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Modeling and Grey Relational Multi-response Optimization of Chemical Additives and Engine Parameters on Performance Efficiency of Diesel Engine

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Abstract: Singular optimization of engine conditions for better engine performance have been studied extensively. However, in the practical sense, more than one performance characteristics are essential in the optimization of engine conditions. The current study investigates the effect, optimization, and modeling of engine conditions on multi-characteristics of a single cylinder-dual direct injection-water cooled diesel engine with the help of Taguchi-grey relational and regression analyses. The engine conditions employed are engine load, hydrogen, multi-walled carbon nanotubes (MWCNTs), ignition pressure, and ignition timing, at four different levels. The engine performance characteristics analyzed were brake thermal efficiency (BTE), brake specific fuel consumption (BSFC), hydrocarbons (HC), nitrogen oxide (NOx), carbon monoxide (CO), and carbon dioxide (CO_2). The results showed that there was a similar behavioral pattern of the effect of engine conditions on engine performance, except for ignition timing. The optimal settings for better engine performance were obtained at 25% engine load, 20% hydrogen, 50 ppm MWCNTs, 220 bar ignition pressure, and 21 obTDC ignition timing. Interestingly, the discovered optimal did not fall within the considered experimental runs, however, the predicted optimal engine performance was within 95% confidence bounds. It is recommended that the experimental work based on the obtained optimal settings should be conducted to elucidate the efficacy of the confirmation analysis. The analysis of variance showed that the engine load was the most significant factor on the overall engine performance, having a contribution of 71.47%, followed by hydrogen and MWCNTs. Also, the ignition pressure and timing were not significant on the overall engine performance, which showed a need to place more attention on the significant factors for better engine performance. The mathematical and graphical modeling showed the efficacy of the design analysis, while the interaction plots showed broader detailed factor settings for better engine performance.

Keywords: Grey relational optimization; diesel engine; brake thermal efficiency; fuel consumption; emissions

1. Introduction

In ongoing many years, all-out overall energy utilization has been expanded essentially. It prompts unnatural weather change and brings about higher temperatures on the earth (Masoudi &

Zaccour, 2017) and undermines energy security (Wallington *et al.*, 2013). This effect is detrimental to human well-being and the ecosystem (Lin *et al.*, 2011; Arbab *et al.*, 2013). A lot of researches have shown that fossil fuels contribute significantly to ozone layer depletion (Oparanti *et al.*, 2022). The pace of energy utilization has been reported by International Energy Organization (IEA) to reach about 53% by 2030 (Taufiqurrahmi & Bhatia, 2011). Meaning, the adverse effect of the utilization of fossil fuels on ozone layers depletion by 2030 is likely to be unbearable. Several pieces of research have been conducted on the several ways to mitigate these challenges. Abu-Jrai *et al.* (2009) researched the likelihood of improving performance efficiency and reducing combustion emissions of a single-cylinder-direct injection-diesel engine. In their work, simulated reformer product gas was added to a typical ultra-low Sulphur diesel (ULSD) and a replacement ultra-clean synthetic GTL (gas-to-liquid) fuel to research engine performance, combustion, and emissions at different operating conditions. They concluded that an optimal combination of GTL and simulated reformer product gas significantly improved both NOx and smoke emissions. Ren *et al.* (2008) investigated combustion and emissions of a diesel direct engine injection (DI) powered by diesel-oxygenate blends. They observed that there was a discount in smoke concentration no matter the kinds of oxygenating additives, however, the smoke reduced when oxygen mass fraction within the blends was increased without increasing the NOx and engine thermal efficiency. Conversely, it had been noticed that CO and HC concentrations reduced with a rise in oxygen mass fraction within the blends. Li *et al.* (2015) fueled an immediate injection diesel with pentanol to research the combustion and emissions of the compression ignition of the engine. It had been discovered that NOx and soot emissions were significantly reduced for pentanol with comparable efficiencies under one injection strategy without exhaust gas recirculation (EGR). It had been also observed that the employed pentanol fuel offered obvious characteristics to realize a smoother heat release rate with reduced peak pressure-rise rate in contrast to the diesel oil. Prabhu and Ramanan (2020) studied the effect of emission and performance characteristics in an unmodified diesel powered by pentanol-diesel mixtures at different ratios. They found that pentanol acted as a catalyst (oxidizing) thereby reducing the carbon monoxide gas and hydrocarbon emissions. It had been also discovered that there was a substantial reduction in NOx emission and also a discount in fuel consumption which increased the brake thermal efficiency of the engine. Kalam *et al.* (2011) investigated the emissions and performance characteristics of an indirect ignition diesel fueled with a waste vegetable oil. They found that there was a discount in brake power compared with ordinary diesel oil. However, a discount in exhaust emissions like unburned hydrocarbon (HC), smoke, carbon mono-oxide (CO), and nitrogen oxides (NOx) was generated by the blended fuels.

