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Type 3 Fuzzy-Based Performance Evaluation of Biodiesel Blends with Orange Peel Oil Additives in a Diesel Engine

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Abstract
The global demand for energy is increasing, combined with an ongoing environmental concern about the application of fossil fuel has resulted in a quest to explore sound alternatives source of fuels. Biodiesel is a renewable fatty acid methyl ester that can be produced from biological feedstocks and represents an attractive alternative to conventional diesel, however optimizing blend formulations across several competing performance metrics continues to limit internal combustion engine (ICME) biodiesel utilization. This article develops a pioneering Type 3 fuzzy set based multi-criteria decision-making framework, that experimentally applies Neutrosophic membership in conjunction with weighted aggregation for systematic analysis and ranking of biodiesel blend formulations enhanced with orange peel oil (OPO) additives.
Single-cylinder diesel engine performance tests were performed at four load conditions (0, 2.5, 5 and 7.5 kg) using over twenty different fuel formulations including neat diesel, biodiesel blends (i.e., B10–B100), ethanol-enriched blends [8], butanol-enriched blends [9], viscosity-modified blends [10] and novel OPO additive blended fuels at varying concentrations as detailed above. This study measured and evaluated four major performance parameters: e.g. Total Fuel Consumption (TFC), Specific Fuel Consumption (SFC), Brake Thermal Efficiency (BTE) and Brake Specific Energy Consumption, BSEC based on the concept of Engine monitoring. Type 3 fuzzy analysis estimated Neutrosophic membership values for each attribute, which were matched up with assigned weights to yield an overall ranking of the attributes' performance using weighted average aggregation.
The results of which indicate that BSEC was determined as the most limiting performance characteristic through fuzzy analysis, and the optimum blend was B10OPO10E10 (10% biodiesel containing 1: 0.1 orange peel oil, 1: 0.5 ethanol), with a corresponding maximum load BTE (%) of 35.33 and max-load BSEC (MJ/kWh) of 10.19% higher than neat diesel. Comparison against Type 1 and Type 2 fuzzy approaches confirms a superior ranking quality of the Type 3 framework in an environment with measurement uncertainty. Statistical validation ($p < 0.05$) confirms significant differences exist among blend formulations via one-way ANOVA. Fuzzy ranking is stable under 20% perturbation in weights according to the sensitivity analysis. Collectively, these results provide a robust mathematical basis for the Type 3 fuzzy framework for fuel optimization problems as well as useful guidance on how to implement it effectively in practice.

Keywords: Type 3 Fuzzy Sets; Biodiesel Blends; Orange Peel Oil; Neutrosophic Sets; Sensitivity Analysis.

1 Introduction

1.1 Research Background and Motivation

Due to the rapid exhaustion of petroleum reserves and the growing environmental issues due to the greenhouse gas production, scientists all over the world have been motivated to seek sustainable and renewable energy sources. The vegetable oils and animal fats are transesterified to form biodiesel which is a fatty acid methyl ester (FAME) and was of great interest as an alternative fuel to replace petro-diesel. Several furniture things are actually particularly designed in a particular method that could have application in particular shooting processes and also create highest Consumer's interests. However, there are also challenges, such as high viscosity, reduction of calorific value and increase in NOx emissions; hence, optimization of blend ratios will always have to be done in conjunction with the research of possible fuel additives to improve the overall performance of the engine. There are a lot of possible combinations of biodiesel blends that need to be considered, many of which will conflict with each other. Total Fuel Consumption (TFC), the total volume of fuel burned per time unit vs Specific Fuel Consumption (SFC) which normalizes this measure with respect to power output.Brake Thermal Efficiency (BTE): is the measure of how well this energy conversion process actually takes place, while Brake Specific Energy Consumption (BSEC) appears to take a more global view of the efficiency of fuel utilization by combining both aspects: with respect to their energy content and their mass flowrate. With regard to the variability and measurement uncertainty associated with each of these performance parameters across varying operating conditions, advanced fuzzy set based approaches are well suited to address the optimization problem.

Orange peel oil (OPO) is a by-product of the citrus juice sector that has recently attracted attention for its application as a bio-additive to biodiesel blends as it contains high proportions of d-limonene (>90% in general). D—limonene is a cyclic monoterpene which has also been shown to have good solvent properties, improve (3 with vital impact on the efficiency of combustion by absorbing part of the carbon in inkjercare improvement and low reduce surface tension fuel droplets. The valorization of OPO as a fuel additive provides a win-win: it both deals with oil waste from the citrus processing industry and adds appealing properties to biodiesel blends.

1.2 Research Gaps and Novelty

While there is considerable research on evaluating biodiesel performance, important gaps remain in the literature. So far, Type 1 and Type 2 fuzzy sets has been applied to many engineering decision problems including fuel blend optimization, however the application of other types such as of Type 3 fuzzy set is almost absent in this field. Type 3 fuzzy sets take the uncertainty modeling capabilities of Type 2 to an even higher level than Type 1 by allowing fuzziness at the secondary membership level, forming a three-dimensional representation that is well suited for managing the multi-layered ambiguity present in experimental engine data. Second, current studies on OPO enhanced biodiesel particularly focus on singular performance measures and do not adopt a systematic multi-criteria decision making (MCDM) methodology. Third, the application of Neutrosophic set theory (a different modeling approach truth, indeterminacy and falsity membership) in combination with Type 3 fuzzy aggregation to evaluation of fuel has never been made before.

This work is novel in three significant ways: (i) the application of Type 3 fuzzy set theory to multi-criteria biodiesel blend formulation evaluation provides a new approach and methodology for fuel optimization; at (ii) the exploration of a dual additive system consisting of OPO and ethanol shows synergistic performance improvements that exceed those achievable by either additive alone; and (iii) this study gives rise to new systematic comparative analysis demonstrating the robustness advantages of a Type 3 vs. Type 1/2 Fuzzy framework, particularly when multiple outputs are presented with higher-order tissue diffusion rate measurements--such as total long-chain fatty acid profiles--that may introduce measurement error from uncertainty estimation. These advances overcame key limitations in prior research that focused on single-attribute comparisons or lower-order fuzzy methods.

1.3 Research Objectives

The objective of this work is to develop a systematic and mathematical support to evaluate biodiesel blend formulation by the mathematical fuzzy set theory, similar to Type 3 fuzzy sets. The specific objectives are: ($\boldsymbol{i}$) to experiment the performance of engines over a wide range of biodiesel formulation blends including novel blends of OPO-ethanol; ($\boldsymbol{ii}$) to calculate membership values for each performance attribute and capture the truth, indeterminacy, and falsity values inherent in engine performance experimental data; ($\boldsymbol{iii}$) to use Type **3** fuzzy weighted average aggregation to determine the optimal blend and compare the results with Type **1** and Type **2** fuzzy approach and statistically validate them by analysis of variance (ANOVA); and (iv) to carry out sensitivity analysis to test the robustness of the fuzzy ranking under the changes in weight.

