

Multi-Objective Optimization Using Fuzzy-Logic of Exhaust Emissions and Performance of Mahua and Jatropha Biodiesel–Bio-Additive Blends

Praveen B¹, Pugazhenthir R^{2*}

¹Research Scholar, Department of Mechanical Engineering, VISTAS, India. Email: praveenvijay0007@gmail.com

²Professor, Department of Mechanical Engineering, VISTAS, India. Email: pugaz4@gmail.com

ABSTRACT

Background: The main challenge for the widespread use of biodiesel in compression ignition engines is to reduce exhaust emissions without compromising the performance of the engine; to do this, the key responses (oxides of nitrogen (NO_x), smoke, unburnt hydrocarbon (HC), carbon monoxide (CO), brake thermal efficiency (BTE) and brake specific fuel consumption (BSFC)) are varied in counterproductive ways by fuel and operating variables.

Methods: The aim of this study is to combine these six responses into a single intelligently interpretable multi-response performance index (MRPI) for 20 % mahua (MEOM) and jatropha (MEOJ) methyl-ester blends with and without a bio derived additive in a variable-compression-ratio (VCR) diesel engine using a hierarchical Mamdani fuzzy inference system (FIS) and an environment-weighted rule base.

Results: The operating points were ranked, the analysis of variance (ANOVA) was used to allocate the contributions of the factors and the ranking was independently confirmed by the TOPSIS multi-criteria method and a rule-based sensitivity analysis. In the smoke, HC and CO emission of the optimum for the jatropha biodiesel-additive blend (B20MEOJBA3ml) at the compression ratio of 17.5. it was found that around 24 % less, 12 % less and 36 % less respectively compared to the plain Mahua blend at the same compression ratio with no gain in NO_x with slight increase in efficiency.

Conclusion: The same point was also ranked by TOPSIS ($p = 0.77$) and the optimal was not affected by the different rule bases based on the environment, balance and performance, respectively, indicating the robustness of the fuzzy recommendation.

Keywords: Biodiesel; Exhaust emissions; Fuzzy logic; Mamdani inference; multi-objective optimization; TOPSIS; Variable compression ratio.

Introduction

Despite the fact that diesel engines are essential for transportation, agriculture and distributed power generation, they are also a major contributor to urban NO_x and particulate pollution. Biodiesel produced from non-edible feedstocks, like Mahua (*Madhuca indica*) and Jatropha (*Jatropha curcas*), is a renewable, largely carbon neutral alternative and is expected to produce a fuel-bound oxygen which results in more complete combustion, reducing smoke, HC and CO [1,2]. It is well known that it comes with a relatively small increase in in-cylinder NO_x due to higher in-cylinder temperatures, as well as a slight efficiency decrease at higher blend ratios [3,4]. There are two practical levers to control this behaviour: a high engine compression ratio (CR) will increase the efficiency of the combustion process and oxidise smoke, HC and CO pollutants, but increase NO_x emissions; additives will shorten the ignition delay and reduce the products of incomplete combustion even further [5,6]. As these effects are opposing each other, no setting optimizes all responses and so the setting of a best operation point is intrinsically a multi-criteria decision problem.

Fuzzy logic provides a tool for this purpose well suited to these conditions: a Mamdani inference system represents engineering judgement in a transparent way as linguistic rules, gives room for imprecision in experiments, and combines contradicting answers to linguistic rules into a single interpretable index without an explicit differentiable objective or a fixed weight vector [7,8]. Present work develops an environment-weighted hierarchical fuzzy system to optimize the output emissions and performance of mahua and jatropha biodiesel–additive blends for various compression ratios, and presents the results by ANOVA to find the controlling factor and, unlike most fuzzy engine studies, validates the results independently by TOPSIS multi-criteria method and sensitivity analysis by rule base.

Literature review

The literature review is carried out under three themes: biodiesel exhaust emissions and the NO_x – smoke trade-off, compression ratio and additives as levers for emission control, and tools for optimization and multi-criteria decision

making. Table 1 provides a summary of the key experimental studies. On all the feedstocks, the use of biodiesel reduces the products of incomplete combustion and slightly increases NO_x. Mahua biodiesel has seen a decrease in HC and smoke by about 22–23 % and an increase in NO_x by 6 % [1] and similar behaviour is seen for jatropha blends [2]. This NO_x–smoke (and NO_x–efficiency) opposition is a common theme in biodiesel research and this is why single-objective tuning is insufficient; extensive reviews have been conducted on the trend and the key ways of NO_x reduction [3]. The nano-additive and hybrid-fuel options further move the balance — such as the 20–40 % reduction of CO, HC and smoke in mahua blends with metal-oxide nanoparticles [11] — but do not usually solve the problem. Higher compression ratio resulted in higher benefit of BTE (7–10 %) with increased peak pressure as compression ratio increases [9,12] and higher compression ratio resulted in decreasing smoke, HC and CO and increasing NO_x. Combustion-improving and antioxidant additives counteract the NO_x-penalty of biodiesel and reduce products of incomplete combustion: NO_x from jatropha-biodiesel engines has been reduced by antioxidant additives [7] and reviews of both ether and antioxidant/cetane-improver additives showed consistent reduction of HC, CO and smoke [6,8]. The experimental VCR study on which the present data is based, indicated that the efficiency of diesel – jatropha B20 with bio-additive was maximum at CR 17.5 for the additive blend B20MEOJBA [5].