Furthermore, many studies are conducted on the optimization of input parameters on the emissions and performance efficiency of diesel engines. Sivaramakrishnan and Ravikumar (2014) optimized some operation parameters on the performance and emissions of a diesel fueled with biodiesel. It had been found that a compression ratio of 17.9, 10 you look after fuel blend, and 3.81 kW of power were the optimum parameters for the test engine. Leung *et al.* (2006) optimized engine parameters namely; injection pressure, injection timing, and fuel pump plunger diameter. Their findings showed that that individual setting of the engine parameters couldn't cause an honest balance between PM and NOx emissions, but multiparameter settings with the consideration of their cross-interactive effects could reduce particulate matters and hydrocarbon without increasing NOx emission and trading off fuel combustion efficiency. Koten *et al.* (2014) discovered the optimum operating conditions for a diesel when it had been fueled with compressed biogas (CBG) and pilot diesel dual-fuel. Their findings showed that there have been significantly lower NOx emissions emitted under dual-fuel operation for all cases compared to single-fuel mode in the least engine load conditions. Ramachander *et al.* (2021) optimized the emission and combustion characteristics of diesel engines operating under the reactivity-controlled compression ignition mode. The operating parameters investigated were fuel injection system timings, injection pressure, and variable engine load, using Box-Behnken-based response surface methodology. Manigandan *et al.* (2020) administered optimization on the engine conditions of one cylinder-dual direct injection-water cooled diesel fueled under hydrogen, multiwall carbon nanotubes (MWCNTs), ignition pressure, and ignition timing. Their findings reflected that there's an improvement in brake power by 13% and a discount in brake-specific fuel consumption by 8% at full engine load conditions. It had been also added in their findings that there was a big emission reduction.

Taguchi design of experiment (DOE) has to do with the reduction of robust laboratory work or experiment to determine the effect of processing parameters or variables on the response of a system, product, or process (Taguchi & Phadke, 1989; Taguchi *et al.*, 2000; Taguchi *et al.*, 2005). However, Taguchi is only capable of optimizing a singular response of a process, product, or system. However, the Taguchi DOE method with the assistance of grey relational analysis (GRA) can optimize multiple responses. In other words, when there is a complex situation or uncertainty, like in the case of a need to optimize more than one characteristic of a system, product, or process, GRA can be employed to simplify the situation for possible optimization (Julong 1989; Javed *et al.*, 2019). GRA is employed to convert multiple response characteristics into a singular response understood by the Taguchi DOE technique. GRA has been explored in several applications in the past studies. Tosun (2006) employed GRA for the optimization of multi-responses in drilling operations. Hamzaçebi and Pekkaya (2011) determined stock investments using GRA. Li *et al.* (2019) employed GRA in combination with the incremental capacity analysis technique in the application of accurate battery state-of-health (SOH) monitoring for the safe and reliable operation of electric vehicles. Wu *et al.* (2020) incorporated TRIZ, AD, fuzzy, and GRA design as a novel design approach in the designing and manufacturing of a product. Senthilkumar *et al.* (2021) blended and optimized a transformer oil with vegetable oil using the Taguchi-GRA technique. This review shows that GRA has applications in invariably all areas of endeavors.

Having discussed the state of the art of the subject matter, it is important to state that several studies have considered the optimization of engine conditions for better engine performance and reduced emissions. These studies mostly considered the optimization of singular performance characteristics, which is an actual sense, there is a need to consider optimization of engine conditions for all the important performance characteristics of an engine, such as engine conditions, fuel blends, etc. This will lead to efficient optimization. Multiple performance characteristics optimization is complicated because all the design of experiment (DOE) techniques can optimize singular performance characteristics of a system, process, or product. Due to this challenge, Manigandan *et al.* (2020) evaluated all the multiple performance characteristics of a diesel engine using the Taguchi DOE technique. They optimized those characteristics individually, which is somewhat not good enough for efficient optimization (Ofodu & Abifarin, 2022). Hence, this study identified the gap by employing grey relational analysis (GRA) to assist the Taguchi DOE technique for multiple performance characteristics of a single cylinder-dual direct injection-water cooled diesel engine. GRA technique is employed to assist the Taguchi design technique because the engine performance conditions were complex to optimize due to incomplete and uncertain information present in this study. GRA has been proven to mitigate this very challenge (Javed 2019; Javed *et al.*, 2019; Abifarin, 2021; Abifarin *et al.*, 2022a).

2. Research design and methodology

2.1 Experimental data curation and research design

This study followed the study of Manigandan *et al.* (2020). The experimental data was obtained from their work for analysis. Tables 1, 2, and 3 show the experimental factors considered, the experimental runs, and the corresponding data, respectively for the analysis in this study. The Taguchi design and modeling were done using Minitab 16 software, while interaction plots and other plots were done using Origin 19 software.

2.2 Research methodology and data analysis

Grey relational analysis was conducted on the experimental data presented in Table 3. The data was first normalized using grey relational generation. The break thermal efficiency (BTE) was normalized using the higher-the-better normalization condition, as giving in Equation 1.

Table 1. Experimental factors and levels

Factors	Engine load (%)	Hydrogen (%)	MWCNTs (ppm)	Ignition pressure (bar)	Ignition timing (°bTDC)
Factors symbols	A	B	C	D	E
Level 1	25	0	0	180	21
Level 2	50	10	30	200	23
Level 3	75	20	50	220	27
Level 4	100	30	80	240	31

Table 2. Experimental runs

Exp. runs	Engine load (%)	Hydrogen (%)	MWCNTs (ppm)	Ignition pressure (bar)	Ignition timing (°bTDC)
1	25	0	0	180	21
2	25	10	30	200	23
3	25	20	50	220	27
4	25	30	80	240	31
5	50	0	30	220	31
6	50	10	0	240	27
7	50	20	80	180	23
8	50	30	50	200	21
9	75	0	50	240	23
10	75	10	80	220	21
11	75	20	0	200	31
12	75	30	30	180	27
13	100	0	80	200	27
14	100	10	50	180	31
15	100	20	30	240	21
16	100	30	0	220	23