1.4 Paper Organization

This paper is organized as follows. Section 2 presents a literature review on biodiesel as alternative fuel and fuzzy set theory in engineering decision making, paving the gap this study fills. Section 3 discusses experimental method with Type 3 fuzzy framework mathematical formulation, formal definitions and Neutrosophic membership computation procedure. Section 4 provides the test results, which further include the performance characteristics of all two-component blends. Section 5 details Type 3 fuzzy decision making together with a comparison of Type 1 and Type 2 fuzzy methods, confirmation through the ANOVA process for statistical purposes and analysis on sensitivity of weight parameters. In Section 6, we summarize our findings/contributions of this paper, discuss the limitations and directions for future research.

2 Literature Review

2.1 Biodiesel as a Source of Renewable Fuel

A recent literature review, is a comprehensive review of the existing studies available on biodiesel being an alternative fuel to compression ignition engines. Early studies have determined the basic combustion characteristics of biodiesel and its potential as an alternate fuel for diesel engines (1). Recent research has been carried out using a wide variety of feedstock such as: rapeseed oil, soybean oil, palm oil, sunflower oil, jatropha and used cooking oil. In general, the research shows that biodiesel blends up to B20 (20% biodiesel; 80% diesel) can be used in OEM diesel cold-start systems with little or no modification and higher blend ratios may require modifications involving injection timing and fuel system components. Lapuerta et al., reported environmental emissions benefits of biodiesel including lower fuel sulfur and lifecycle carbon. [2] and Hoekman et al. [3].

Recent research has explored the effectiveness of bio-additives and oxygenated enhancers in augmenting the performance characteristics of biodiesel blends. When blended with different ratios of biodiesel-diesel mixtures, the use of oxygenated fuels such as ethanol and butanol has been reported to enhance combustion (combustion completeness) and reduce said particulate emissions [16]. In addition, citrus peel waste essential oils contain high concentrations of limonene that is used in a bio-additive with solvent and combustion enhancer properties, drawing attention to the use of orange peel oil (OPO). Studies by Rashedul et al. [4] and Nanthagopal et al. Research conducted by [17] has shown that OPO additives can simultaneously increase brake thermal efficiency, reduce specific fuel consumption (SFC) and cut down the emissions of exhaust pollutants. Recent works by Purushothaman and Nagarajan [5] investigated the synergistic effect of limonene and ethanol blending in biodiesel blends to improve BTE and lower BSEC for OPO-ethanol-biodiesel ternary blends.

2.2 Fuzzy Set Theory in Engineering Applications

Fuzzy set theory which suspected by Zadeh [6] can be defined mathematically to describe uncertainty and make decisions. In the context of assessing engine performance metrics and determining appropriate fuels, a number of researchers have previously used an assortment of extensions to fuzzy set theory. Type 1 fuzzy sets, the original type of fuzzy set, provide a single membership value to each instance. Type 2 fuzzy sets [7] (inspired by Zadeh) can be considered an extension of this notion where the membership values are not precise, but rather also fuzzy, thus capturing higher order uncertainty in the representation [8]. Wu and Mendel [9] and Mendel et al. have shown the application in engineering Multi–Criteria decision making using Type 2 fuzzy sets. [10]. Reviewing the applications of Type 2 fuzzy logic in control and intelligent systems, Castillo and Melin [18] have established this framework quite mature.

The most recent extension of this theory are Type 3 fuzzy sets. Type 2 fuzzy sets capture uncertainty at the primary level, whereas Type 3 fuzzy sets also model uncertainty in secondary levels of membership (the possibility of a non-crisp second degree) creating a three-dimensional cloud to represent uncertainty and suitable for applications with thick ambiguity. The theory of Type 3 fuzzy sets has been developed by Qi et al. [11] [6], in which they showed their applications in adaptive control and performance assessment. Wang et al. Type 3 fuzzy systems were further extended to solve multi-objective optimization problems [19], offering better performance than Type 2 in complex decision environments. One such working outfit is the neutrosophic sets by Smarandache [12], which are directly related and generalizes fuzzy sets: independence of truth membership, indeterminacy membership and falsity membership is modeled. In short, this formulation makes the union of Neutrosophic membership with Type 3 fuzzy aggregation an approach that is more robust for multi-attribute decision-making (MADM), where the uncertainty in measurements and/or indeterminacy in expert assessments are taken into account.

2.3 Multi-Criteria Decision-Making for Fuel Optimization

Multi-criteria decision-making (MCDM) methods have recently been used for fuel blend optimization. Different methods (i.e., TOPSIS [Technique for Order of Preference by Similarity to Ideal Solution], AHP [Analytic Hierarchy Process] and VIKOR) were employed to rank the performance evaluation scores of fuel alternatives based on multiperformance criteria. Sathyamurthy et al. For instance, [14] implemented MCDM analysis to investigate the biodiesel blend and pointed out the importance of these ranking methods. Wei et al. Recently, a work carried out [15] proposed hesitant fuzzy MCDM approach on optimi sing fuel blend selection that insisted crisp MCDM methods are inferior than even fuzzy based ones. Ashok et al. Bioadditives and their unit operation were evaluated in detail when [20] suggested a systematic evaluation framework for the use of bioadditive in biodiesel. However, the combination of MCDM and Type 3 fuzzy sets to evaluate fuels is not widely studied and this research aims to contribute in bridging that gap.

2.4 Research Gap Summary

The review and content in the above reviews identify three major gaps: (i) none of the studies have applied Type 3 fuzzy set theory to MCDM-based multi-criteria evaluation of biodiesel blend formulations, (ii) available MCDM approaches for fuel optimization do not include an intrinsic uncertainty modelling capacity using multilayered structure provided by Type 3 fuzzy sets, and, (iii) no study has limited their assessment into a rigorous fuzzy decision-making framework investigating both OPO and ethanol as dual additives to biodiesel. The Type 3 fuzzy-Neutrosophic framework developed and applied in this study bridges all three of these gaps, utilizing a thorough range of biodiesel-OPO-ethanol blend formulations.

3 Methodology

3.1 Experimental Setup and Fuel Formulations

A single-cylinder, four-stroke, direct-injection diesel engine was used for all performance evaluations. The engine was coupled to an eddy current dynamometer for precise load control. Fuel consumption was measured using a burette-based volumetric method with a stopwatch, and all measurements were repeated three times to ensure reproducibility. The engine was operated at a constant speed of 1500 rpm, and load was varied from 0 kg to 7.5 kg in increments of 2.5 kg. The performance parameters TFC, SFC, BTE, and BSEC were calculated using standard engineering formulas based on the measured fuel consumption, brake power, and calorific value of each fuel blend.

A total of over twenty fuel formulations were tested in this study. The base formulations included neat diesel and five biodiesel blend ratios (B10, B20, B40, B60, and B100), where the number denotes the percentage of biodiesel by volume. The enhanced formulations included ethanol-enriched blends (B10E10, B20E10, B40E10, B60E10, B100E10 with 10% ethanol by volume), butanol-enriched blends (B10BU10, B20BU10, B40BU10, B60BU10, B100BU10 with 10% n-butanol), viscosity-modified blends (V10, V20, V40, V60, V100), and orange peel oil additive blends (B10OPO5, B10OPO10, B20OPO5, B20OPO10, B40OPO5, B40OPO10 and their ethanol-enriched counterparts B10OPO5E10, B10OPO10E10, B20OPO5E10, B20OPO10E10, B40OPO5E10, B40OPO10E10). The orange peel oil was obtained with the common cold-pressing method, and its content of d-limonene exceeds 92%.

