x 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, NO_x emissions also increased, as the increased engine speed also increased the internal temperature of the cylinder. On the other hand, NO_x 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 CO_2 and O_2 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, CO_2 and O_2 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, CO_2 and O_2 emissions increased. For HC, O_2 and CO_2 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

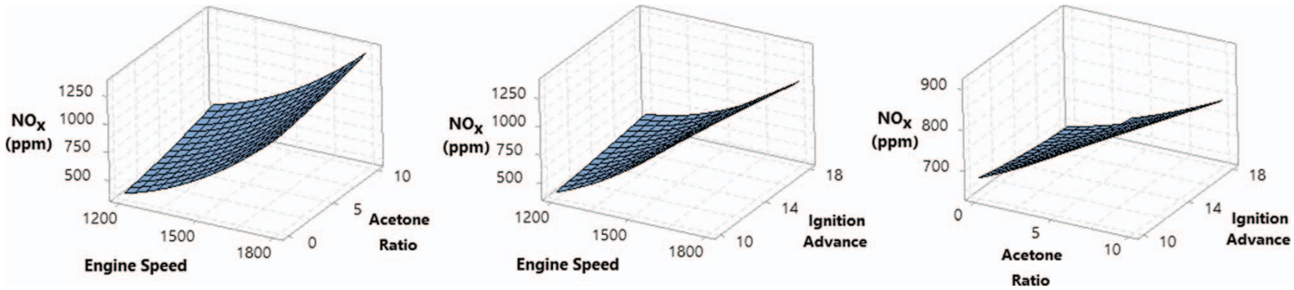

Fig. 6. Simultaneous impacts of process factors on NO_x emission.

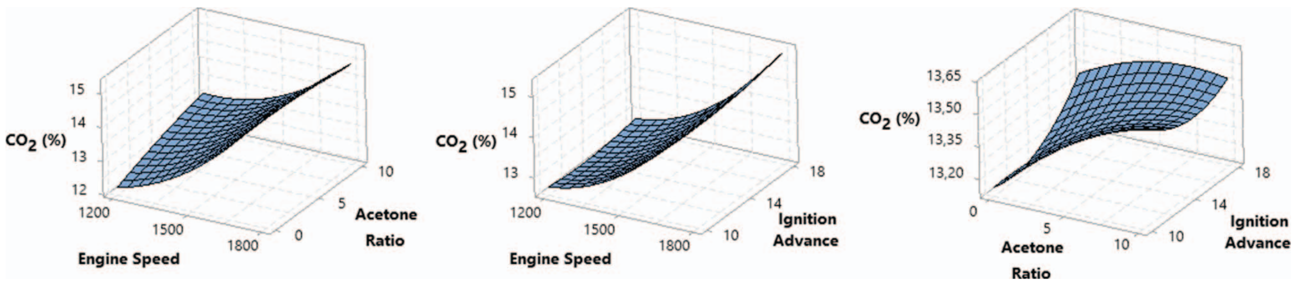

Fig. 7. Simultaneous impacts of process factors on CO_2 emission.

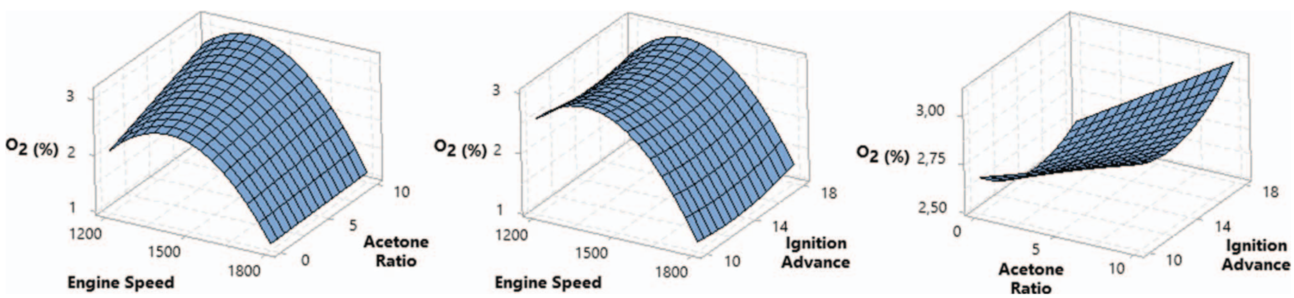

Fig. 8. Simultaneous impacts of process factors on O_2 emission.

