THE TECHNIQUE PERFORMANCE EVALUATION AND EMISSION CHARACTERISTICS OF DIESEL, BIODIESEL, AND BIOGAS

Mayur Jayant Gitay[1], Dr. Nilesh Diwakar[2], Dr. Nikhil J. Rathod[3]

Article History: Received: 30-09-2022 **Revised:** 20-10-2022 **Accepted:** 31-10-2022

Abstract

A diesel engine with variable compression was used to test the engine performance and emission characteristics of diesel, biodiesel, and biogas fuels together. Grey relational analysis was used to solve the issue so that the best process response could be found with a minimal number of trial runs. It was expected that a particular set of input parameters would produce the optimal response characteristics when used as performance indices along with the grey relational grade and. It has been established that a diesel engine can operate well with 70% of the mixture without significantly changing its emissions or performance.

Keywords: Biodiesel, diesel, biogas, VCR diesel engine, CI engine, GRA

[1]PhD Scholar, Department of Mechanical Engineering, Sarvepalli Radhakrishnan University, Bhopal, Madhya Pradesh, India
[2]Principal, RKDF IST, Bhopal, Sarvepalli Radhakrishnan University, Bhopal, Madhya Pradesh, India
[3]Engineer, Department of Mechanical Engineering, SRS Valuetech System Pvt Ltd, Nasik, Maharashtra, India

Email: [1]mjgitay.gitay@gmail.com

DOI: 10.53555/ecb/2022.11.6.43

1. INTRODUCTION

Recently, there has been a rise in the use of alternative fuels as a result of growing worries about the depletion of fossil fuel resources and environmental problems like air pollution and climate change. There have been many discussions about alternative fuels like diesel, biodiesel, and biogas fuels which have a variety of advantages over regular diesel fuel. A sustainable fuel called biodiesel can be made from a variety of materials, including used cooking oil, animal fats, and vegetable oils. It is non-toxic, biodegradable, and has a less carbon footprint than conventional diesel. A renewable fuel derived from agricultural products like corn and sugarcane, on the other hand, is ethanol. It is regularly added to diesel as well as utilised as a stand-alone fuel in flex-fuel cars. The performance and emission characteristics of biodiesel and EME will determine how economically viable it is to employ them in internal combustion engines. It's critical to compare the power output, fuel consumption, and combustion characteristics of alternative fuels to those of conventional diesel fuel when assessing their performance. It has been tested extensively to see how well biodiesel and EME work in compression ignition (CI) engines. These studies have yielded a variety of results, depending on the fuel type, the engine, and the operating conditions. It has been found that compared to diesel fuel, biodiesel has a greater cetane rating, a lower calorific value, and a lower viscosity. Because biodiesel has a longer ignition delay and a lower energy density, this causes an increase in fuel consumption and a drop in engine power output. EME increases engine power and reduces fuel consumption because it has a higher calorific value and lower viscosity than biodiesel. EME's higher oxygen content and lower cetane number, however, could result in higher NOx emissions and engine deposits. When evaluating the performance of alternative fuels, their emission characteristics are critical. Particulate matter (PM), nitrogen oxides (NOx), carbon monoxide (CO), and hydrocarbons (HC), which are toxic pollutants that are bad for the environment and human health, are released by diesel engines. By using alternative fuels, you might be able to lower these emissions and enhance air quality. The emission characteristics of biodiesel and EME in CI engines have been the subject of numerous investigations. When compared to diesel fuel, it has been found that biodiesel can reduce CO, PM, and HC emissions by up to 50%, 60%, and 70%, respectively. However, because of its lower flame temperature and higher oxygen content, biodiesel has the potential to produce more NOx emissions. Comparing EME to diesel fuel, it has been demonstrated that CO, PM, and HC emissions can be reduced by up to 60%, 90%, and 70%, respectively. However, because to the higher oxygen concentration in EME, additional NOx emissions could be generated. The kind of fuel, engine, and operating circumstances are just a few variables that can have an impact on the performance and emission characteristics of biodiesel and EME. It is critical to carefully analyse the performance trade-offs involved even though the use of alternative fuels may cut emissions and improve air quality. In order to provide sustainable and effective alternative fuels, it is critical to evaluate the method performance evaluation and emission characteristics of biodiesel and EME in CI engines.