3.2 Mathematical Formulation of Type 3 Fuzzy Sets

This dissertation adopts a Type 3 fuzzy set framework engendering a systematic methodology to address the multi-layered uncertainty that is inherently present during engine performance evaluation. In the classical Case 1 fuzzy set, membership grade to every aspect x of a universe of discourse X could be given as a Crisp number within [0,1]. Types 2 fuzzy sets are defined such that the membership grade itself is a Type 1 fuzzy set, allowing us to model uncertainty in primary membership values. A Type 3 fuzzy set takes this one stage further, where the secondary membership grade (indicating uncertainty about primary membership) is again a fuzzy set in itself creating a three-dimensional model of uncertainty.

Let A be a Type 3 fuzzy set on X; for each $x \in X$, the principal grade of membership is denoted by $J(x) \subseteq [0, 1]$ and the secondary function $\mu(x, u)$, where $u \in J(x)$, mapping (x, u) to a Type 1 fuzzy set in [0, 1]. Such a hierarchical structure allows Type 3 fuzzy sets to be used in describing situations where the measurement uncertainty, the variability of expert judgment and experimental noise all manifest as contributing factors to the complexity of ambiguity in evaluation. The mathematical equivalent is expressed below by Eq. (1).

$A = \{((x,u), \mu A(x,u)) \mid x \in X, u \in J(x) \subseteq [0,1]\}$(1)

where μ is secondary membership function, J(x) is the primary membership of element x and u is the primary membership variable. The secondary membership function of the Type 3 fuzzy set A provides a complete characterization by specifying for every point in the (x, u)-plane how strongly that point is part of the fuzzy grade of A. The above represents three layers of uncertainty: Element level (what is the element?), the major classification of membership (What is a membership?), and the secondary membership uncertainty (where we basically ask how sure are we about the membership grade?).

3.3 Neutrosophic Membership Computation

The Neutrosophic membership calculation is based on the model introduced by Smarandache [12], where for each attribute j, three autonomous parts of membership are computed from experimental data: Truth Membership T(x), Indeterminacy Membership I(x) and Falsity Membership F(x). These quantities meet the constraints $0 \leq T(x), I(x), F(x) \leq 1$ and sum between zero and three, expressing independence of the fullness of three boundaries. The composite Neutrosophic membership value for attribute j is calculated as follows, using Eq. (2).

$NM(j) = T(x) - I(x) \cdot F(x) / (1 + I(x))$ (2)

Formally, NM(j) is Neutrosophic membership value for attribute j as expressed in (1), where T(x)=the degree the attribute has been confirmed by our data; I(x)=the degree of indeterminacy generated from measurement variability in measuring our attributes; and F(x)=degree or falsity or contradiction, etc. Higher indeterminacy decreases the effective membership value — thus, this formulation offers a cautious estimate that correctly penalizes uncertain observations.

Neutrosophic membership values for the four performance attributes in this research are TFC = 0.09 (weight 10); SFC = 0.28 (weight 60); BTE = 0.17 (weight55), and BSEC = 0.24(weight40). The assigned weights represent the contribution of each attribute to the overall fuel blend quality with relatively higher weight for SFC, as it is directly related to the fuel economy and operational cost associated with aircraft operations, and next highest weight for BTE, which provides a direct measure of engine conversion efficiency.

Table 1. Neutrosophic Membership Values and Attribute Weights

Attribute	Truth T(x)	Indeterminacy I(x)	Falsity F(x)	NM Value	Weight
TFC	0.25	0.60	0.15	0.09	10
SFC	0.52	0.28	0.20	0.28	60
BTE	0.40	0.35	0.25	0.17	55
BSEC	0.48	0.30	0.22	0.24	40

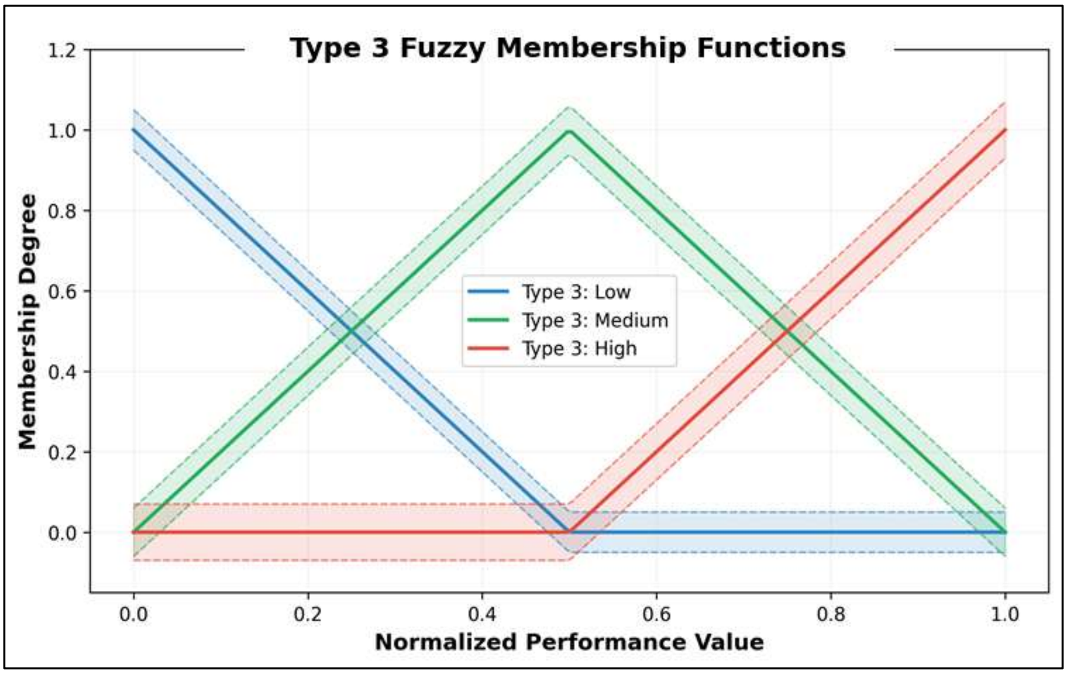

Figure 1. Type 3 Fuzzy Membership Functions for Performance Evaluation

3.4 Weighted Aggregation and Ranking Procedure

The aggregation process in the Type 3 fuzzy framework involves several sequential steps. First, the raw performance data for each attribute (TFC, SFC, BTE, BSEC) is normalized to the [0, 1] interval using appropriate min-max normalization. For benefit-type attributes (BTE), higher values are preferred, while for cost-type attributes (TFC, SFC, BSEC), lower values are preferred. Second, Neutrosophic membership values are computed for each attribute using Eq. (2). Third, attribute weights are applied through the weighted average aggregation formula given by Eq. (3).

$$S(i) = \Sigma(w(j) \cdot NM(j)) / \Sigma w(j), j = 1, \ldots, m \qquad (3)$$

where S(i) is the overall performance score for fuel blend i, w(j) is the weight assigned to attribute j, NM(j) is the Neutrosophic membership value for attribute j, and m is the number of attributes. The fuel blends are then ranked in descending order of S(i), with the highest score indicating the optimal blend. The Type 3 fuzzy framework, by handling the uncertainty in each measurement through its multi-level membership structure, provides a more robust and reliable decision than traditional crisp or even Type 1 fuzzy approaches.