Table 3. Experimental multiple responses of the tested diesel engine

Exp. runs	BTE	BSFC	HC	NOx	CO	CO_2
1	32.65	755	8.65	120	0.09	2.61
2	33.88	735	8.5	112	0.08	2.55
3	37.3	708	8	108	0.05	2.1
4	35.25	715	8.25	105	0.06	2.32
5	33.95	662	10.8	210	0.128	4.05
6	32.15	625	10.2	235	0.125	3.95
7	34.35	539	9.4	210	0.12	3.8
8	36.98	468	9.2	198	0.1	3.52
9	33.55	490	13.05	265	0.135	5.52
10	35.12	452	12.19	265	0.149	4.32
11	33.84	485	11.95	280	0.14	4.25
12	34.5	435	11.25	242	0.132	4.15
13	33.56	375	14.68	365	0.158	7.25
14	34.1	355	13.72	315	0.155	6.75
15	35.95	348	12.68	298	0.145	4.45
16	35.05	368	15.66	338	0.151	6.2

The reason for the higher-the-better normalization is that break thermal efficiency is required as high as possible. Then, the rest of the data, namely; break specific fuel consumption (BSFC), hydrocarbons (HC), nitrogen oxide (NOx), carbon monoxide (CO), and carbon dioxide (CO_2) were normalized using the smaller-the-better normalization condition, as shown in Equation 2. The smaller-the-better normalization condition was chosen because we require those characteristics as low as possible. A comparison was done with an ideal sequence, $x_o(k)$ (k = 1, 2,…,16) for the six performance characteristics.

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{max\ y_i(k) - \min y_i(k)} \quad (1)$$

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{max\ y_i(k) - \min y_i(k)} \quad (2)$$

$x_i(k)$ is the data being preprocessed for the *i*th experiment, and $y_i(k)$ is the initial sequence of the mean of the responses. The deviation sequence (Equation 3) was subsequently calculated to enable the determination of grey relational coefficient (GRC). The grey relational generation and the deviation sequence of the six experimental data are shown in Table 4.

$$\Delta_{oi}(k) = |x_o(k) - x_i(k)| \quad (3)$$

where $\Delta_{oi}(k)$, $x_o(k)$, and $x_i(k)$ are the deviation, reference sequence, and normalized data, respectively. The GRC values were calculated using Equation 4. The GRC values show the relationship between the expected and obtained experimental data.

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(k) + \zeta\Delta_{max}} \quad (4)$$

where $\xi_i(k)$ is the GRC value of the individual experimental data, computed as a function of Δmin and Δmax, the minimum and the maximum deviations of each experimental data. ζ is the distinguishing coefficient, whose value is widely assumed to be 0.5 (Mahmoudi *et al.*, 2020; Abifarin *et al.*, 2021a).

Lastly, the grey relational grade (GRG) was calculated using Equation 5. The GRC, GRG, and signal to noise (S/N) ratios are displayed in Table 5. The GRG (the converted singular response) gives the overall multiple performance characteristics for the six experimental data, which made it possible for Taguchi DOE technique to analyze. As always require in GRA Optimization, the higher-the-better signal to noise ratio is considered for the Taguchi DOE analysis (Taguchi & Phadke, 1989; Taguchi *et al.*, 2000; Taguchi *et al.*, 2005; Abifarin, 2021; Abifarin *et al.*, 2021b; Abifarin *et al.*, 2022b; Awodi *et al.*, 2021).

$$\gamma_i = \frac{1}{n}\sum_{i=1}^{n} \xi_i(k) \quad (5)$$

γ_i is the GRG value obtained for the *i*th experiment and *n* is the number of performance characteristics.

Table 4. Grey relational generation and deviation sequence

	Generation						Deviation sequence					
	BTE	**BSFC**	**HC**	**NOx**	**CO**	**CO2**	**BTE**	**BSFC**	**HC**	**NOx**	**CO**	**CO2**
1	0.097	0	0.915	0.942	0.630	0.901	0.903	1	0.085	0.058	0.370	0.099
2	0.336	0.049	0.935	0.973	0.722	0.913	0.664	0.951	0.0653	0.027	0.278	0.087
3	1	0.116	1	0.989	1	1	0	0.885	0	0.012	0	0
4	0.602	0.098	0.967	1	0.907	0.957	0.398	0.902	0.033	0	0.093	0.043
5	0.350	0.229	0.635	0.596	0.278	0.621	0.651	0.772	0.366	0.404	0.722	0.379
6	0	0.319	0.713	0.5	0.306	0.641	1	0.681	0.287	0.5	0.694	0.359
7	0.427	0.531	0.817	0.596	0.352	0.670	0.573	0.469	0.183	0.404	0.648	0.330
8	0.938	0.705	0.843	0.642	0.537	0.724	0.062	0.295	0.157	0.358	0.463	0.276
9	0.272	0.651	0.341	0.385	0.213	0.336	0.728	0.349	0.659	0.615	0.787	0.664
10	0.577	0.745	0.453	0.385	0.083	0.569	0.423	0.256	0.547	0.615	0.917	0.431
11	0.328	0.663	0.484	0.327	0.167	0.582	0.672	0.337	0.516	0.673	0.833	0.418
12	0.456	0.786	0.576	0.473	0.241	0.602	0.544	0.214	0.424	0.527	0.759	0.398
13	0.274	0.934	0.128	0	0	0	0.726	0.066	0.872	1	1	1
14	0.379	0.983	0.253	0.192	0.028	0.097	0.621	0.017	0.747	0.808	0.972	0.903
15	0.738	1	0.389	0.258	0.120	0.544	0.262	0	0.611	0.742	0.880	0.456
16	0.563	0.951	0	0.104	0.065	0.204	0.437	0.049	1	0.896	0.935	0.796