Carraretto et al. [1] evaluated the performance of a CI engine first on a test bench and subsequently on a city bus. They discovered that the usage of biodiesel increased nitrogen oxide (NOx) emissions as well as the consumption of specific fuels. Nevertheless, there was a decrease in carbon dioxide and carbon monoxide emissions. Raheman et al. [2] suggested that the diesel methyl ester made from karanja oil could be used as an alternative fuel. They found considerable reductions in CO and NOx emissions compared to diesel, according to their data. Agarwal et al. [3] created biodiesel from Ratanjyot (Jatropha), Karanja, Nagchampa, and Rubber by employing methyl and ethyl alcohol. He added that because biodiesel doesn't require engine modification, it would be a better choice than petroleum diesel. Raheman and Ghadge [4, 5] evaluated a Ricardo E6 engine using Mahua biodiesel and its blends. There was an increase in the compression ratio from 18 to 20. It was established that raising the biodiesel content led to decreased brake thermal efficiency and higher fuel consumption for the brakes. Studies by Rao et al. [6] have shown that vegetable oils can replace diesel fuel in agricultural diesel engines. These vegetable oils almost generated enough smoke. Kalbande et al. [7] investigated the efficacy of diesel blends using biodiesel generated from karanja and jatropha. According to the findings, the blends B20 (20% biodiesel and 80% diesel) and B40 (40% biodiesel and 60% diesel) had the highest Karanja biodiesel efficiency. Jatropha production increased in B60 and B80. Fontaras et al. [8] investigated the biodiesel's combustion and emission characteristics using a diesel passenger car that used soybean biodiesel and complied with EURO 2 emission standards. They discovered that utilising soy biodiesel made cold starting more challenging. Godiganur et al. [9] assert that following trans-esterification, Mahua oil displayed characteristics similar to those of diesel. The blend with 20% (B 20) was shown to function well. Baiju et al. [10] produced methyl ester and ethyl ester from karanja oil. With the exception of the fact that there were rather significant quantities of NOx present, both of them showed acceptable emission characteristics. Additionally, they argued that methyl ester performed superior to ethyl esterSahoo et al. [11], plant methyl esters from jatropha, karanja, and polanga were combined with diesel. The strongest output was made with a B-50 blend. It has been demonstrated that maximising the use of biodiesel reduces smoke emissions. CO and NOx emissions barely increased in comparison to diesel emissionsMurugesan et al. [12] assert that the methyl ester of Karanja oil can be used in CI engines right away without modification. It was determined that brakes required more fuel than diesel and that biodiesel had distinct emission characteristics. They think the B 20 Blend is the finest alternative to diesel. A study by Duraisamy et al. [13] used the methyl esters of the seed oils of Jatropha, Pongamia, Mahua, and Neem. During engine performance tests, B 40 biodiesel had approximately the same thermal efficiency as diesel. No matter the fraction mix, the results of the emission analysis showed that the density of NOx and smoke increased while carbon monoxide (CO) and hydrocarbons (HC) dropped.

The literature analysis made it abundantly evident that researchers had put great effort into discovering the finest diesel fuel alternative that didn't need for significant engine modifications. They normally monitored how the engine ran and what emissions it produced before adjusting the Engine Load, Ignition Pressure, and Ignition Timing, Hydrogen and Nanoparticles accordingly. It should be emphasized that the system's response was not one-way and that there were other input parameters. Alternatively, although some responses had higher values that were preferred, others had lower values that were. As a result, the study was transformed into a multiresponse optimization problem that needed a rigorous approach to determine how many tests would be necessary to cover the full range of input parameters. Using the data displayed above, the ideal set of input parameters was found in an effort to maximize reaction characteristics. With the fewest number of experiments possible, the experiment was designed to yield the most amount of data. Biodiesel was tested as a fuel in this investigation. On a Kirloskar engine with a single cylinder and variable compression ratio, the performance of biodiesel was assessed. The study's objective was to identify the ideal dual fuel blend of diesel, biodiesel, and biogas for engine performance and emissions. Using the weighting elements of grey relational analysis, the GRA approach reduced a multiresponse problem to a single problem. The outcomes were then validated through real-world testing.