Addressing the multi-response problem has become more and more popular using statistical and soft-computing methods. Biodiesel-engine responses have been optimized using the Taguchi and grey-relational schemes [10] and fuzzy logic has been used to both predict and optimize engine behaviour: Taguchi optimization of compression ratio and injection timing for oxygenated blends using fuzzy logic [15], grey-Taguchi optimization of the performance–emission trade-off using fuzzy logic [16] and fuzzy multi-objective studies of CRDI biodiesel engines [17, 24] are representative. Optimal blends have been determined by ranking alternatives against an ideal solution using multi criterion decision making (MCDM) methods like TOPSIS, VIKOR and ANP [19–22] and recently work has been found which explicitly incorporates fuzzy optimization with TOPSIS/VIKOR for cross validation [23, 22]. This precedent encourages the current validation approach.

Table 1. Representative studies on biodiesel emissions and multi-response optimization

Ref.	Fuel / feedstock	Method	Key finding	Gap addressed here
[1]	Mahua B20–B100	Experimental	HC/smoke –22–23 %, NO _x +6 %	No formal multi-objective balance
[5]	Diesel & jatropha B20 + additive	VCR experimental (source)	Best efficiency: B20MEOJBA, CR 17.5	No emission-weighted optimization
[7]	Jatropha + antioxidant	Experimental	NO _x mitigation with additive	Single response only
[9]	Jatropha ester	VCR, CR 16.5–18.5	BTE +9.6 %, smoke lower	Trade-off not optimized
[11]	Mahua + nanoparticles	Experimental + ML	CO/HC/smoke –20–40 %	No decision-making method
[15]	Oxygenated blends	Fuzzy-Taguchi	Optimal CR / injection timing	No emissions focus / validation
[16]	CI-engine biodiesel	Fuzzy-grey-Taguchi	Performance–emission optimum	No independent MCDM check
[17]	Schleichera biodiesel (CRDI)	Fuzzy multi-objective	Emission–stability trade-off	Not for mahua/jatropha + CR
[20]	Fish-oil biodiesel	ANP–TOPSIS / VIKOR	B20 best blend	No fuzzy inference / additive

The reviewed studies find the NO_x–smoke trade-off for the operation of biodiesel, the role of compression ratio and additives and they show fuzzy and MCDM optimization separately. But there are still three gaps. First, emission reduction is rarely the main goal and performance is a constraint and most optimizations are performance driven. Second, very few studies have been carried out that validate the result of fuzzy-logic optimizations of biodiesel engines when compared to an independent decision-making method, or that test the sensitivity of the result to the rule base. Thirdly, none of the studies use environment weighted fuzzy system for Mahua and Jatropha Biodiesel–Additive blend for different compression ratio. These gaps provide impetus to the current research.

To the authors' knowledge, this work is the first to (i) develop an environment weighted hierarchical Mamdani fuzzy system, which integrates four emissions and two performance measurements into one single index to assess performance of the mahua/jatropha biodiesel–additive operation for varying compression ratios; (ii) use ANOVA on the above index to show that the fuel blend is a controlling factor and the compression ratio is not, in the emission–performance balance; and (iii) validate the fuzzy optimum with an independent TOPSIS ranking, and also with a rule-base sensitivity analysis, which has confirmed the robustness of the recommendation. The framework can be applied to other feedstocks, additives, emission priority scenarios.

Materials and methods

Test fuels and engine

MEOM, MEOJ, and B20 were blended at 20 % by volume (B20) and a bio-derived additive (BA) was dosed at 3 ml/l to get B20MEOMBA3ml and B20MEOJBA3ml. A single cylinder, four stroke, water-cooled VCR diesel engine (Kirloskar TV1 type, 3.5 KW at 1500 rpm) was used for the tests which were fitted with an eddy-current dynamometer, an AVL smoke meter and a five-gas analyser. Tables 2 and 3 provide details of the specifications and fuel properties.

Table 2. Engine specifications.

Parameter	Specification
Engine type	Single cylinder, 4-stroke, DI, water-cooled VCR
Bore × stroke	87.5 mm × 110 mm
Rated output	3.5 kW @ 1500 rpm
Compression-ratio range	15.5 – 17.5 (variable)
Injection timing / pressure	23° bTDC / 220 bar
Emission bench	Smoke meter + five-gas analyser

Table 3. Properties of the test fuels.

Property	Diesel	B20MEOM	B20MEOJ	B20 + BA
Density (kg/m ³)	830	868	865	860
Kinematic viscosity (cSt)	2.6	3.6	3.4	3.3
Calorific value (kcal/kg)	10896	9823	10280	~ 10280
Cetane number	48	51	52	53

Design of experiments

Two factors examined at three levels were Fuel Blend (A) and Compression Ratio (B) for a full 3 × 3 (nine-run) design (Table 4). Six responses were measured at rated load – NO_x, smoke, HC and CO (environmental) and BTE and BSFC (performance).

Table 4. Factors and levels.

Factor	Level 1	Level 2	Level 3
A — Fuel blend	B20MEOM	B20MEOMBA3ml	B20MEOMBA3ml
B — Compression ratio	17.5	16.5	15.5

Fuzzy inference system

The following benefit scales on [0,1] (1 = most desirable) were used for each response: Larger-the-better for BTE (Eq. 1) and smaller-the-better for BSFC, NO_x, smoke, HC and CO (Eq. 2).

$$x^*_i = (x_i - \min x) / (\max x - \min x) \quad (1)$$

$$x^*_i = (\max x - x_i) / (\max x - \min x) \quad (2)$$

The responses were combined together in the MRPI by a hierarchical Mamdani system, as shown in Fig 4. Combustion emissions was calculated as a combustion-emission index $CEI^* = (\text{smoke}^* + \text{HC}^* + \text{CO}^*)/3$. An emission fuzzy system was used to map NO_x^{*} and CEI^{*} to an emission index (EI); a performance system was used to map BTE^{*} and BSFC^{*} to a performance index (PI); and, a final system weighted for the environment was used to map EI and PI to the MRPI. Three triangular input membership function (Low, Medium, High) and five output membership function (Very Low...Very High) on [0, 1] (Fig 3), min-implication, max-aggregation and centroid defuzzification (Eq. 3) were used for each sub-system.

$$\text{MRPI} = \int \mu(z) \cdot z \, dz / \int \mu(z) \, dz \quad (3)$$

The monotonic nine rules base for the emission sub-systems and performance sub-systems were used, and an environment-weighted nine-rule base (Table 5) was used for the final system: with a high MRPI at moderate performance, a favourable emission index supported a high MRPI even at moderate performance.