Table 5. Grey relational coefficient (GRC), grey relational grade (GRG) and S/N ratio

Exp. Runs	GRC						GRG	S/N ratio
	BTE	BSFC	HC	NOx	CO	CO2		
1	0.356	0.333	0.855	0.897	0.575	0.835	0.642	-3.853
2	0.430	0.345	0.885	0.949	0.643	0.851	0.684	-3.304
3	1	0.361	1	0.977	1	1	0.890	-1.015
4	0.557	0.357	0.939	1	0.844	0.921	0.770	-2.275
5	0.435	0.393	0.578	0.553	0.409	0.569	0.490	-6.205
6	0.333	0.424	0.635	0.5	0.419	0.582	0.482	-6.338
7	0.466	0.516	0.732	0.553	0.436	0.602	0.551	-5.179
8	0.890	0.629	0.761	0.583	0.519	0.645	0.671	-3.464
9	0.407	0.589	0.431	0.448	0.389	0.430	0.449	-6.956
10	0.542	0.662	0.478	0.448	0.353	0.537	0.503	-5.965
11	0.427	0.598	0.492	0.426	0.375	0.545	0.477	-6.427
12	0.479	0.701	0.541	0.487	0.397	0.557	0.527	-5.566
13	0.408	0.883	0.364	0.333	0.333	0.333	0.443	-7.082
14	0.446	0.967	0.401	0.382	0.340	0.356	0.482	-6.339
15	0.656	1	0.450	0.403	0.362	0.523	0.566	-4.949
16	0.534	0.911	0.333	0.358	0.348	0.386	0.478	-6.406

3. Results and discussion

3.1 Effect and optimization of control factors on the engine multiple performance characteristics (GRG)

The effect of control factors on the multiple performance characteristics (GRG) of the diesel engine has been illustrated in Figure 1. The results showed that there GRG value decreased with an increase in engine load, while there was an increase in GRG when hydrogen was increased to 20% before it dropped slightly at 30%. Similar to the effect of hydrogen on the GRG value, MWCNTs and ignition pressure, an increase in GRG value was noticed up to level 3, but dropped at level 4. But for ignition timing factor, there the value of GRG was inconsistent with the increase in ignition timing. In conclusion, the figure shows the optimal settings of those factors for better performance of the tested engine, which are 25% engine load, 20% hydrogen, 50 ppm MWCNTs, 220 bar ignition pressure, and 21 obTDC ignition timing.

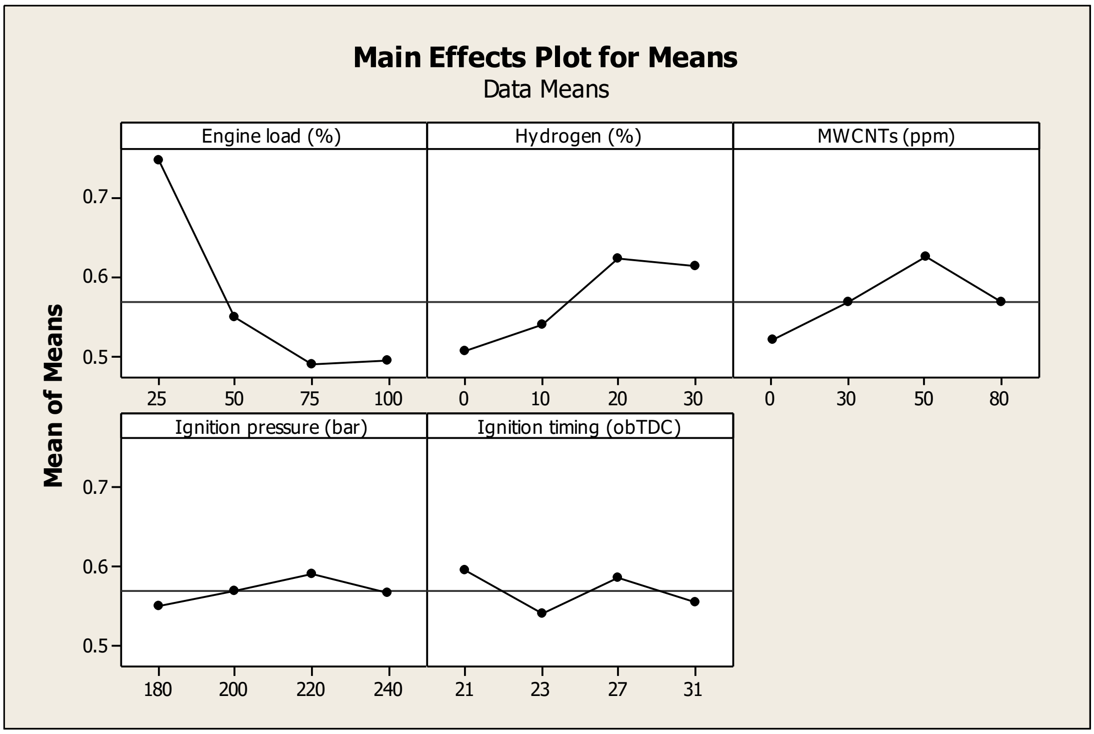

Fig 1. Effect of control factors on multiple performance characteristics

3.2 Significance of control factors on multiple performance of the diesel engine

The variance analysis (ANOVA) of the engine performance is shown in Table 6. It displays the effect and weight of each factor on the resultant performance. It is found that engine load is the most significant factor, showing a contribution of 71.47%, followed by hydrogen (15.36%), and MWCNTs (8.66%). The other two factors reflected a very little contribution of ignition pressure and timing. Thus, much attention should be placed on the significantly influenced factors to achieve better engine performance efficiency.