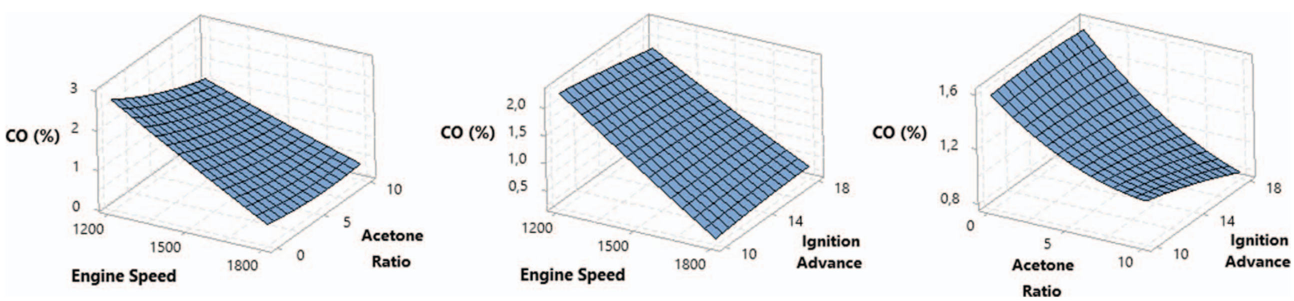

Fig. 9. Simultaneous impacts of process factors on CO emission.

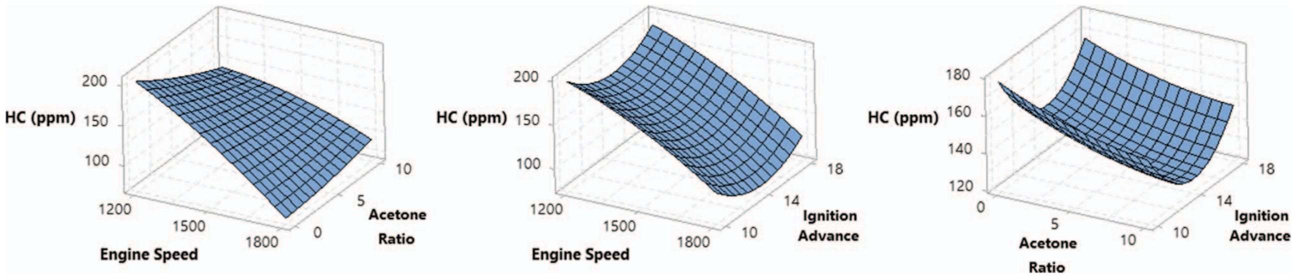

Fig. 10. Simultaneous impacts of process factors on HC emission.

Table 8. Difference of test, ANN and RSM findings for BTE and BSFC.

Trial No.	Input			Responses									
				BTE (%)					BSFC (kg/kWh)				
	Engine speed	Acetone ratio	Ignition advance	Test	ANN	RSM	% Error/ ANN	% Error/ RSM	Test	ANN	RSM	% Error/ ANN	% Error/ RSM
1	1200	0	10	38.55	37.550	39.170	2.594	1.608	0.200	0.190	0.203	5.020	1.700
2	1800	0	10	41.99	42.243	43.580	0.602	3.787	0.210	0.217	0.183	3.327	12.857
3	1200	0	14	36.25	37.375	37.003	3.103	2.077	0.230	0.224	0.213	2.479	7.433
4	1500	0	14	38.74	39.890	39.850	2.969	2.865	0.210	0.209	0.194	0.473	7.474
5	1800	0	14	39.25	38.250	41.257	2.548	5.113	0.220	0.220	0.197	0.091	10.316
6	1500	0	18	37.68	37.337	38.654	0.911	2.585	0.200	0.230	0.191	15.000	4.512
7	1800	0	18	38.85	39.850	39.983	2.574	2.917	0.210	0.215	0.196	2.386	6.488
8	1500	5	10	41.03	41.180	41.518	0.366	1.188	0.205	0.204	0.186	0.659	9.500
9	1800	5	10	41.30	42.300	42.967	2.421	4.035	0.200	0.200	0.185	0.012	7.688
10	1200	5	14	35.08	36.080	37.009	2.851	5.500	0.230	0.217	0.219	5.668	4.674
11	1500	5	14	40.05	40.890	39.820	2.097	0.574	0.215	0.204	0.199	5.334	7.373
12	1200	5	18	36.60	36.019	36.440	1.588	0.438	0.230	0.226	0.215	1.719	6.417
13	1500	5	18	36.75	36.715	39.173	0.095	6.592	0.220	0.218	0.198	0.904	10.209
14	1800	5	18	38.89	39.890	40.466	2.571	4.052	0.220	0.221	0.201	0.476	8.436
15	1200	10	10	36.85	37.850	37.972	2.714	3.045	0.225	0.226	0.201	0.547	10.800
16	1800	10	10	40.65	41.440	42.238	1.943	3.907	0.200	0.198	0.174	0.978	12.850
17	1200	10	14	37.31	38.310	36.901	2.680	1.097	0.220	0.219	0.214	0.536	2.889
18	1500	10	14	37.99	38.990	39.676	2.632	4.437	0.205	0.225	0.192	9.856	6.320
19	1200	10	18	35.89	36.086	36.879	0.547	2.756	0.220	0.228	0.211	3.695	3.929
20	1800	10	18	39.60	38.700	40.833	2.273	3.114	0.230	0.250	0.195	8.654	15.410
Overall error (%)							2.004	3.084				3.391	7.864