Table 5. Environment-weighted rule base of the final fuzzy system (cell = MRPI level).

EI \ PI	PI = Low	PI = Medium	PI = High
EI = Low	Very Low	Low	Medium
EI = Medium	Medium	Medium	High
EI = High	High	Very High	Very High

Validation by TOPSIS and sensitivity analysis

For the same design matrix, the fuzzy recommendation result has been compared with the independent TOPSIS result to ensure that the fuzzy recommendation is not due to the method. The decision matrix was vector-normalized, weighted, the positive and negative ideal solutions were constructed (benefit for BTE, and cost for the remaining answers), the Euclidean separations from each ideal were calculated, and the ranking was obtained by calculating the closeness coefficient $C_i = S^- / (S^+ + S^-)$. The criterion weights were made equal in the primary comparison and the degree of agreement with the fuzzy ranking was quantified by Spearman rank-correlation coefficient (ρ). Moreover, the final stage fuzzy rule base was switched between the environment weighted one, a balanced one and the performance weighted one and the stability of the optimum was examined.

Results And Discussion

Exhaust emissions

The emissions are displayed in the four runs in 9 runs as shown in Fig 1. The smoke, HC and CO (products of incomplete combustion) are least for the jatrophia-additive blend at the highest compression ratio where the oxygen present in the fuel promotes complete combustion along with the higher cetane number and higher temperature. The additive blends reduced the smoke by up to about 24 % and CO by about a third compared to plain mahua blend at the same compression ratio. NO_x is the opposite – increasing with the compression ratio because of the higher

peak temperature – it is highest at CR 17.5, and drops significantly at CR 16.5 and 15.5. The crux of the optimization is this NO_x – smoke opposition.

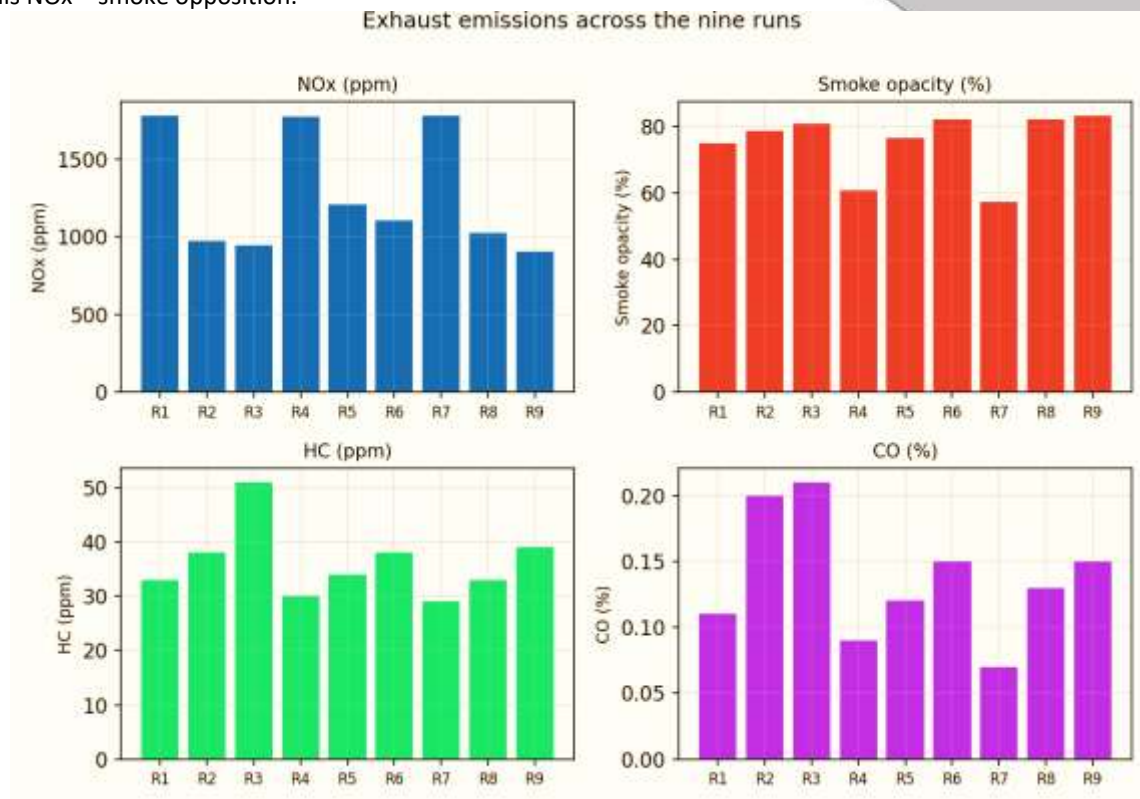


Fig 1. Exhaust emissions (NO_x, smoke, HC, CO) across the nine runs

Engine performance

The brake thermal efficiency is maximum and specific fuel consumption is minimum at CR 17.5 for all blends and the additive blends is slightly better than the plain mahua blend (Fig 2), this is reduced with the decrease in compression ratio. This thus means that performance is opposed to the NO_x objective and favours the high compression ratio.