3.3 Confirmation analysis

If γ_0 is the highest engine performance efficiency at optimal settings and γ_m is the average engine performance efficiency, while q is the number of the factors, then the predicted grey relational grade (engine performance efficiency) is

$$\gamma_{predicted} = \gamma_m + \sum_{i=1}^{q} \gamma_0 - \gamma_m \tag{6}$$

The predicted engine performance efficiency at optimal settings was known to be 0.8997, and thus confidence interval (CI) was obtained using probability distribution analysis of the various GRG values to check perhaps all the experimental GRG values and the predicted optimal GRG value are within 95% confidence bounds. The confidence bounds and the experimental GRG value (engine performance) are displayed in Figure 2. The graph shows the possibility that the predicted

Table 6. ANOVA for engine performance

Factors	Degree of Freedom (DF)	Adj SS	Adj MS	Contribution (%)	Remark
Engine load (%)	3	0.17646	0.05882	71.47	Most significant
Hydrogen (%)	3	0.03792	0.01264	15.36	Significant
MWCNTs (ppm)	3	0.02138	0.00713	8.66	Significant
Ignition pressure (bar)	3	0.00321	0.00107	1.30	Insignificant
Ignition timing (°bTDC)	3	0.00796	0.00265	3.22	Insignificant
Residual error	0				-
Total	15	0.24693	0.08231		

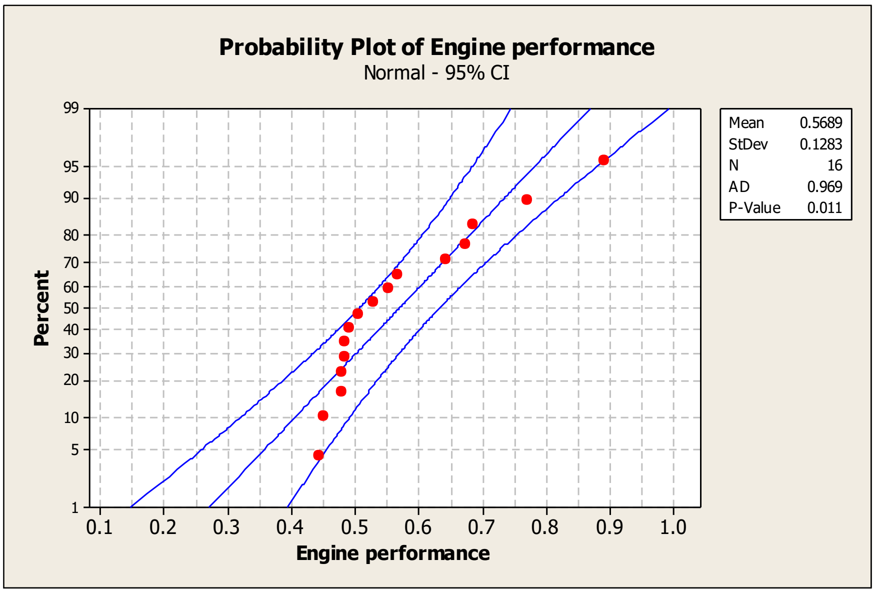

Fig 2. Confidence bounds of the engine performance (GRG)

optimal GRG value obtained fall within the 95% confidence bounds. However, further experimental work is recommended to be done considering the discovered optimal settings in this study. Because the discovered optimal settings were not among the experimental runs considered in the initial experimental work.

3.4 Modeling and interaction of chemical additives and engine parameters on engine performance

The Equation (7) shows the mathematical modeling of the engine performance (EP), while Figure 3 shows the experimental engine performance versus the modeled engine performance. The modeling was done using regression analysis with Mintab 16 software. Figure 3 shows that the predicted engine performance based on modeling followed the behavioral pattern of the experimental. This elucidates the validity of the design and model.

$$EP = 0.656 - 0.00329A + 0.00401B + 0.000716C + 0.000351D - 0.00174E \tag{7}$$

Figure 4 reflects the interaction plots of various factors on the engine performance. This explains the combination of factors settings for various engine performance efficiency. The figure shows the detailed combination of all the various factors levels to achieve engine performance as high as possible.

4. Conclusion

This study has successfully investigated the effect, optimization and modeling of engine conditions on multiple performance characteristics of a single cylinder-dual direct injection-water