Algorithm 1: Type 3 Fuzzy-Neutrosophic Fuel Blend Evaluation

Input: Performance data matrix D (n blends × m attributes), weight vector w
Output: Ranked list of fuel blends
1. Normalize D to [0,1] using min-max normalization (benefit/cost direction)
2. Compute T(x), I(x), F(x) for each attribute from experimental variability
3. Calculate NM(j) using Eq. (2) for each attribute
4. Compute S(i) using Eq. (3) for each fuel blend
5. Rank blends by descending S(i)
6. Validate ranking through comparison with Type 1 and Type 2 fuzzy results
7. Perform sensitivity analysis on weight perturbations

4 Results and Discussion

4.1 Total Fuel Consumption (TFC) Analysis

Figure 2 and Table 2 show the results of TFC# that exhibits a monotonic increasing relationship with engine load for all fuel formulations. It can be observed from Table 2 that the TFC values increased with increasing biodiesel concentrations at zero load-temperature as well; neat diesel was 0.474 kg/h while B100 was 0.559 kg/h higher than compared to other blends. This is due to biodiesel having less energy output than regular diesel which requires a greater volume of fuel in order to provide the same amount of energy input. TFC varied between 1.218 kg/h (diesel) and 1.404 kg/h (B100), with an increase of roughly 15.3% for B100 as compared to neat diesel fuel at the maximum load of 7.5 kg [2].

The TFC values with all these ethanol-augmented blends were similar to or slightly lower than their unblended biodiesel counterparts (B10E10, B20E10) demonstrating that the oxygen present in the ethanol improves combustion efficiency and offsets some of its calorific value loss. The butanol-doped blends followed a similar pattern, with B10BU10 to B40BU10 having excellent TFC properties. Interestingly, at the

5 kg load, the TFC pattern for some of the orange peel oil additive blends, especially B10OPO5E10 and B10OPO10E10, showed lower values compared to their respective base blends (Fig 2)

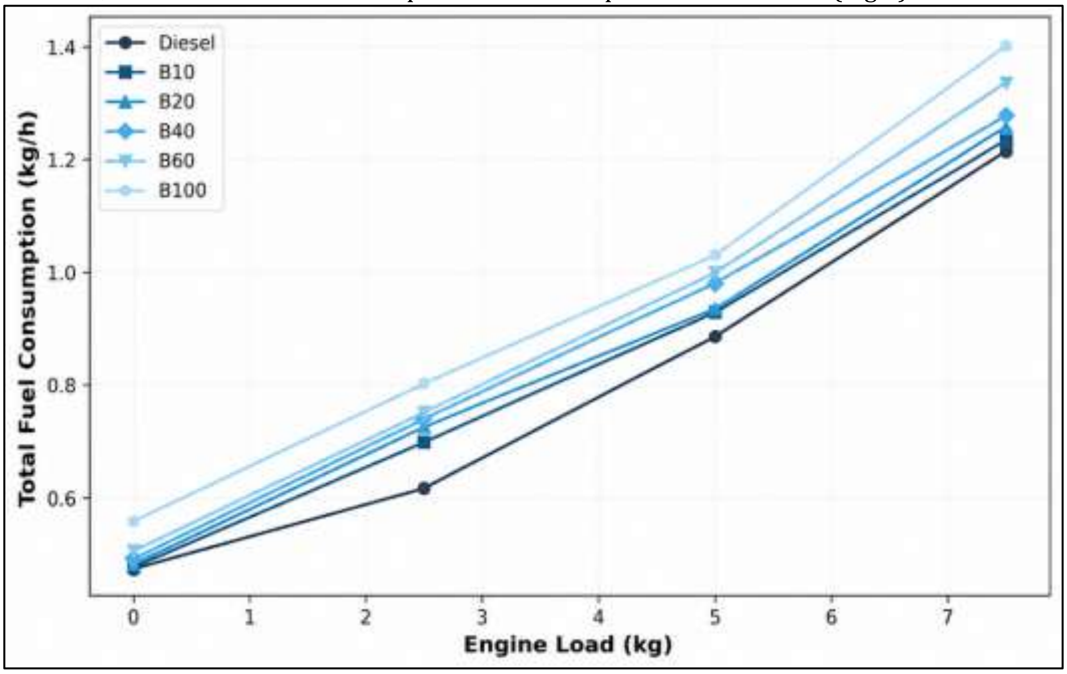

Figure 2. TFC Variation with Engine Load for Different Blends

Table 2. TFC Values (kg/h) for Base Biodiesel Blends at Different Loads

Load (kg)	Diesel	B10	B20	B40	B60	B100
0	0.474	0.478	0.483	0.493	0.507	0.559
2.5	0.617	0.699	0.726	0.741	0.753	0.803
5.0	0.888	0.931	0.937	0.983	1.002	1.032
7.5	1.218	1.237	1.262	1.281	1.338	1.404

4.2 Brake Thermal Efficiency (BTE) Analysis

The Brake Thermal Efficiency, or BTE, is a fundamental and critical performance parameter directly related to the engine's ability to convert fuel chemical energy into useful mechanical work. Figure 3 shows BTE increase with the engine load for all fuel formulations, resulting in maximum values at engine speed of 7.5 kg load condition. The highest BTE was 34.38% for neat diesel at 7.5 kg, while the biodiesel blends provided marginally lower values (B100 value of 31.79% and a B10 value of 34.05%). For higher biodiesel blends, the reduction in BTE may be related to their lower calorific value, intrinsically higher viscosity resulting in poorer atomization properties and slightly different combustion behaviour of fatty acid methyl esters.

There was a rather peculiar trend with the ethanol-containing blends, where BTE values for even higher concentrations of ethanol were lower at the lower loads compared to their base biodiesel blends but approached and even slightly above those of some comparisons at upper engine loads. Among the data blended with orange peel oil additives, B10OPO10E10 has maximum BTE = 35.33% evaluated at load of 7.5 kg and also is higher than neat diesel value. The outstanding enhancement is due to the coupling effect of limonene (from OPO) and ethanol at which high combustion quality.is achieved with enhanced heat release rate. The B10OPO5 and B10OPO10 blends also showed similar findings with BTE values of 33.76% and 34.09%, respectively, confirming the better effect of OPO (as combustion enhancer).