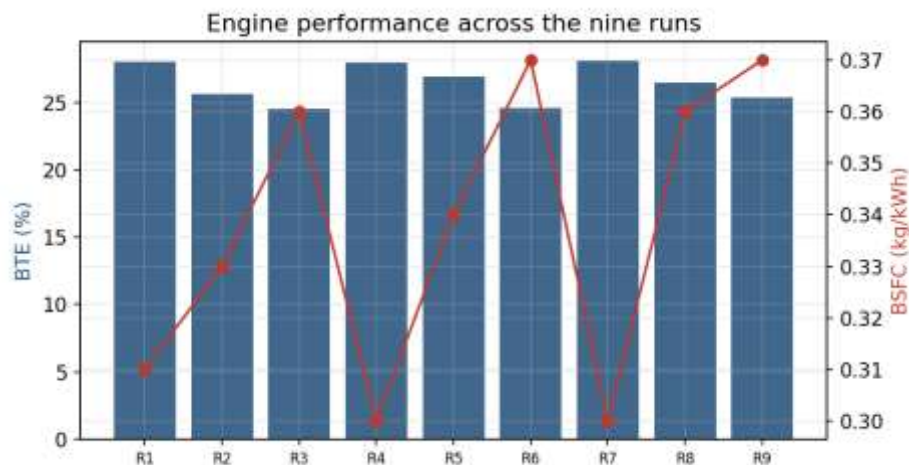


Fig 2. Brake thermal efficiency (bars) and specific fuel consumption (line) across the nine runs

Emission–performance trade-off

This conflict becomes apparent in the plot of brake thermal efficiency and NO_x as shown in Fig 3, where each point is coloured by its fuzzy MRPI. The non-dominated (Pareto) front is from the low-NO_x, lower-efficiency jatropa runs

to low compression ratio to the high-efficiency, higher-NOx additive runs at CR 17.5. There is no one unique point that minimizes NOx and maximizes efficiency at once, and thus, a compromise selection is needed. The fuzzy optimum (R7) is located at the high efficiency end of the front since its combustion emissions and efficiency are the best available, and its emission of NOx, although high, is compensated in the environment weighted index by the very low smoke, HC and CO.

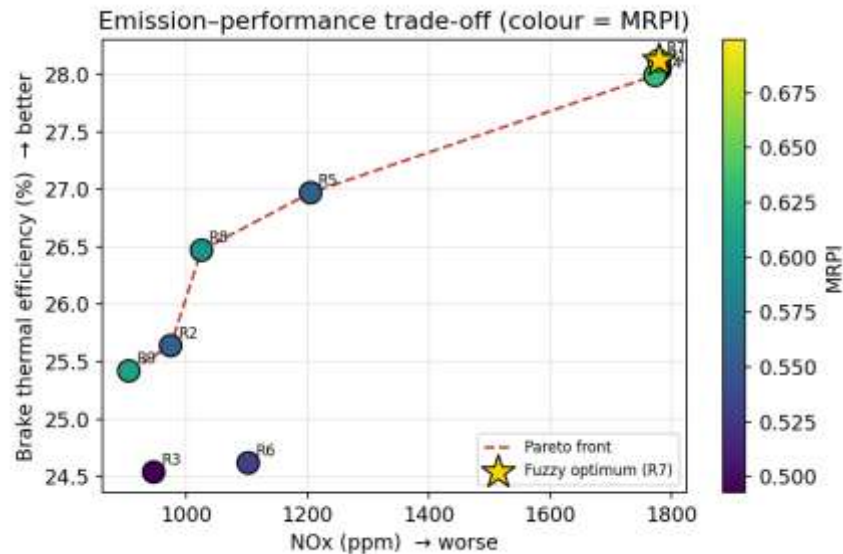


Fig 3. Emission–performance trade-off: brake thermal efficiency versus NOx, coloured by MRPI, with the Pareto front and the fuzzy optimum

Fuzzy modelling

The hierarchical system of Fig 4 was used for the processing of the normalized responses with the membership functions of Fig 5. The three combustion emissions were combined in a single rule base which remain small and interpretable (nine rules), while the final rule base is weighted by the environment, and thus the priority of the study.