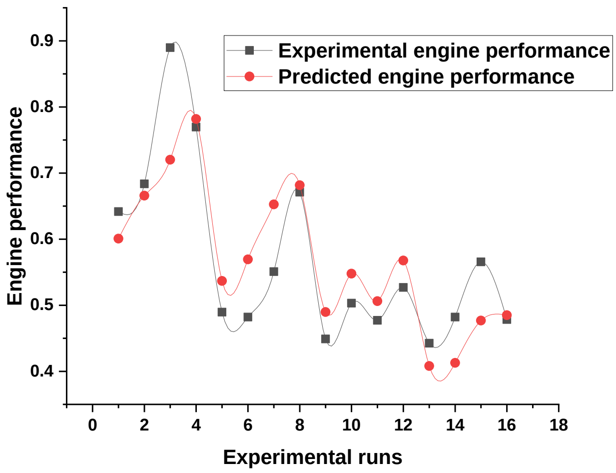

Fig 3. Experimental versus predicted engine performance

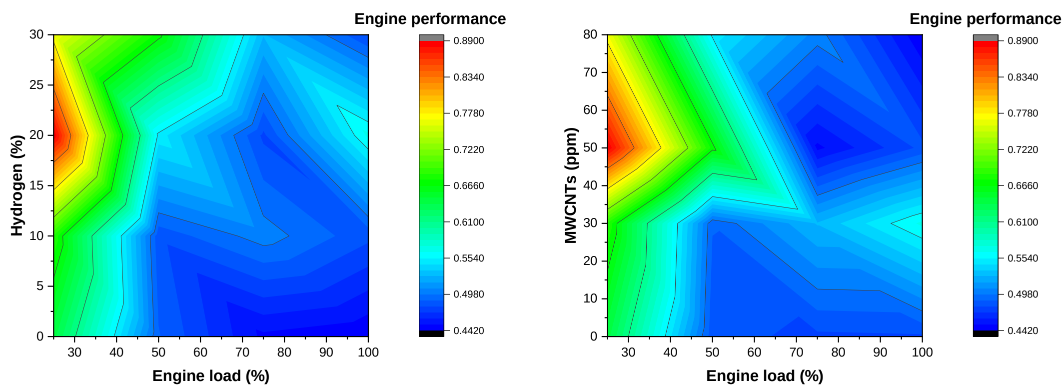

Fig 4. Interaction plots of parameters on engine performance

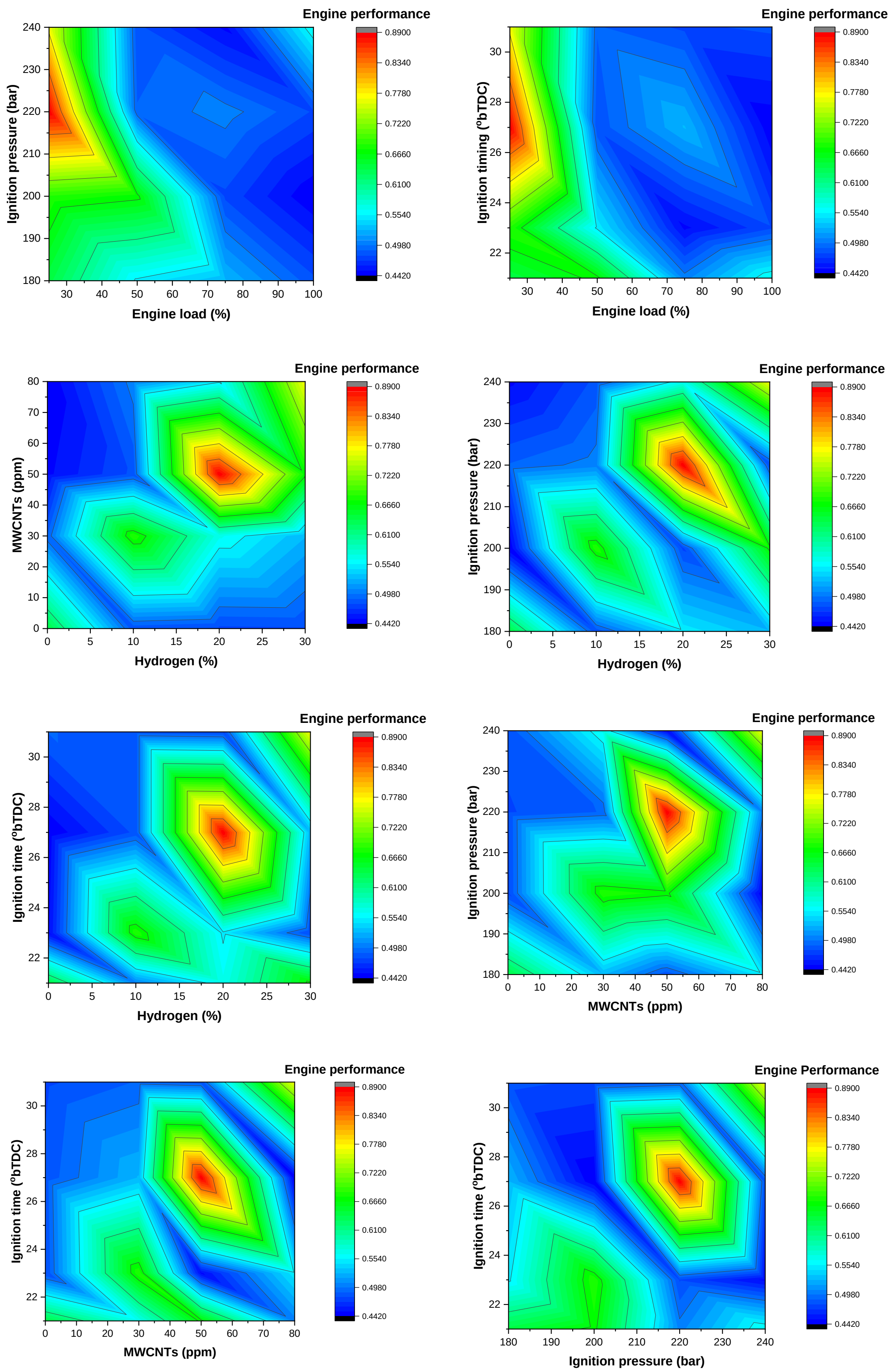

Fig 4. Interaction plots of parameters on engine performance (continued)