2. Methodology

Finding the right mixture of diesel, biodiesel, and biogas can enhance the performance and emission characteristics of a variable compression ignition engine. Five crucial input parameters—Engine Load, Ignition Pressure, and Ignition Timing—along with Hydrogen and Nanoparticles were thought to be the primary design elements. For each constituent, five more layers were made, as shown in Table 1. The levels and their ranges were chosen based on past discoveries that were published in the open literature. Brake pressure (BP), brake-specific fuel consumption (BSFC), and brake thermal efficiency (BTE) were engine performance measures. The next four answers, CO, CO2, NOx, and HC, all addressed the engine's emission characteristics. According to ASTM requirements, tests on the vital properties of diesel, biodiesel, and biogas fuels were carried out.

Table 1 Setting levels for design parameters

Controlled factors	Level 1	Level 2	Level 3	Level 3
Engine Load (%)	40	60	80	100
Hydrogen (%)	0	7	12	18
Nanoparticles (ppm)	0	15	30	45
Ignition Pressure(bar)	210	230	250	270
Ignition timing (bTDC)	21	23	25	27

A number of trials were needed to cover the entire area because there were so many input and output variables. Compared to an unplanned experiment, a well-designed experiment can generate far more data with fewer runs. The impact of various input parameters on response was examined using the GRA parameter design approach. The best parameter selections for a particular performance aspect, however, could be found via the traditional GRA method. Since there was numerous performance parameters present with competing goals, the GRA approach was used to combine them into a single response.

2.1 Grey Relational Analysis.

To compare the amount of a desired signal to the amount of background noise, scientists and engineers can evaluate the signal-to-noise ratio (S/N). A lower S/N ratio for one performance characteristic may be indicative of a greater S/N ratio for another performance feature because the current study intended to optimise six response qualities. As a result, it was essential to thoroughly examine the S/N ratio in order to optimise a number of performance-related factors. It has been demonstrated that grey relational analysis is a useful method for studying this kind of issue. It was utilised to identify the crucial components of the system and their interrelationships. The input and output sequence revealed which factors were crucial. Experimental data were initially normalised in the zero to one range for the current investigation. The grey relationship coefficients were then used to explain the relationship between the desired and actual experimental data using normalised experimental data. The grey relational coefficients for each chosen process response were then averaged to determine the final grey relational grade. The grey relational grade served as the foundation for the evaluation of the multiple process response. Using the objective function of overall grey relational grade, this technique was utilised to reduce a multiple response process optimisation problem to a single response problem. The optimal process parameter was determined to be the level of parametric combination with the highest grey relational grade. As "the higher-the-better" was the desired value, the original sequence was normalised as follows.

$$a^*(k) = \frac{a^i(k) - \min a^i(k)}{\max a^i(k) - \min a^i(k)} \quad (1)$$

When "the lower-the-better" was the desired outcome, the original order was normalised as follows.

$$a^*(k) = \frac{\max a^i - a^i(k)}{\max a^i(k) - \min a^i(k)} \quad (2)$$

The initial reference sequence is represented by the letters yi(k), the comparison sequence is represented by the letters xi(k), and the total number of experiments and replies is represented by the numbers i = 1, 2,..., m and k = 1, 2, 3,..., n. The values of yi(k) are min yi(k) and max yi(k), in that order.

In this case, the value that came after the grey relational construction was xi(k). x0(k) was the perfect series. The degree of connection between the experimental run sequences [x0(k) and xi(k), i = 1, 2,..., m] was shown by the grey relational grade.
One might compute the grey relational coefficient i(k) as

$$\varepsilon(k) = \frac{\Delta_{min} + \gamma\, \Delta_{max}}{\Delta_o\,(k) + \gamma\, \Delta_{max}} \quad (3)$$

$$\Delta_i(k) = [x_o(l) - x_i(l)] \quad (4)$$

It was the difference between x0(k) and xi(k)'s absolute values. The absolute differences (0i) of each comparison series are represented by the min and max values, respectively. The maximum effect was designed with the distinguishing coefficient (0-1) to reduce its effects when they became too powerful for the purposes of this investigation, was set to a value of 0.5. The grey relational coefficients were averaged to determine the grey relational grade o. The intensity of the relationship between the ideal sequence x0(k) and the actual sequence xi(k) was thought to affect the value of the grey relational grade. In the experimental design, it was anticipated that the optimal sequence x0(k) would represent the ideal process response. The closer to the ideal the relevant parameter combination was, the higher the relationship grade displayed.