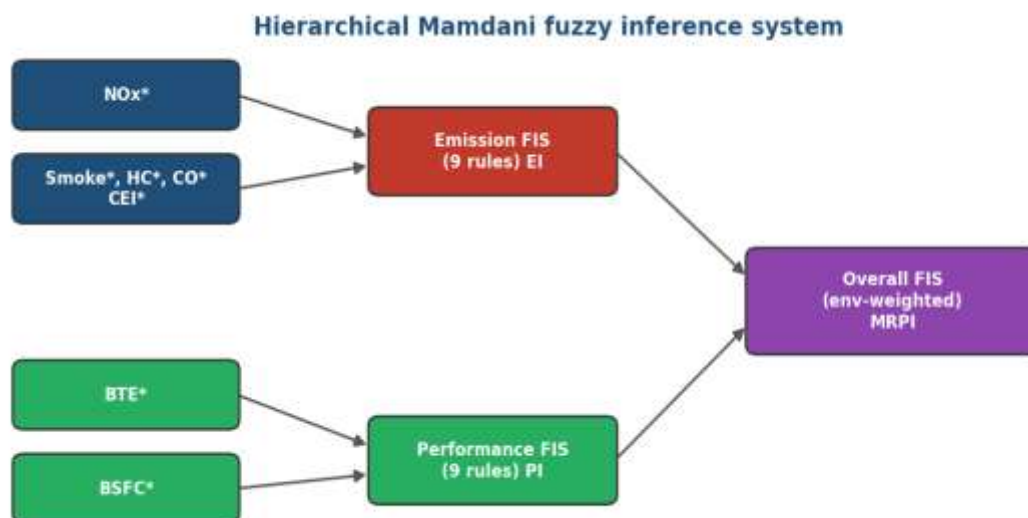


Fig 4. Hierarchical Mamdani fuzzy inference architecture producing the MRPI

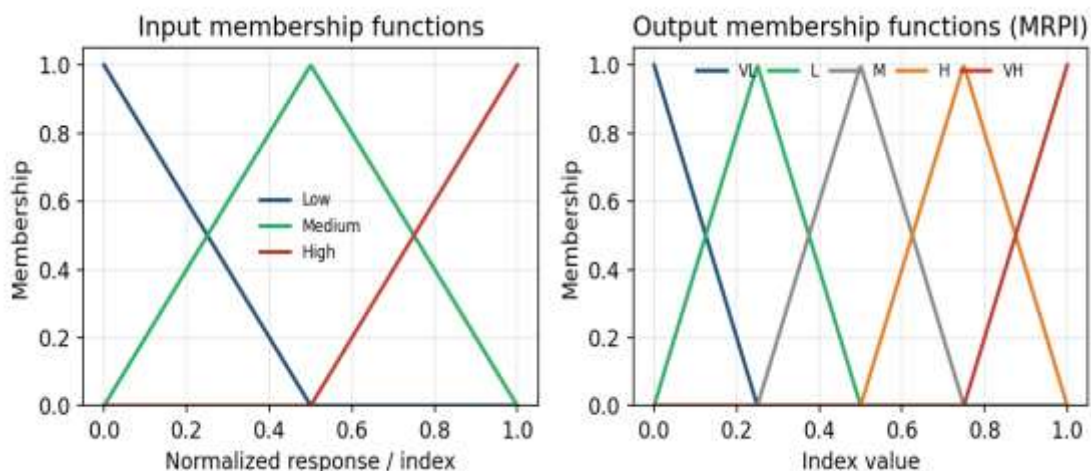


Fig 5. Triangular membership functions of fuzzy inputs (left) and the MRPI output (right)

Multi-response performance index and optimum

The design matrix along with six responses, sub-indices and MRPI is presented in Table 6. The best performance, in terms of clean combustion emissions, as measured by the highest MRPI value, 0.699, is achieved by run 7 — the jatropha biodiesel–additive blend at CR 17.5. The low compression ratio jatropha achieve high emission indices (low NO_x) but with a lower efficiency, as expected, and consequently are lower. Fig 6 lists the runs in ranked order, and the radar plot of the top three runs reveals that run 7 is the best for BTE, smoke, HC and CO, competing only for NO_x.

Table 6. Design matrix, responses and fuzzy MRPI (bold = optimum)

Run	Blend	CR	BTE	BSFC	NO _x	Smoke	HC	CO	MRPI
1	MEOM	17.5	28.0	0.310	1781	75	33	0.11	0.535
2	MEOM	16.5	25.6	0.330	974	79	38	0.20	0.554
3	MEOM	15.5	24.5	0.360	946	81	51	0.21	0.493
4	MEOMBA3ml	17.5	28.0	0.300	1773	61	30	0.09	0.632
5	MEOMBA3ml	16.5	27.0	0.340	1205	77	34	0.12	0.558
6	MEOMBA3ml	15.5	24.6	0.370	1102	82	38	0.15	0.534
7	MEOJBA3ml	17.5	28.1	0.300	1779	57	29	0.07	0.699
8	MEOJBA3ml	16.5	26.5	0.360	1025	82	33	0.13	0.598
9	MEOJBA3ml	15.5	25.4	0.370	905	83	39	0.15	0.610

BTE (%); BSFC (kg/kWh); NO_x (ppm); smoke opacity (%); HC (ppm); CO (%)

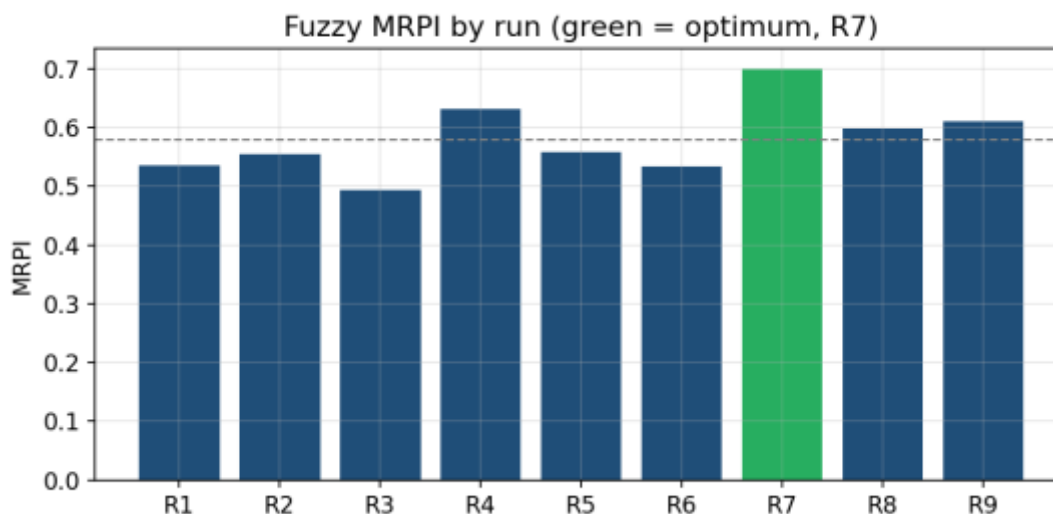


Fig 6. Fuzzy MRPI by run; the green bar marks the optimum (run 7)

Optimal levels and analysis of variance

The mean MRPI at each level is given in the response table (Table 7); the best run is A3B1 (B20MEOJBA3ml, CR 17.5) which is optimum. ANOVA reveals that the most important factor is fuel blend with approximately 57 % followed by compression ratio with approximately 30 %. This puts feedstock and additive (smoke, HC, CO) as the most important lever (Fig 7), reversing the hierarchy of performance-only studies.