cooled diesel engine with the help of Taguchi grey relational and regression analysis. The multiple performance characteristics, namely; the break thermal efficiency (BTE), break specific fuel consumption (BSFC), hydrocarbons (HC), nitrogen oxide (NOx), carbon monoxide (CO), and carbon dioxide (CO_2) converted to a singular response, which made it feasible for Taguchi design technique to analyze. The results showed that there was similar behavioral pattern of the effect of engine conditions, except for ignition timing. The optimal settings for better engine performance were obtained to be 25% engine load, 20% hydrogen, 50 ppm MWCNTs, 220 bar ignition pressure, and 21 obTDC ignition timing. The discovered optimal settings for better engine performance did not fall within the experimental runs considered in the analysis. Although, confirmation analysis showed that there is possibility that the predicted optimal engine performance was within the confidence bound, however, there is a need to conduct experimental work based on the gotten optimal settings to elucidate the efficacy of the confirmation analysis. The analysis of variance (ANOVA) shows that engine load was the most significant factor with a contribution of 71.47%, followed by hydrogen and MWCNTs. The analysis revealed that the ignition pressure and timing were not significant on the overall engine performance. This shows that much attention is needed on the significant factors for better engine performance efficiency. The mathematical and graphical modeling of the overall engine performance were presented in this study. The modeling showed the efficacy of the design and analysis. Also, the interaction plots showed a broader detail of factor settings for better engine performance.

References

Abifarin, J. K. (2021). Taguchi grey relational analysis on the mechanical properties of natural hydroxyapatite: effect of sintering parameters. *The International Journal of Advanced Manufacturing Technology*, *117*, 49–57. https://doi.org/10.1007/s00170-021-07288-9

Abifarin, J. K., Fidelis, F. B., Abdulrahim, M. Y., Oyedeji, E. O., Nkwuo, T., & Prakash, C. (2022a). Response Surface Grey Relational Analysis On The Manufacturing of High Grade Biomedical Ti-13Zr-13Nb. *Research Square*. https://doi.org/10.21203/rs.3.rs-1225030/v1

Abifarin, J. K., Obada, D. O., Dauda, E. T., & Oyedeji, E. O. (2021a). Taguchi grey relational optimization of the multi-mechanical characteristics of kaolin reinforced hydroxyapatite: effect of fabrication parameters. *International Journal of Grey Systems*, *1*(2), 20-32. https://doi.org/10.52812/ijgs.30

Abifarin, J. K., Prakash, C., & Singh, S. (2021b). Optimization and significance of fabrication parameters on the mechanical properties of 3D printed chitosan/PLA scaffold. *Materials Today: Proceedings*, *50* (Part 5), 2018-2025. https://doi.org/10.1016/j.matpr.2021.09.386

Abifarin, J. K., Suleiman, M. U., Abifarin, E. A., Fidelis, F. B., Oyelakin, O. K., Jacob, D. I., & Abdulrahim, M. Y. (2022b). Fabrication of mechanically enhanced hydroxyapatite scaffold with the assistance of numerical analysis. *The International Journal of Advanced Manufacturing Technology*, *118*, 3331–3344. https://doi.org/10.1007/s00170-021-08184-y

Abu-Jrai, A., Rodríguez-Fernández, J., Tsolakis, A., Megaritis, A., Theinnoi, K., Cracknell, R. F., & Clark, R. H. (2009). Performance, combustion and emissions of a diesel engine operated with reformed EGR. Comparison of diesel and GTL fuelling. *Fuel*, *88*(6), 1031-1041. https://doi.org/10.1016/j.fuel.2008.12.001

Arbab, M. I., Masjuki, H. H., Varman, M., Kalam, M. A., Imtenan, S., & Sajjad, H. (2013). Fuel properties, engine performance and emission characteristic of common biodiesels as a renewable and sustainable source of fuel. *Renewable and Sustainable Energy Reviews*, *22*, 133-147. https://doi.org/10.1016/j.rser.2013.01.046

Awodi, E., Ishiaku, U. S., Yakubu, M. K., & Abifarin, J. K. (2021). Experimentally Predicted Optimum Processing Parameters Assisted by Numerical Analysis on the Multi-physicomechanical Characteristics of Coir Fiber Reinforced Recycled High Density Polyethylene Composites. *Research Square*. https://doi.org/10.21203/rs.3.rs-591200/v1

Hamzaçebi, C., & Pekkaya, M. (2011). Determining of stock investments with grey relational analysis. *Expert Systems with Applications*, *38*(8), 9186-9195. https://doi.org/10.1016/j.eswa.2011.01.070

Javed, S. A. (2019). A novel research on grey incidence analysis models and its application in project management (PhD dissertation). *Nanjing University of Aeronautics and Astronautics. Nanjing, PR China.*

Javed, S. A., Khan, A. M., Dong, W., Raza, A., & Liu, S. (2019). Systems evaluation through new grey relational analysis approach: an application on thermal conductivity—petrophysical parameters' relationships. *Processes*, *7*(6), 348. https://doi.org/10.3390/pr7060348

Julong, D. (1989). Introduction to Grey System Theory. *The Journal of Grey System*, *1*(1), 1-24.