results. 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 CO_2, NO_x and O_2. 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 CO_2 with 1.146%, while the maximum error was 8.957% with estimated of 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 CO_2 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.

Table 9. Difference of test, ANN and RSM findings for CO and HC emission.

Trial No.	Input			Responses									
				CO (%)					HC (ppm)				
	Engine speed	Acetone ratio	Ignition advance	Test	ANN	RSM	% Error/ ANN	% Error/ RSM	Test	ANN	RSM	% Error/ ANN	% Error/ RSM
1	1200	0	10	2.859	2.861	2.864	0.074	0.175	227	227.58	233.76	0.256	2.978
2	1800	0	10	0.370	0.383	0.380	3.489	2.703	114	118.68	103.86	4.104	8.895
3	1200	0	14	2.640	2.812	2.760	6.516	4.545	211	214.88	203.36	1.840	3.621
4	1500	0	14	1.774	1.789	1.616	0.818	8.918	174	180.13	146.54	3.521	15.782
5	1800	0	14	0.415	0.397	0.483	4.290	16.280	166	114.36	143.34	31.110	13.651
6	1500	0	18	1.758	1.752	1.598	0.318	9.090	168	166.50	166.96	0.892	0.619
7	1800	0	18	0.450	0.439	0.533	2.388	18.400	127	116.67	103.70	8.134	18.346
8	1500	5	10	1.066	1.089	1.236	2.197	15.971	156	145.89	161.38	6.479	3.446
9	1800	5	10	0.361	0.371	0.372	2.659	2.978	133	122.92	118.50	7.581	10.902
10	1200	5	14	2.186	2.183	2.083	0.140	4.732	185.6	188.85	168.85	1.749	9.025
11	1500	5	14	1.183	1.091	1.189	7.745	0.495	142	121.72	132.30	14.284	6.835
12	1200	5	18	1.631	1.677	1.872	2.823	14.773	162	183.04	190.71	12.986	17.722
13	1500	5	18	1.161	1.118	1.103	3.674	4.991	118	112.92	124.10	4.308	5.165
14	1800	5	18	0.446	0.381	0.388	14.516	12.971	122	126.93	101.10	4.044	17.131
15	1200	10	10	1.847	1.801	1.852	2.507	0.271	154	158.05	169.18	2.629	9.857
16	1800	10	10	0.397	0.444	0.370	11.726	6.801	115	98.85	120.34	14.040	4.643
17	1200	10	14	1.780	1.818	1.612	2.135	9.461	149	142.07	141.54	4.649	5.007
18	1500	10	14	0.675	0.988	0.968	46.409	43.467	130	120.06	125.25	7.646	3.654
19	1200	10	18	1.346	1.380	1.333	2.550	0.981	186	181.05	164.78	2.662	11.409
20	1800	10	18	0.354	0.575	0.350	62.515	1.130	105	109.34	115.70	4.129	10.190
Overall error (%)							8.974	8.957				6.852	8.944

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% CO_2, 1062.3 ppm NO_x and 1.569% O_2. 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 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

Table 10. Difference of test, ANN and RSM findings for CO_2, NO_x, and O_2 emission.