Table 7. Response table for the MRPI and ANOVA

Level	Blend (A)	CR (B)	
Level 1	0.5274	0.6223	CR 17.5
Level 2	0.5746	0.5700	CR 16.5
Level 3	0.6357	0.5454	CR 15.5
Delta	0.1082	0.0768	
Contribution	56.9 %	29.8 %	err 13.3 %

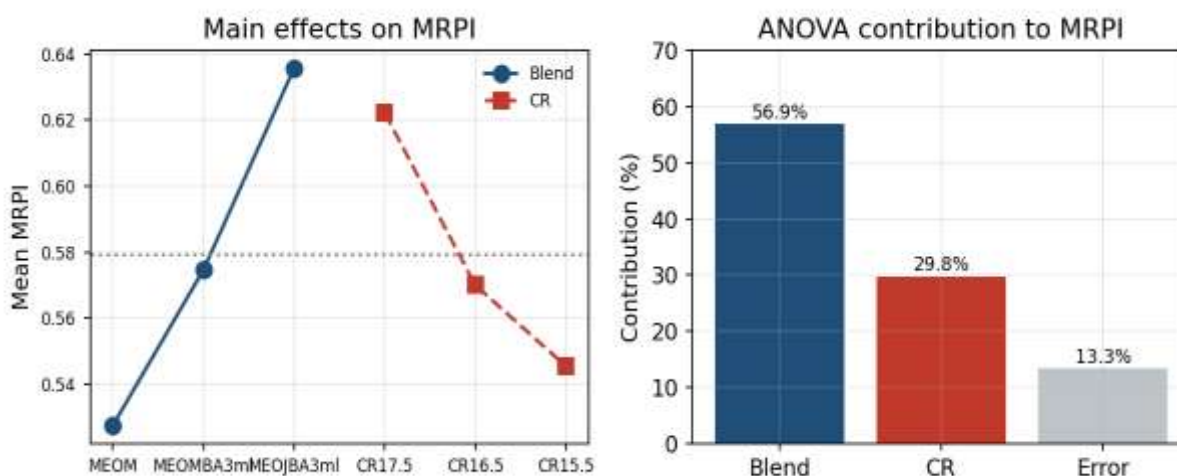


Fig 7. Main effects on the MRPI (left) and ANOVA contributions (right)

Independent validation by TOPSIS

TOPSIS independently ranked the nine runs without varying the criterion weights. The two methods agree closely (Fig 8): the closeness coefficient increases monotonically with the fuzzy MRPI, both methods places run 7 first, and the concordance of the two methods is measured by the Spearman rank-correlation coefficient that is equal to $\rho = 0.77$, which is a strong level. Both methods also predict the worst condition (low compression ratio mahua blend). If the TOPSIS weights are then changed to be heavily biased toward the emissions, the first choice becomes the mid-compression-ratio additive runs ($\rho = 0.67$) whose NOx are much lower — corresponding to the secondary, NOx priority, operating point discussed below. Thus, the independent method is able to validate the fuzzy optimum under a balanced weighting and, simultaneously, to exhibit the same trade-off behavior under an emission-heavy weighting.

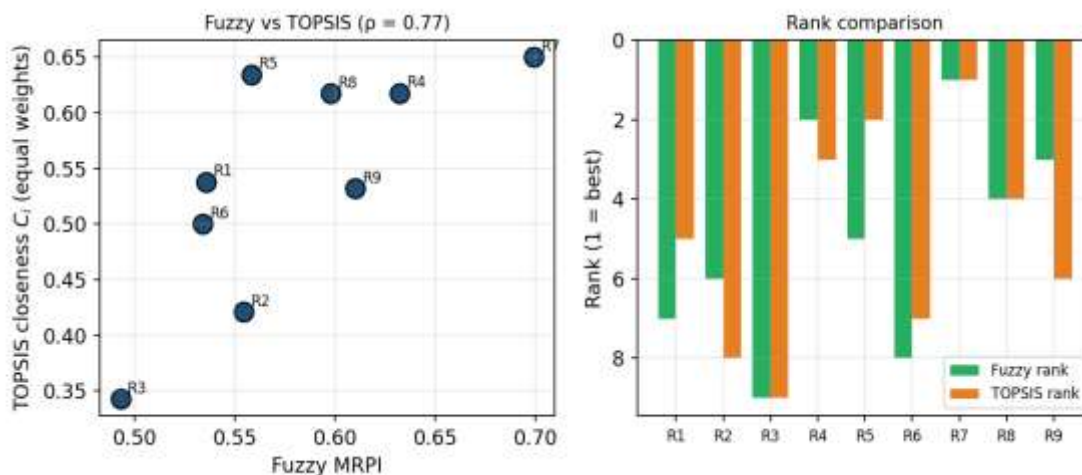


Fig 8. Validation against TOPSIS: closeness coefficient versus MRPI (left) and rank comparison (right)

Sensitivity to the environmental weighting

The final stage rule base was tried with environment weighted, balanced and performance weighted rule bases (Fig 9) because the recommendation is dependent on the weightage of the emissions. Run 7 shows the highest MRPI in all three cases and it can be seen that the optimum is not sensitive to the choice of the weighting, with the additive blends being consistently among the top. The most significant impact of de-emphasizing emissions is to increase the gap between the high compression ratio runs, while the opposite is true for emphasising emissions, and the mid compression ratio run for jatropha-additive (R8) is being raised with a slight penalty on efficiency, but significant benefit on NOx reduction. This framework therefore explicitly expresses and allows one to modify the priorities of the decision-maker in a fixed weight vector.