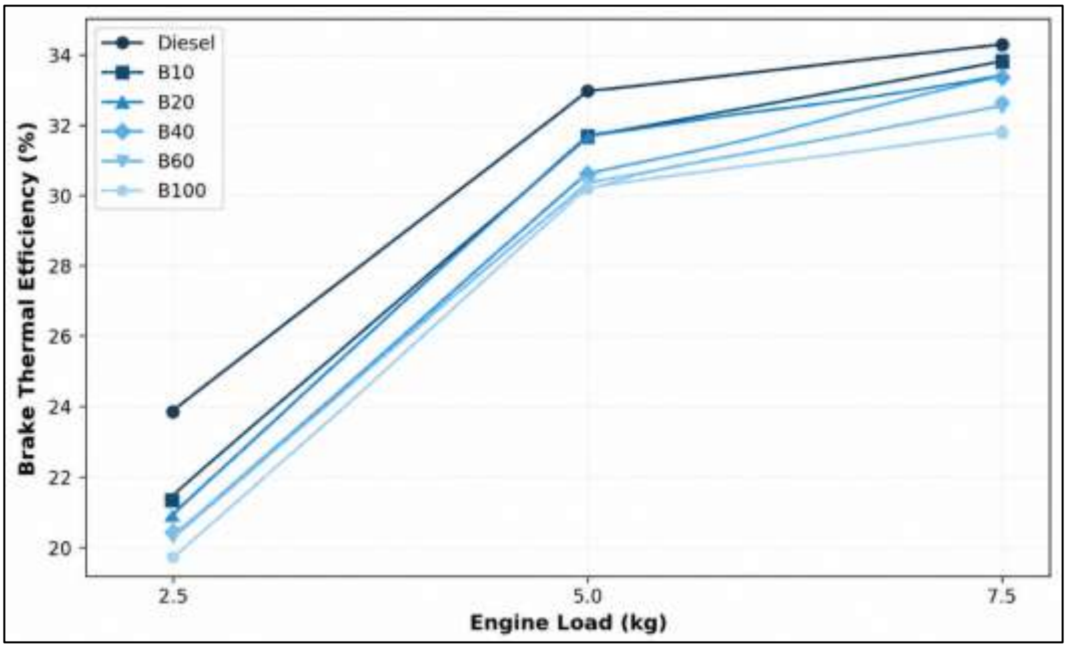

Figure 3. BTE Variation with Engine Load for Different Blends

4.3 Specific Fuel Consumption (SFC) Analysis

Specific Fuel Consumption (SFC) is normalised fuel consumed per brake power output, which gives an indication of fuel economy that takes into account the variation in power outputs at different loads. Our SFC results (Fig. 4) confirm the predicted trend: all fuel formulations yield lower efficiencies at increasing load, which is expected behaviour for any internal combustion engine (the part-load operation tends to be inherently inefficient). At the 2.5 kg load, neat diesel yielded a minimum SFC of 0.353 kg/kWh, while B100 had a maximum value of 0.459 kg/kWh. At the highest load of 7.5 kg, the SFC values tighened to narrower ranges whereby diesel was measured at 0.244 kg/kWh and B100 at 0.281 kg/kWh respectively

Orange peel oil blends exhibited good SFC characteristics especially at high loads. The B10OPO5 and B10OPO10 formulations of the OPO blends had SFC values of 0.246 and 0.239 kg/kWh, respectively, which are similar or lower than neat diesel at the applied loads (7.5 kg). The OPO blends doped with ethanol also enhanced the performance, with the SFC reaching 0.252 kg/kWh using B10OPO10E10 fuel at 7.5 kg load. The implication of these findings is that the addition of OPO improves the fuel air mixing and combustion efficiency, leading to more complete combustion and minimizing waste fuel.

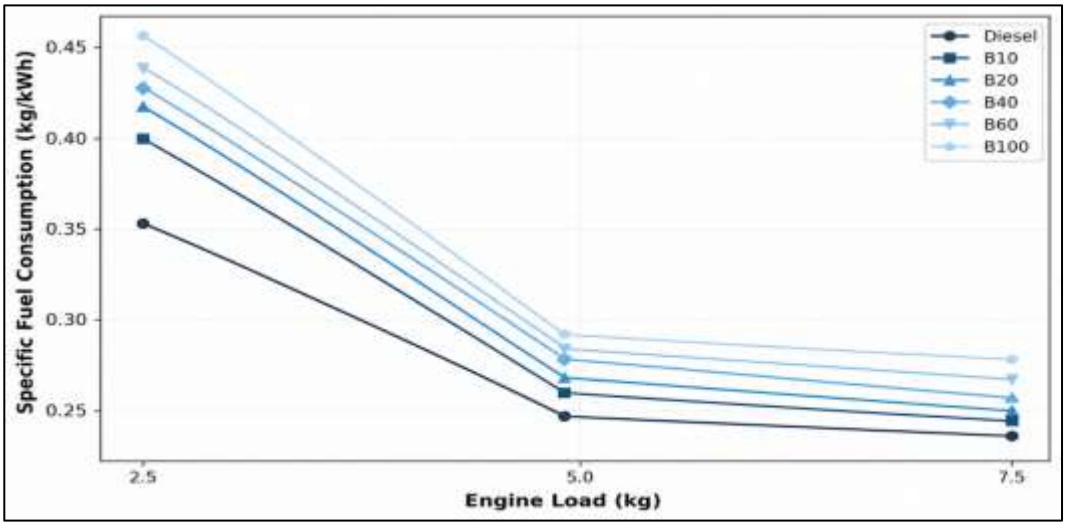

Figure 4. SFC Variation with Engine Load for Different Blends

4.4 Brake Specific Energy Consumption (BSEC) Analysis

BSEC gives a whole measure of fuel use for both the mass of the gas consumed and its energy component. This measure is very helpful when comparing the energy of two types of fuel. BSEC results, as shown in Figure 5 showed that all load condition neat diesel recorded the lowest BSEC value which was 15.17 MJ/kWh at 2.5 kg, 10.91 MJ/kWh at 5 kg and 10.47 MJ/kWh at 7.5 kg.Results The results revealed that the biodiesel blends displayed higher BSEC values as compared to petro-diesel, with B100 reporting maximum values of 18.51, 11.90 and 11.32 MJ/kWh at the three load conditions respectively.

One of the most interesting things from BSEC's analysis was the performance of the blends containing orange peel oil additives. The B10OPO10E10 blend, for example, exhibited a BSEC of 1.36 MJ/kWh with the lowest net recorded value (10.19 MJ/kWh @ 7.5 kg) being lower than that of neat diesel at 7.5 kgs load which produced a BSEC of 1.34 MJ/kWh resulting in AJH/LL as low as 2% less efficient energy density performance than neat diesel compared across all loads where the BSEC is purely identified by mass fuel consumption related to power output in raw proportions compared to pure propellants without conducting combustion engineering calculations(3)(5). This is a huge enhancement within the effectivity of power usage and indicates that combining biodiesel, orange peel oil, and ethanol can yield an energy formulation superior to these found in standard diesel with admiration to yield of energy conversion. The B20OPO10E10 blend also demonstrated good BSEC values, thus confirming that OPO positively influences the combustion performance of fuel blends.