Trial No.	Input			Responses														
				CO_2 (%)					NO_x (ppm)					O_2 (%)				
	Engine speed	Acetone ratio	Ignition advance	Test	ANN	RSM	% Error/ ANN	% Error/ RSM	Test	ANN	RSM	% Error/ ANN	% Error/ RSM	Test	ANN	RSM	% Error/ ANN	% Error/ RSM
1	1200	0	10	12.12	12.40	12.09	2.270	0.231	352	322.0	300.6	8.518	14.614	2.70	3.10	2.62	14.815	3.000
2	1800	0	10	15.23	15.08	15.15	1.011	0.512	1250	1556.7	1273.2	24.534	1.853	1.06	1.10	1.22	3.765	15.283
3	1200	0	14	12.23	12.22	12.12	0.116	0.884	346	356.0	370.2	2.882	6.983	1.39	1.33	1.28	4.532	8.140
4	1500	0	14	13.15	13.08	13.10	0.555	0.381	590	610.5	653.9	3.475	10.836	2.71	2.76	2.45	1.956	9.651
5	1800	0	14	15.09	15.06	15.16	0.167	0.450	1273	1173.1	1158.9	7.850	8.962	1.17	1.30	1.17	10.720	0.068
6	1500	0	18	13.06	13.40	13.31	2.575	1.918	588	747.7	640.6	27.166	8.940	2.61	2.67	2.72	2.299	4.123
7	1800	0	18	15.98	15.80	15.36	1.137	3.902	1080	1068.0	1053.6	1.109	2.441	1.22	1.27	1.37	4.099	12.492
8	1500	5	10	13.78	13.80	13.36	0.153	3.022	826	583.0	773.3	29.421	6.386	2.35	2.37	2.31	1.000	1.734
9	1800	5	10	15.03	15.24	15.13	1.399	0.639	1252	1283.6	1363.0	2.524	8.863	1.12	1.49	1.38	33.078	23.482
10	1200	5	14	12.64	12.70	12.63	0.488	0.042	469	474.8	453.8	1.241	3.249	2.59	2.68	2.48	3.436	4.154
11	1500	5	14	13.63	13.55	13.31	0.587	2.383	740	731.3	730.3	1.173	1.307	2.84	3.07	2.71	7.994	4.437
12	1200	5	18	12.96	12.88	12.78	0.615	1.381	551	540.8	511.7	1.844	7.129	2.78	2.71	2.84	2.662	2.324
13	1500	5	18	13.33	13.39	13.44	0.450	0.822	711	720.8	696.4	1.378	2.058	2.81	3.10	2.50	10.184	11.130
14	1800	5	18	15.01	15.58	15.18	3.820	1.120	1105	1108.7	1102.2	0.361	0.227	1.22	1.07	1.21	12.188	0.652
15	1200	10	10	13.00	12.83	13.14	1.322	1.069	529	536.0	546.0	1.326	3.206	2.81	2.86	2.70	1.779	3.986
16	1800	10	10	15.18	15.13	14.97	0.300	1.390	1557	1553.9	1489.8	0.202	4.319	1.25	1.29	1.09	3.200	12.700
17	1200	10	14	13.06	13.07	13.02	0.099	0.333	486	327.5	574.4	32.616	18.181	2.64	2.68	2.61	1.667	1.311
18	1500	10	14	13.41	13.41	13.38	0.035	0.227	904	797.4	843.7	11.796	6.667	3.10	3.27	2.49	5.484	19.555
19	1200	10	18	13.23	13.17	13.09	0.479	1.083	654	790.5	611.7	20.868	6.465	2.86	2.81	2.70	1.888	5.509
20	1800	10	18	15.04	15.06	14.87	0.140	1.139	1140	1140.0	1187.8	0.002	4.196	1.24	1.29	1.47	4.858	19.368
Overall error (%)							0.886	1.146				9.014	6.344				6.580	8.155

Table 11. Optimization constraints for RSM.

Response	Aim	Lower	Aim	Higher	Weight	Significance
BTE	Maximum	35.08	41.990	41.990	1	1
BSFC	Minimum	0.200	0.200	0.23	1	1
CO	Minimum	346.000	346.000	1557.00	1	1
HC	Minimum	12.120	12.120	15.98	1	1
CO_2	Minimum	1.060	1.060	3.10	1	1
NO_x	Minimum	1.660	1.660	227.00	1	1
O_2	Minimum	0.354	0.354	2.86	1	1

Table 12. Optimum process parameters and corresponding responses.