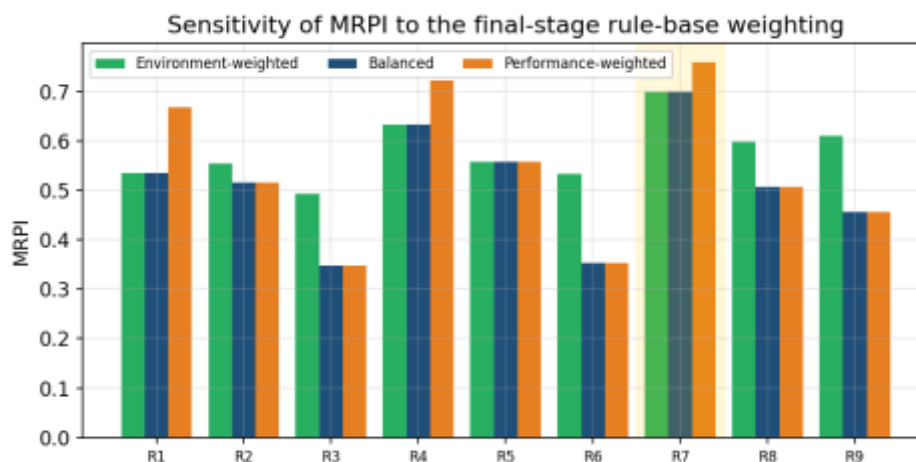


Fig 9. Sensitivity of the MRPI to the final-stage rule-base weighting; run 7 remains optimal throughout

Emission reduction and confirmation

The optimum amount of smoke reduction is about 24 % when compared to the plain mahua baseline (B20MEOM, CR 17.5), about 36 % of CO and about 12 % of HC are reduced in the optimum scenario, while the NO_x is essentially unchanged (-0.1 %) and the efficiency gain is marginal (0.3 %) (Fig 10). The MRPI predicted by the additive Taguchi model at the selected levels is 0.679 which is very near to the measured value, 0.699. The analysis shows that where NO_x is the primary constraint, CR 16.5 with the jatropha-additive blend is a secondary point in which a minor loss of efficiency is balanced against a significant decrease in NO_x.

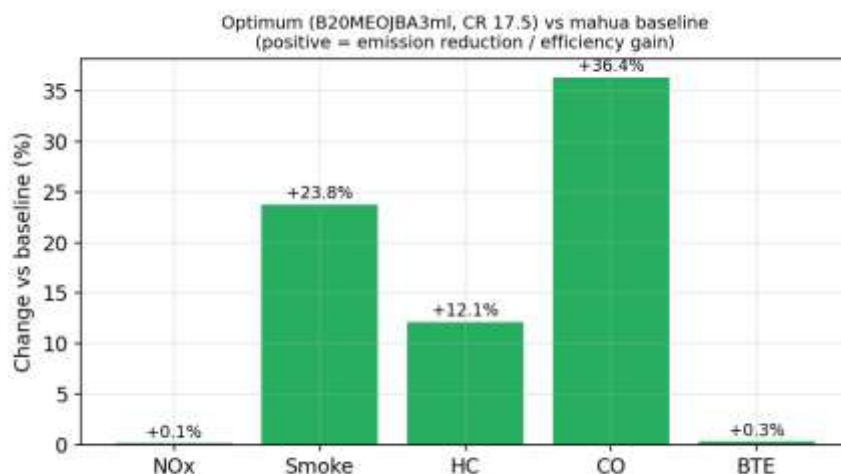


Fig 10. Change in emissions and efficiency at the optimum relative to the mahua baseline

CONCLUSIONS

1. Environment-weighted hierarchical Mamdani fuzzy inference system was used to combine four exhaust gas emission parameters (NO_x, smoke, HC, CO) and two performance parameters (BTE, BSFC) into a single interpretable multi-response performance index to determine the performance of mahua and jatropha biodiesel-additive blends at three compression ratios.
2. Optimum was found to be the jatropha biodiesel-additive blend B20MEOJBA3ml at CR 17.5 (higher MRPI of 0.699), which yielded minimum products of incomplete combustion at higher MRPI without compromising the optimum efficiency, smoke, CO and HC decreased by ~24 %, 36 % and 12 % compared to the mahua baseline, respectively, while no increase in NO_x was observed.
3. ANOVA showed that feedstock and additive selection is the main lever for the environment, fuel blend was the controlling factor ($\approx 57\%$) and compression ratio ($\approx 30\%$) were not — opposite results to performance-only optimizations.
4. Independent TOPSIS ranking revealed the same optimum with balanced weighting (Spearman $\rho = 0.77$) and the optimum was stable when the weighting was based on environment, balance and performance fuzzy rule bases, thus proving the robustness.
5. Fuzzy logic with cross validation with MCDM and sensitivity analysis is an effective and transparent framework to resolve the NO_x – smoke – performance trade-off; can be re-tuned for stricter NO_x or particulate targets for which CR 16.5 with jatropha – additive blend is identified as a secondary operating point.
- 6.

Nomenclature

BTE – Brake thermal efficiency (%); BSFC – Brake specific fuel consumption (kg/kWh); CEI – Combustion-emission index (-); C_i – TOPSIS closeness coefficient (-); CO – Carbon monoxide (%); CR – Compression ratio (-); EI – Emission index (-); HC – Unburnt hydrocarbon (ppm); MRPI – Multi-response performance index (-); NO_x – Oxides of nitrogen (ppm); PI – Performance index (-); S^+ , S^- – Separation from ideal and anti-ideal solutions (-), respectively; x^* – Normalized benefit response (-); $\mu(z)$ – Aggregated output membership (-); ρ – Spearman rank-correlation coefficient (-).