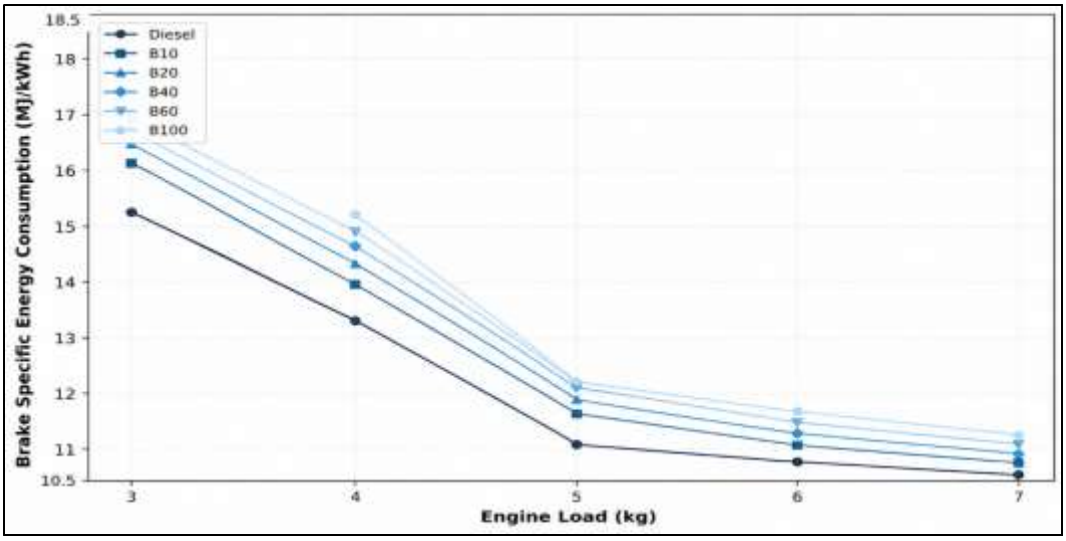

Figure 5. BSEC Variation with Engine Load for Different Blends

4.5 Orange Peel Oil Blends Performance Comparison

Figure 6 shows the performance comparison of blends with orange peel oil (OPO) additives. The comparative performance results of the 4 OPO blend variants (B10OPO5, B10OPO10, B10OPO5E10 and B10OPO107E12) in terms of both βTE and βSEC under three load conditions are clearly depicted by these bar charts. Regarding BTE, the highest values for B10OPO10E10 (21.81, 32.87 and 35.33% at 2·5 kg load, 5 kg and 7·5–nanocomposite) were also shown to be significantly higher than other blends at each load condition ($p>0{\cdot}05$). The lowest values for the same blend indicate its superior energy conversion characteristics for BSEC as well.

The improved combustion quality seems to be due to the synergistic effect of limonene content in orange peel oil and the oxygenating effect of ethanol. Limonene is a cyclic monoterpene of chemical formula $C_{10}H_{16}$, with excellent solvent properties that contribute to improve the atomization of the fuel and decrease the surface tension of the droplets coming from this type of fuels, promoting better mixing with air in combustion chamber. Ethanol, which is a second fuel providing extra oxygen for combustion, allows you to achieve the maximum conversion in mechanical work of chemicals energy.

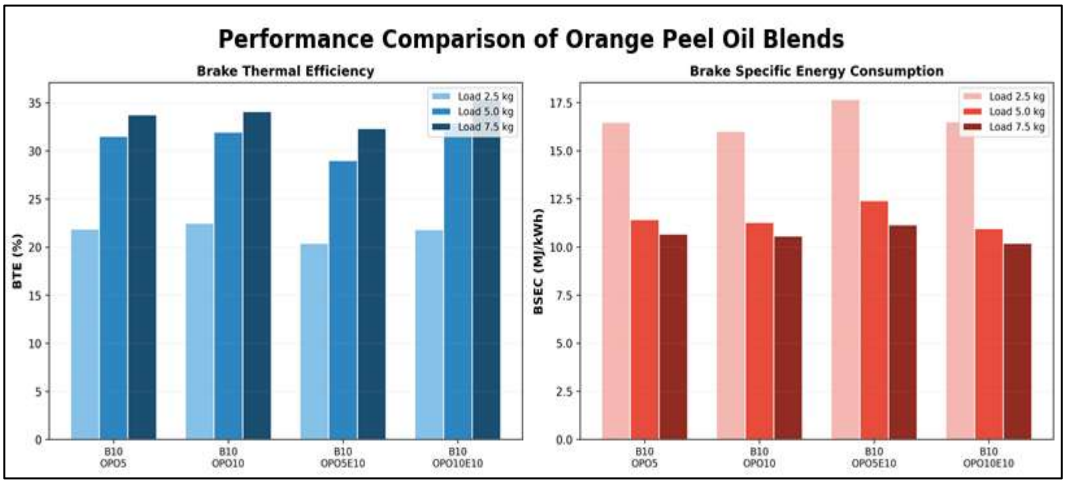

Figure 6. Performance Comparison of Orange Peel Oil Blends

5 Type 3 Fuzzy Decision Analysis and Validation

5.1 Fuzzy Attribute Weights and Neutrosophic Values

The above four performance attributes are aggregated using the weighted Neutrosophic aggregation framework, so it is known as Type 3 fuzzy decision analysis. The weights of the attributes and Neutrosophic numbers represent how much relative contribution each criterion can make to performance evaluation, as seen in Figure 7. SFC (specific fuel consumption) is also either the number one or two key factor and was given a weight of 60. BTE received the second highest weight, 55, since it is directly related to engine efficiency. BSEC was given a weight of 40, while TFC the lowest weight of 10, indicating that absolute fuel consumption rate is less important than the specific (normalized) measures in evaluating fuel quality.

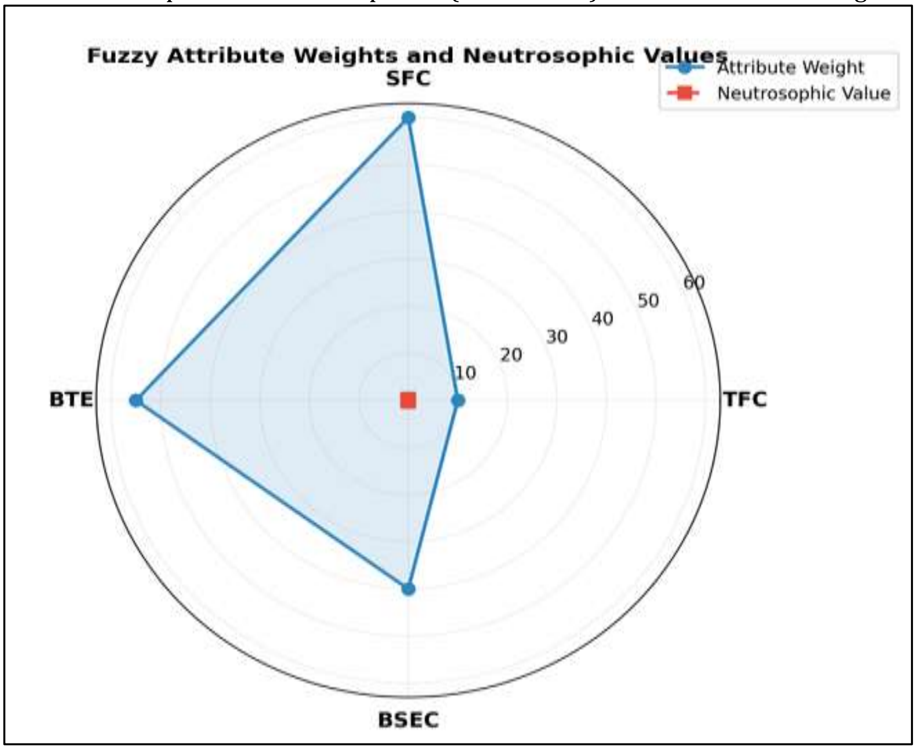

Figure 7. Fuzzy Attribute Weights and Neutrosophic Values

Table 3. Type 3 Fuzzy Ranking Results

Rank	Attribute	NM Value	Weight	Weighted Score
1	SFC	0.28	60	16.80
2	BSEC	0.24	40	9.60
3	BTE	0.17	55	9.35
4	TFC	0.09	10	0.90