Acetone ratio	Engine speed	Ignition advance	BTE	BSFC	CO	HC	CO_2	NO_x	O_2
2	1700	11	41.023	0.207	0.686	116.33	14.460	1062.3	1.569

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%.

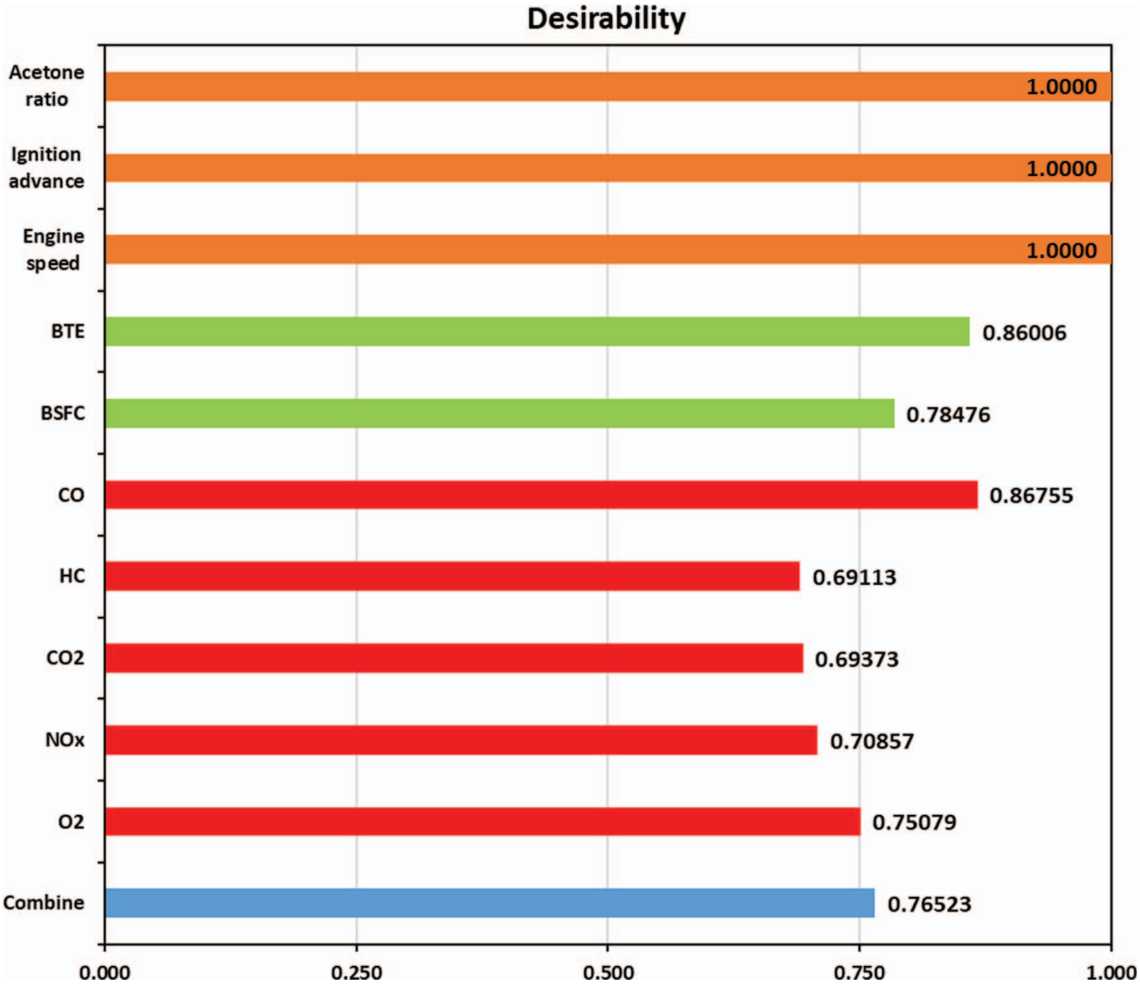

Fig. 11. Desirability values.

Table 13. Verification test with error proportion.

	BTE	BSFC	CO	HC	CO_2	NO_x	O_2
Optimal responses	41.023	0.207	0.686	116.33	14.46	1062.3	1.569
Test responses	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

- 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 NO_x, CO_2 and O_2 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.

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