References

1. Reddy, S., et al. (2019). Performance, combustion and emission characteristics of a DI diesel engine using mahua biodiesel. In *Advances in Eco-Fuels for a Sustainable Environment*. Woodhead Publishing/Elsevier.
2. Pandhare, A., & Padalkar, A. (2013). Investigations on performance and emission characteristics of a diesel engine with biodiesel (jatropha oil) and its blends. *International Journal of Renewable Energy*, 2013, 163829.
3. Palash, S. M., Kalam, M. A., Masjuki, H. H., Masum, B. M., Fattah, I. M. R., & Mofijur, M. (2013). Impacts of biodiesel combustion on NO_x emissions and their reduction approaches. *Renewable and Sustainable Energy Reviews*, 23, 473–490.
4. Agarwal, A. K. (2007). Biofuels (alcohols and biodiesel) applications as fuels for internal combustion engines. *Progress in Energy and Combustion Science*, 33(3), 233–271.
5. Ruban, M., Ramasubramanian, S., Pugazhenth, R., & Sivaganesan. (2017). Investigation of performance analysis and emission characteristics of waste plastic fuel. *IOP Conference Series: Materials Science and Engineering*, 183(1), 012037.
6. A comprehensive review on the effect of ethers, antioxidants and cetane-improver additives on biodiesel–diesel blends in CI-engine performance and emission characteristics. (2023). *Journal of Traffic and Transportation Engineering*.
7. Varatharajan, K., Cheralathan, M., & Velraj, R. (2011). Mitigation of NO_x emissions from a jatropha-biodiesel-fuelled DI diesel engine using antioxidant additives. *Fuel*, 90(8), 2721–2725.
8. Ileri, E., & Koçar, G. (2014). Experimental investigation of the effect of antioxidant additives on NO_x emissions of a diesel engine using biodiesel. *Fuel*, 125, 44–49.
9. Kumar, N., et al. (2014). Combustion and emission characteristics of a VCR engine fuelled with *Jatropha curcas* ethyl-ester blends at different compression ratios. *International Journal of Renewable Energy*, 2014, 872923.
10. Karnwal, A., Hasan, M. M., Kumar, N., Siddiquee, A. N., & Khan, Z. A. (2011). Multi-response optimization of diesel-engine performance parameters using thumba biodiesel–diesel blends by the Taguchi method and grey relational analysis. *International Journal of Automotive Technology*, 12(4), 599–610.
11. Ranjit, P. S., & Balakrishna, B. (2026). Performance, emission and combustion characteristics of TiO₂ and CeO₂ nanoparticle-enhanced mahua biodiesel–diesel blends. *Scientific Reports*, 16, 8594.
12. Impact of variation in compression ratio on the emissions and efficiency of karanja-oil-biodiesel-fuelled diesel engines. (2025). In *Recent Advances in Mechanical Engineering*. Springer.
13. Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, 7(1), 1–13.
14. Kumar Chidambaram, R., Sonthalia, A., Poornananadan, G., Varuvel, E. G., & Subramanian, T. (2021). Optimization of compression ratio and injection timing of a diesel engine fuelled with oxygenated blends using a fuzzy-logic-based Taguchi method. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*.
15. Dey, S., Deb, M., & Das, P. K. (2019). Application of a fuzzy-assisted grey-Taguchi approach for engine-parameter optimization on the performance–emission of a CI engine. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*.
16. Gugulothu, S. K. (2021). Fuzzy-methodology-based multi-objective optimisation of the performance, emission and stability trade-off of a CRDI diesel engine powered with *Schleichera oleosa* biodiesel/diesel blends. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*.
17. Dey, S., et al. (2020). A hybrid ANN–fuzzy approach for optimization of engine operating parameters of a CI engine fuelled with a diesel–palm-biodiesel–ethanol blend. *Energy*, 202, 117813.
18. Sakthivel, G., Ilankumaran, M., et al. (2015). A hybrid multi-criteria decision-modelling approach for the best biodiesel-blend selection based on ANP–TOPSIS analysis. *Ain Shams Engineering Journal*, 6(1), 239–256.
19. Sakthivel, G., et al. (2017). Compression-ignition engine performance modelling using hybrid MCDM techniques for the selection of optimum fish-oil biodiesel blend at different injection timings. *Energy*, 139, 483–505.
20. Yilmaz, E., et al. (2025). Multi-criteria optimization and prediction of diesel–fusel-oil dual-fuel engine performance using ANN, RSM, fuzzy logic and MCDM (TOPSIS/VIKOR) approaches.
21. Hwang, C. L., & Yoon, K. (1981). *Multiple Attribute Decision Making: Methods and Applications*. Springer.
22. Vinod Kumar, T., Chandrasekaran, M., Pugazhenth, R., Sharma, A., Yadav, A. S., Kumar, R., & Kaliyaperumal, G. (2023). Experimental investigation of corrosion effect of automotive fuel tank for biofuels. In *Conference of Innovative Product Design and Intelligent Manufacturing System* (pp. 365–377). Springer Nature Singapore.

23. Heywood, J. B. (2018). Internal Combustion Engine Fundamentals (2nd ed.). McGraw-Hill.
24. Pugazhenth, R., Chandrasekaran, M., Muthuraman, R. K., Vivek, P., & Parthiban, A. (2017). A comparative characteristic study of jatropha and cardanol biodiesel blends. IOP Conference Series: Materials Science and Engineering, 183(1), 012038.
25. Vairavel, M., Kathiresan, G., Govindarasan, D., & Selvaraj, V. (2025). Ecological innovation: Thermosetting resins and water hyacinth fiber in high-performance bio-composite materials for sustainable waste management. Global Nest Journal, 27(3).
26. Madeshwaran, V., Selvaraj, P., & Gopal, M. (2025). Biodegradation of untreated low-density polyethylene by *Stenotrophomonas maltophilia* isolated from *Galleria mellonella*. Safety in Extreme Environments, 7(1).
27. Madeshwaran, V., Vairavel, D. K., & Mahadevan, S. (2025). Enhanced corrosion resistance of copper for agricultural equipment using superhydrophobic stearic acid coatings. Revista Materia, 30.
<https://doi.org/10.1590/1517-7076-RMAT-2024-0647>