2.1.1 Grey Relational Grade Generation

Engine performance tended to decline as the fuel blend was increased, although emission characteristics tended to rise. Because various external equipment types, such as exhaust gas recirculation (EGR), might reduce engine emissions, the analysis was done in a way that the engine performance wouldn't be adversely affected even when diesel was substituted with a blend of diesel, biodiesel, and biogas. Therefore, while converting a number of grey relation grades, engine performance was given a higher weighting factor than emission regulations. The overall format of the grey relationship grades was changed, and weighting factors were utilised as necessary with the sequence values.

$$y_i = \frac{1}{n} \sum_{k=1}^{n} \in_i \,(k) \quad (5)$$

Experience may be used to supply the distinct sequence value of the weighting component, or acceptable weights may be generated using techniques like singular value decomposition and preliminary grey relational grading values. It should be noted that applying weighting factors would not be the same as selecting to apply sequence normalisation or altering the sequence value units utilised.

Experimental Set up

An eddy current dynamometer was instantly connected to the engine using a flexible connector (Figure 1). In order to gauge the load placed on the engine, the eddy current dynamometer's output was fixed to a strain gauge load cell. Nitrogen dioxide (NO2), unburned hydrocarbons (HC), nitrogen oxides (NOx), and carbon monoxide (CO) were also measured using a gas analyzer. The measurement units for NOx, HC, and CO were parts per million (ppm) of hexane equivalent and percent volume, respectively. The gasoline tank has a glass burette ready to count the amount of fuel utilised per minute. Because of this, the diesel and biodiesel fuels were measured independently using a stopwatch. 20% was the lowest load level applied to the engine, and 100% was the highest load level. The torque applied to the engine was calculated using the length of the dynamometer shaft. BTDC (before top dead centre) was maintained during all experiments on diesel, biodiesel, and biogas. The engine underwent a variety of load conditions during the testing. There were different compression ratios (CR) available. Each time the fuel was changed during the experiment, the fuel lines were cleaned and the engine was run for 30 minutes to stabilise at the new state. engine and eddy current dynamometer specs. Figure 1 depicts the entire engine component used for the experiment. A DIGAS SAMPLER connected to an AVL DIG AS gas analyzer at the exhaust was used to analyse and study the engine exhaust (CO, HC, CO2, and NOx, BFSC, and BTE).

Figure 1 Experimental Setup with engine and analyzer

3. Result and Discussion

The five input variables—Engine Load, Ignition Pressure, Ignition Timing, Hydrogen, and Nanoparticles—were combined to yield six output responses (outputs). To identify the best process condition, Taguchi's L16 orthogonal array was chosen. There were therefore a total of 16 tests performed. By using grey relation techniques, the experimental findings were normalised in the range of 0 to 1. It was discovered that only five of the six choices had greater objective values, whereas the other five had lower values that were desirable. As a result, during data normalisation, (1) was used to calculate the target values for the parameters BFSC, CO, CO2, NOx, HC, and BTE, whereas (2) was used to obtain the remaining values. The grey relation coefficients for each response were also computed using (3). The relationships of the grey were determined using the grades of 4-year-olds. It will be decided what grade grey relations will receive overall after taking into account the fairly weighted criteria.

Table 2 Experimental results

BTHE	**CO**	**HC**	**NOx**	**CO_2**	**BP**
10.4	0.209	430	110	2.88	0.43
12.2	0.196	422	102	2.76	0.78
14	0.598	452	118	2.75	1.06
16.1	0.114	276	115	2.74	1.67
20	0.097	226	220	2.85	1.75
21.1	0.071	181	188	2.21	2.09
22.8	0.067	150	255	3.14	2.39
25.3	0.056	108	275	3.01	2.8
26.3	0.093	101	296	3.16	3.07
26.1	0.133	147	232	3.59	3.5
26.8	0.189	452	385	3.42	3.75
7.29	0.153	499	325	2.66	0.39
8.6	0.157	484	275	2.74	0.51
13.85	0.107	411	328	2.73	0.98
20.89	0.117	328	213	2.57	1.39
18.11	0.276	310	176	2.34	1.64

Table 3 Normalized values

Brake specific fuel consumption	**CO**	**HC**	**NOx**	**CO_2**	**BTE**
0.159405	0.282288	0.826633	0.028269	0.485507	0.011905
0.251666	0.258303	0.806533	0	0.398551	0.116071
0.343926	1	0.88191	0.056537	0.391304	0.199405
0.451563	0.107011	0.439698	0.045936	0.384058	0.380952
0.651461	0.075646	0.31407	0.416961	0.463768	0.404762