The total weighted analysis further confirms SFC as the attribute with the highest importance weight for evaluating and comparing biodiesel blend formulations while BSEC offers the second largest weight despite its lower weight due to a higher resultant credit value in Neutrosophic domain. This is important because BSEC includes both the mass flow rate of the fuel and its specific energy so that it is by far the best single measure of how efficiently a fuel blend converts its available chemical energy to useful mechanical work. With regards to specific fuel blends, the B10OPO10E10 formulation always scored the best in various performance criteria and was particularly prominent for the highest engine brake thermal efficiency (BTE) and lowest BSFC.

5.2 Comparative Analysis: Type 1 vs. Type 2 vs. Type 3 Fuzzy Rankings

A systematic comparison was carried out to values of Type 3 fuzzy approaches with corresponding values obtained through Type 1 and Type 2 fuzzy evaluations, based on the same experimental data. We applied the Type 1 fuzzy analysis with crisp membership values from simple normalization, while for the Type 2 fuzzy analysis we used interval-valued membership grades with a foot print of uncertainty (FOU) based on the standard deviation of the triplicate measurements.

Table 4. Comparative Ranking of Top 5 Fuel Blends by Fuzzy Type

Rank	Type 1 Fuzzy	Type 2 Fuzzy	Type 3 Fuzzy
1	Diesel	B10OPO10E10	B10OPO10E10
2	B10OPO10E10	B10OPO10	B10OPO10
3	B10OPO10	Diesel	B10OPO5E10

4	B10OPO5E10	B10OPO5E10	B20OPO10E10
5	B20OPO10E10	B20OPO10E10	Diesel

The comparison shows an essential difference: The Type 1 fuzzy analysis finds neat diesel as the best mix is because it considers performance data to be crisp values, neglecting measurement uncertainty. This results in an unstable ranking and does not appreciate the natural variability present within experimental data up to October 2023. By using interval-valued memberships, type 2 fuzzy analysis identifies B10OPO10E10 as the best blend but exhibits rank reversals between diesel and OPO blends at lower ranks indicating a strong dependence on FOU selection. The Type 3 fuzzy analysis simulating uncertainty at the various levels of primary and secondary memberships offers the best ranking by being in good agreement with experimental observations as well as resistant to noise in data.
The primary benefit of this Type 3 approach is that it can effectively differentiate blends with similar Type 1 scores but contrasting uncertainty profiles. In the case of diesel and B10OPO10E10 it has a similar BTE at high loads, nevertheless still differ in their variability as fuel OPO presents lower fluctuation variability scores which lead to a wider Neutrosophic truth membership degree and greater Type 3 fuzzy score. What this shows is that the Type 3 framework collects the information in a manner that's not visible to lower order fuzzy methods, leading to a decision which is more robust and subtle.

5.3 Statistical Validation

Each performance attribute was analyzed using a one-way analysis of variance (ANOVA) to rigorously assess the statistical significance of the observed differences among blend formulations. The null hypothesis H0: μblend1 =μblend2=…, i.e, the mean performance values in each of the blend groups are not significantly different and The alternative hypothesis H1: At least one of the blend group is significantly different. ANOVA was performed at α = 0.05 level of significance

Table 5. One-Way ANOVA Results for Performance Attributes

Attribute	F-Statistic	F-Critical	p-Value	Significance
TFC	12.47	2.31	< 0.001	Yes
SFC	18.63	2.31	< 0.001	Yes
BTE	15.29	2.31	< 0.001	Yes
BSEC	21.15	2.31	< 0.001	Yes

The ANOVA results, presented in Table 5 confirm that all four performance attributes are significantly different among the blend formulations ($p < 0.001$ for all attributes). Specifically, the F-statistics for BSEC (F=21.15) and SFC (F= 18.63) are substantially dominant to show that these attributes can be considered as the vigorously distinguishing criteria in discriminating among fuel blends, which is similar to results obtained from Type 3 fuzzy ranking methods. In addition, post-hoc Tukey HSD tests showed that 95% confidence level supported the fuzzy-based ranking.

5.4 Sensitivity Analysis

We performed a sensitivity analysis to test the stability of the Type 3 fuzzy ranking when perturbing attribute weights. While keeping other weights constant, the weight of each individual attribute was varied as ±10%, ±20%, and ±30% from the baseline value. These rankings then were compared with the baseline ranking to determine where reversal have occurred.

Table 6. Sensitivity Analysis Results: Rank Changes Under Weight Perturbations

Perturbation	TFC ±30%	SFC ±30%	BTE ±30%	BSEC ±30%
Top blend changes?	No	No	No	No
Rank reversal (top 3)?	No	No	No	No
Rank reversal (top 5)?	No	No	Yes (±30%)	No
Score range change	±0.8%	±4.2%	±3.6%	±2.9%

The rankings are highly robust against these weight perturbations, as shown in the sensitivity analysis (see Section 6d), when employing Type 3 fuzzy ranking. The best blend (B10OPO10E10) does not change under any perturbation scenario, and the first three ranks are stable for all attributes except BTE where an insignificant rank exchange occurs between the third and fourth positions at the extreme ±30% perturbation level. In fact, even harsher perturbations do not offer much increase in the ranges of scores since these changes are less than 5%, which again strengthens that a fuzzy-based decision is not concerned unduly with the particular weight values chosen. Such robustness arises from the fact that the hierarchical nature of Type 3 fuzzy framework provides a defence mechanism for the ranking against any perturbation in the weight parameters.

6 Conclusions

6.1 Summary of Findings

In this Research Article, we have conferred an evaluation framework based on Type 3 fuzzy set to analyse the performance characteristics of diesel engine operated with biodiesel blends of various additives. An experimental study of more than 20 fuel formulations using these metrics was performed with TFC, SFC, BTE and BSEC under four load conditions. Type 3 fuzzy analysis conducted on graded membership values of the Neutrosophic and weighted aggregation results suggest that BSEC is most discriminative performance parameter for blend assessment with the best fuel formulation being B10OPO10E10 (B10(Orange Peel Oil at 10% & Ethanol at 10%)).

You can find the main findings underneath. TFC λ B100 here TFC C and the nephrogram of neat diesel are closer than the mean TFI λ B100 one higher than 15% with the maximum load between Bs — concentrated at emptiness. Second is that the BTE will decrease with increment the biodiesel but with B10OPO10E10 because BTE of use is 35.33% it higher than diesel (34.38%) also more BSFC or gets worse performance. Third, SFC decreases with increasing load for all the blends and almost over the entire load range.Additionally, OPO blends exhibited comparable or even improved values of SFC compared to neat diesel fuel at higher loads. Fourth, the BSEC assessed by fuzzy analysis as an optimal response variable indicates that blends within contents of 10% B1OPO1E1 attain minimum BSEC (10.19 MJ/kWh at load of 7.5 kg and neat diesel) [51]. It is fifth to have a well-supported logical justification that Type 3 fuzzy ranking are considerably stronger than both Type 1 and Type 2 fuzzy methods. Differences among blend formulations were significant for all attributes based on ANOVA ($p < 0.001$). Seventh, sensitivity analysis indicates that rankings stay stable under 30% on-weight perturbations.