Kalam, M. A., Masjuki, H. H., Jayed, M. H., & Liaquat, A. M. (2011). Emission and performance characteristics of an indirect ignition diesel engine fuelled with waste cooking oil. *Energy*, *36*(1), 397-402. https://doi.org/10.1016/j.energy.2010.10.026

Koten, H., Yilmaz, M., & Zafer Gul, M. (2014). Compressed biogas-diesel dual-fuel engine optimization study for ultralow emission. *Advances in Mechanical Engineering*, *6*, 571063. https://doi.org/10.1155/2014/571063

Leung, D. Y., Luo, Y., & Chan, T. L. (2006). Optimization of exhaust emissions of a diesel engine fuelled with biodiesel. *Energy & Fuels*, *20*(3), 1015-1023. https://doi.org/10.1021/ef050383s

Li, L., Wang, J., Wang, Z., & Liu, H. (2015). Combustion and emissions of compression ignition in a direct injection diesel engine fueled with pentanol. *Energy*, *80*, 575-581. https://doi.org/10.1016/j.energy.2014.12.013

Li, X., Wang, Z., Zhang, L., Zou, C., & Dorrell, D. D. (2019). State-of-health estimation for Li-ion batteries by combing the incremental capacity analysis method with grey relational analysis. *Journal of Power Sources*, *410*, 106-114. https://doi.org/10.1016/j.jpowsour.2018.10.069

Lin, L., Cunshan, Z., Vittayapadung, S., Xiangqian, S., & Mingdong, D. (2011). Opportunities and challenges for biodiesel fuel. *Applied Energy*, *88*(4), 1020-1031. https://doi.org/10.1016/j.apenergy.2010.09.029

Mahmoudi, A., Javed, S. A., Liu, S., & Deng, X. (2020). Distinguishing coefficient driven sensitivity analysis of GRA model for intelligent decisions: application in project management. *Technological and Economic Development of Economy*, *26*(3), 621-641. https://doi.org/10.3846/tede.2020.1189

Manigandan, S., Atabani, A. E., Ponnusamy, V. K., Pugazhendhi, A., Gunasekar, P., & Prakash, S. (2020). Effect of hydrogen and multiwall carbon nanotubes blends on combustion performance and emission of diesel engine using Taguchi approach. *Fuel*, *276*, 118120. https://doi.org/10.1016/j.fuel.2020.118120

Masoudi, N., & Zaccour, G. (2017). Adapting to climate change: Is cooperation good for the environment?. *Economics Letters*, *153*, 1-5. https://doi.org/10.1016/j.econlet.2017.01.018

Ofodu, J. C. & Abifarin, J. K. (2022). Employment of probability based multi-response optimization in high voltage thermofluids. *Military Technical Courier*, *70*(2), 393-408. https://doi.org/10.5937/vojtehg70-35764

Oparanti, S. O., Abdelmalik, A. A., Khaleed, A. A., Abifarin, J. K., Suleiman, M. U., & Oteikwu, V. E. (2022). Synthesis and characterization of cooling biodegradable nanofluids from non-edible oil for high voltage application. *Materials Chemistry and Physics*, *277*, 125485. https://doi.org/10.1016/j.matchemphys.2021.125485

Prabhu, A., & Ramanan, M. V. (2020). Emission and performance analysis of pentanol-diesel blends in unmodified diesel engine. *International Journal of Ambient Energy*, *41*(6), 699-702. https://doi.org/10.1080/01430750.2018.1490356

Ramachander, J., Gugulothu, S. K., Sastry, G. R. K., Panda, J. K., & Surya, M. S. (2021). Performance and emission predictions of a CRDI engine powered with diesel fuel: A combined study of injection parameters variation and Box-Behnken response surface methodology based optimization. *Fuel*, *290*, 120069. https://doi.org/10.1016/j.fuel.2020.120069

Ren, Y., Huang, Z., Miao, H., Di, Y., Jiang, D., Zeng, K., ... & Wang, X. (2008). Combustion and emissions of a DI diesel engine fuelled with diesel-oxygenate blends. *Fuel*, *87*(12), 2691-2697. https://doi.org/10.1016/j.fuel.2008.02.017

Senthilkumar, S., Karthick, A., Madavan, R., Moshi, A. A. M., Bharathi, S. S., Saroja, S., & Dhanalakshmi, C. S. (2021). Optimization of transformer oil blended with natural ester oils using Taguchi-based grey relational analysis. *Fuel*, *288*, 119629. https://doi.org/10.1016/j.fuel.2020.119629

Sivaramakrishnan, K., & Ravikumar, P. (2014). Optimization of operational parameters on performance and emissions of a diesel engine using biodiesel. *International Journal of Environmental Science and Technology*, *11*(4), 949-958. https://doi.org/10.1007/s13762-013-0273-5

Taguchi, G., & Phadke, M. S. (1989). Quality engineering through design optimization. In *Quality Control, Robust Design, and the Taguchi Method* (pp. 77-96). Springer, Boston, MA. https://doi.org/10.1007/978-1-4684-1472-1_5

Taguchi, G., Chowdhury, S., Wu, Y., Taguchi, S., & Yano, H. (2005). *Taguchi's Quality Engineering Handbook*. Wiley-Interscience.

Taguchi, G., Wu, Y., & Chodhury, S. (2000). *Mahalanobis-Taguchi System*. McGraw-Hill Professional.

Taufiqurrahmi, N., & Bhatia, S. (2011). Catalytic cracking of edible and non-edible oils for the production of biofuels. *Energy & Environmental Science*, *4*(4), 1087-1112. https://doi.org/10.1039/C0EE00460J

Tosun, N. (2006). Determination of optimum parameters for multi-performance characteristics in drilling by using grey relational analysis. *The International Journal of Advanced Manufacturing Technology*, *28*(5), 450-455. https://doi.org/10.1007/s00170-004-2386-y

Wallington, T. J., Lambert, C. K., & Ruona, W. C. (2013). Diesel vehicles and sustainable mobility in the US. *Energy Policy*, *54*, 47-53. https://doi.org/10.1016/j.enpol.2011.11.068

Wu, Y., Zhou, F., & Kong, J. (2020). Innovative design approach for product design based on TRIZ, AD, fuzzy and Grey relational analysis. *Computers & Industrial Engineering*, *140*, 106276. https://doi.org/10.1016/j.cie.2020.106276