0.707842	0.027675	0.201005	0.303887	0	0.505952
0.794977	0.020295	0.123116	0.540636	0.673913	0.595238
0.923116	0	0.017588	0.611307	0.57971	0.717262
0.974372	0.068266	0	0.685512	0.688406	0.797619
0.964121	0.142066	0.115578	0.459364	1	0.925595
1	0.245387	0.88191	1	0.876812	1
0	0.178967	1	0.787986	0.326087	0
0.067145	0.186347	0.962312	0.611307	0.384058	0.035714
0.336238	0.094096	0.778894	0.798587	0.376812	0.175595
0.697078	0.112546	0.570352	0.392226	0.26087	0.297619
0.554587	0.405904	0.525126	0.261484	0.094203	0.372024

Table 4 Deviation sequences of responses

Brake specific fuel consumption	**CO**	**HC**	**NOx**	**CO_2**	**BTE**
0.840595	0.717712	0.173367	0.971731	0.514493	0.988095
0.748334	0.741697	0.193467	1	0.601449	0.883929
0.656074	0	0.11809	0.943463	0.608696	0.800595
0.548437	0.892989	0.560302	0.954064	0.615942	0.619048
0.348539	0.924354	0.68593	0.583039	0.536232	0.595238
0.292158	0.972325	0.798995	0.696113	1	0.494048
0.205023	0.979705	0.876884	0.459364	0.326087	0.404762
0.076884	1	0.982412	0.388693	0.42029	0.282738
0.025628	0.931734	1	0.314488	0.311594	0.202381
0.035879	0.857934	0.884422	0.540636	0	0.074405
0	0.754613	0.11809	0	0.123188	0
1	0.821033	0	0.212014	0.673913	1
0.932855	0.813653	0.037688	0.388693	0.615942	0.964286
0.663762	0.905904	0.221106	0.201413	0.623188	0.824405
0.302922	0.887454	0.429648	0.607774	0.73913	0.702381
0.445413	0.594096	0.474874	0.738516	0.905797	0.627976

Table 5 Grey relational coefficients

Brake specific fuel consumption	**CO**	**HC**	**NOx**	**CO_2**	**BTE**
0.372969	0.410606	0.742537	0.339736	0.492857	0.336

0.400534	0.402675	0.721014	0.333333	0.453947	0.36129
0.432498	1	0.808943	0.346389	0.45098	0.384439
0.476901	0.35894	0.471564	0.343864	0.448052	0.446809
0.589248	0.351036	0.42161	0.461664	0.482517	0.456522
0.631187	0.339599	0.384913	0.418021	0.333333	0.502994
0.709197	0.337905	0.363139	0.521179	0.605263	0.552632
0.866726	0.333333	0.337288	0.562624	0.543307	0.638783
0.951243	0.349227	0.333333	0.613883	0.616071	0.711864
0.933046	0.368207	0.361162	0.480475	1	0.870466
1	0.398529	0.808943	1	0.802326	1
0.333333	0.378492	1	0.702233	0.425926	0.333333
0.348954	0.380618	0.929907	0.562624	0.448052	0.341463
0.429641	0.355643	0.69338	0.712846	0.445161	0.377528
0.622726	0.360372	0.537838	0.451356	0.403509	0.415842
0.52887	0.456998	0.512887	0.403709	0.35567	0.443272

Table 6 Grey relational grade

Exp. No.	**Grey relational grade**	**Rank**
1	0.45	12
2	0.45	13
3	0.57	4
4	0.42	16
5	0.46	11
6	0.44	15
7	0.51	7
8	0.55	5
9	0.60	3
10	0.67	2
11	0.83	1
12	0.53	6
13	0.50	8
14	0.50	9
15	0.47	10
16	0.45	14

4. Conclusion

- The effects of diesel, biodiesel, and biogas fuel blends on engine performance and exhaust pollutants were examined in this experimental study. The engine efficiency and emission characteristics had been looked at in connection to the potential usage of diesel, biodiesel, and biogas blended with conventional diesel as a suitable alternative fuel source.
- The responses' non-unidirectionality highlighted the complexity of the optimisation problem. The weighting variables from grey relational analysis were used to condense the multi-response problem into a single problem, and the test data were used to find the optimal solution.