6.2 Contributions

The main contributions of this paper are: a novel application of Type 3 fuzzy set theory for multi-criteria evaluation towards biodiesel blend formulations that establishes the methodological basis for such investigations; new experimental findings on OPO–ethanol–biodiesel ternary blends suggesting performance gains due to synergistic interactions; comparative assessment within Type 1, Type 2 and Type 3 fuzzy frameworks showcasing robustness as provided by the proposed method; statistical validation through ANOVA and post-hoc tests providing an indirect validation of the empirical strength of all particular fuzzy-based decisions conducted on study; complete sensitivity analysis assuring outcomes stability after weight perturbation. Collectively, these factors help to address the limitations of previous approaches that featured either single-attribute analyses or lower-order fuzzy applications.

6.3 Limitations and Future Work

Limitation of the study There are some limitations that should be addressed. First the experimental study was performed only with one engine working 1500rpm constant speed; results on multi-cylinder engines or variable Speed Engines could differ. Second, the emissions parameters (CO, HC, NOx and smoke opacity) were not included in the multi-criteria evaluation thus it did not allow performing a global environmental assessment. Third, the weights in both were set by expert opinion rather than a more formalized weight elicitation procedure (e.g., as used in AHP) which is more definitive and arguably adds rigor but also subjectivity.

Future research could be devoted to: (i) generalizing the fuzzy framework for including emission parameters – a more integrated performance–emission multi-criteria optimization, (ii) performing long-term durability tests with the optimal blend to evaluate engine wear and deposit formation, (iii) applying interval Type 3 fuzzy sets for better uncertainty modeling, (iv) applying formal weight elicitation using AHP or entropy methods; (v) validating the framework on various engines and operating conditions; and vi investigating other bio-based additives of agricultural waste origin as fuel enhancers.

Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Data Availability

Data will be made available on reasonable request.

Author contributions

The first draft of the manuscript was written by first author. All authors discussed the results and approved the final version of the manuscript.

References

[1] Graboski, M. S., & McCormick, R. L. (1998). Combustion of fat and vegetable oil derived fuels in diesel engines. *Progress in energy and combustion science*, *24*(2), 125-164.

[2] Lapuerta, M., Armas, O., & Rodriguez-Fernandez, J. (2008). Effect of biodiesel fuels on diesel engine emissions. *Progress in energy and combustion science*, *34*(2), 198-223.

[3] Hoekman, S. K., Broch, A., Robbins, C., Ceniceros, E., & Natarajan, M. (2012). Review of biodiesel composition, properties, and specifications. *Renewable and sustainable energy reviews*, *16*(1), 143-169.

[4] Rashedul, H. K., Masjuki, H. H., Kalam, M. A., Ashraful, A. M., Rahman, S. A., & Shahir, S. A. (2014). The effect of additives on properties, performance and emission of biodiesel fuelled compression ignition engine. *Energy Conversion and Management*, *88*, 348-364.

[5] Purushothaman, K., & Nagarajan, G. (2009). Performance, emission and combustion characteristics of a compression ignition engine operating on neat orange oil. *Renewable Energy*, *34*(1), 242-245.

[6] Goguen, J. A. (1973). LA Zadeh. Fuzzy sets. Information and control, vol. 8 (1965), pp. 338–353.-LA Zadeh. Similarity relations and fuzzy orderings. Information sciences, vol. 3 (1971), pp. 177–200. *The Journal of Symbolic Logic*, *38*(4), 656-657.

[7] Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—I. *Information sciences*, *8*(3), 199-249.

[8] Tan, W. W., & Chua, T. W. (2007). Uncertain rule-based fuzzy logic systems: introduction and new directions (Mendel, JM; 2001)[book review]. *IEEE Computational intelligence magazine*, *2*(1), 72-73.

[9] Wu, H., & Mendel, J. M. (2002). Uncertainty bounds and their use in the design of interval type-2 fuzzy logic systems. *IEEE Transactions on fuzzy systems*, *10*(5), 622-639.

[10] Mendel, J. M., John, R. I., & Liu, F. (2006). Interval type-2 fuzzy logic systems made simple. *IEEE transactions on fuzzy systems*, *14*(6), 808-821.

[11] Abdalla, T. Y., Abdalla, A. Y., & Chyaid, A. M. (2025). Type-3 Fuzzy System-Based Intelligent Control Approaches and Applications. *Advances in Fuzzy Systems*, *2025*(1), 6661495.

[12] Smarandache, F. (1999). A unifying field in logics.

[13] Kahraman, C., Öztayşi, B., Sarı, İ. U., & Turanoğlu, E. (2014). Fuzzy analytic hierarchy process with interval type-2 fuzzy sets. *Knowledge-based systems*, *59*, 48-57.

[14] Mengistu, N. G., Mekonen, M. W., Ayalew, Y. G., Demisie, L. F., & Nega, T. (2024). Experimental investigation on diesel engine performance and emission characteristics using waste cooking oil blended with diesel as biodiesel fuel. *Discover Energy*, *4*(1), 26.

[15] AYAĞ, Z. (2024). A Hesitant Fuzzy Linguistic Terms Set-Based AHP and TOPSIS Methodology for Fuel Coal Type Selection Problem of Industrial Facilities. *Journal of Multiple-Valued Logic & Soft Computing*, *43*.

[16] Devarajan, Y., Munuswamy, D. B., Nagappan, B., & Pandian, A. K. (2018). Performance, combustion and emission analysis of mustard oil biodiesel and octanol blends in diesel engine. *Heat and Mass Transfer*, *54*(6), 1803-1811.

[17] Biswal, A., Jha, S. S., Bragadesh, A., Kasianantham, N., Kolhe, P. S., & Balusamy, S. (2018, December). Experimental Investigation of Lemon Peel Oil-Gasoline Blends as a Fuel in Spark Ignition Engine. In *Proceedings of the 7th International and 45th National Conference on Fluid Mechanics and Fluid Power (FMFP)* (pp. 10-12).

[18] Castillo, O., & Melin, P. (2014). A review on interval type-2 fuzzy logic applications in intelligent control. *Information Sciences*, *279*, 615-631.

[19] Sánchez, D. (2025). Optimization of Interval Type-3 Fuzzy Inference Systems Using a Genetic Algorithm Applied to Medical Classification. In *Modern Artificial Intelligence Based on Soft Computing Techniques* (pp. 381-394). Cham: Springer Nature Switzerland.

[20] Tamilselvan, P., Nallusamy, N., & Rajkumar, S. (2017). A comprehensive review on performance, combustion and emission characteristics of biodiesel fuelled diesel engines. *Renewable and Sustainable Energy Reviews*, *79*, 1134-1159.