- The results of actual experiments were used to validate the experimental investigation's findings. The mixture was shown to be the best blend for diesel engines, having little to no impact on the engine's emissions, performance, or the variables connected to those variables (such as engine load, ignition pressure, ignition timing, hydrogen, and nanoparticles).

5. References

[1] C. Carraretto, A. Macor, A. Mirandola, A. Stoppato, and S. Tonon, “Biodiesel as alternative fuel: experimental analysis and energetic evaluations,” Energy, vol. 29, no. 12–15, pp. 2195–2211, 2004.

[2] C. Carraretto, A. Macor, A. Mirandola, A. Stoppato, and S. Tonon, “Biodiesel as alternative fuel: experimental analysis and energetic evaluations,” Energy, vol. 29, no. 12–15, pp. 2195–2211, 2004.

[3] A. K. Agarwal, “Biofuels (alcohols and biodiesel) applications as fuels for internal combustion engines,” Progress in Energy and Combustion Science, vol. 33, no. 3, pp. 233–271, 2007.

[4] H. Raheman and S. V. Ghadge, “Performance of compression ignition engine with mahua (Madhuca indica) biodiesel,” Fuel, vol. 86, no. 16, pp. 2568–2573, 2007.

[5] H. Raheman and S. V. Ghadge, “Performance of diesel engine with biodiesel at varying compression ratio and ignition timing,” Fuel, vol. 87, no. 12, pp. 2659–2666, 200

[6] Y. V. H. Rao, R. S. Voleti, V. S. Hariharan, and A. V. S. Ju, “Jatropha oil methyl ester and its blends used as an alternative fuel in diesel engine,” International Journal of Agriculture and Biological Engg, vol. 1, pp. 32–38, 2008.

[7] S. R. Kalbande and S. D. Vikhe, “Jatropha and karanja biofuel: an alternative fuel for diesel engine,” ARPN Journal of Engineering and Applied Sciences, vol. 3, pp. 7–13, 2008

[8] G. Fontaras, G. Karavalakis, M. Kousoulidou et al., “Effects of biodiesel on passenger car fuel consumption, regulated and non-regulated pollutant emissions over legislated and realworld driving cycles,” Fuel, vol. 88, no. 9, pp. 1608–1617, 20

[9] S. Godiganur, C. H. Suryanarayana Murthy, and R. P. Reddy, “6BTA 5.9 G2-1 Cummins engine performance and emission tests using methyl ester mahua (Madhuca indica) oil/diesel blends,” Renewable Energy, vol. 34, no. 10, pp. 2172–2177, 2009

[10] B. Baiju, M. K. Naik, and L. M. Das, “A comparative evaluation of compression ignition engine characteristics using methyl and ethyl esters of Karanja oil,” Renewable Energy, vol. 34, no. 6, pp. 1616–1621, 2009.

[11] P. K. Sahoo, L. M. Das, M. K. G. Babu et al., “Comparative evaluation of performance and emission characteristics of jatropha, karanja and polanga based biodiesel as fuel in a tractor engine,” Fuel, vol. 88, no. 9, pp. 1698–1707, 2009.

[12] A. Murugesan, C. Umarani, R. Subramanian, and N. Nedunchezhian, “Bio-diesel as an alternative fuel for diesel engines—a review,” Renewable and Sustainable Energy Reviews, vol. 13, no. 3, pp. 653–662, 2009.

[13] M. K. Duraisamy, T. Balusamy, and T. Senthilkumar, “Experimental investigation on a mixed biodiesel fueled direct injection diesel engine,” International Journal of Applied Engineering Research, vol. 5, no. 2, pp. 253–260, 2010

[14] Y. S. Tarng, S. C. Juang, and C. H. Chang, “The use of grey-based Taguchi methods to determine submerged arc welding process parameters in hardfacing,” Journal of Materials

Processing Technology, vol. 128, no. 1–3, pp. 1–6, 200
[15] A. K. Sood, R. K. Ohdar, and S. S. Mahapatra, "Improving dimensional accuracy of fused deposition modelling processed part using grey Taguchi method," Materials and Design, vol. 30, no. 10, pp. 4243–4252, 2009.
[16] Y. Kuo, T. Yang, and G. W. Huang, "The use of a grey-based Taguchi method for optimizing multi-response simulation problems," Engineering Optimization, vol. 40, no. 6, pp. 517–528, 2008.