Integrative Analysis of Diesel-Kerosene Blends on Engine Performance and Emissions

Cristian I. Eugenio-Pilliza[1*], **Francisco J. Montalvo-Marquez**[2], **Ángel Portilla** [3]

[1]Technical University of Cotopaxi, Faculty of Engineering and Applied Sciences, Latacunga, Ecuador.
[2] National Polytechnic School, Faculty of Mechanical Engineering, Quito, Ecuador

[3] National Polytechnic School, Faculty of Mechanical Engineering, Quito, Ecuador.

Emails: cristian.eugenio@utc.edu.ec; javier.montalvoupec.edu.ec; angel.portilla@epn.edu.ec

Abstract

Combines diesel fuel with cheese to enhance engine efficiency and mitigate detrimental pollutants. Analyzed using a meticulous approach derived from the ISO 8178 standard, combinations containing different ratios of cheese are investigated. The aim of the research is to conduct a multivariate analysis that provides insights into the rheology of diesel and kerosene mixes, thereby enhancing our understanding of the fuel's properties and performance. The researchers conducted experimental trials utilizing diesel blends with varying proportions of cheese, including 5%, 10%, 15%, 20%, 25%, and 30%. A descriptive and multivariate analysis was conducted to measure parameters such as opacity, NOx, CO, HC emissions, and fuel efficiency under different load circumstances. The study identified key elements that determine gasoline characteristics and emissions, including density, viscosity, calorific value, and sulfur content. It emphasized that the addition of cheese had a significant impact on these crucial factors. Two separate categories were created based on the composition of fuel. Blends containing a lower amount of cheesesine (up to 20%) formed a cluster that exhibited an ideal equilibrium in terms of both performance and emissions. The groupings of factors are interconnected, with substantial correlations shown between the physical qualities of the fuel and emissions. This highlights the direct impact of the fuel composition on the engine's environmental performance.

Keywords: Cluster Analysis, Principal Component Analysis; multivariate analysis; experiment; engine.

1. Introduction

Presently, multiple investigations have been conducted on the utilization of alternate fuels in compression ignition engines (CIE). These investigations investigate the impact on engine performance, efficiency of the combustion process, and the quantifiable results of exhaust gas emissions by measuring opacity levels and particulate matter concentration [1, 2].

The impact on the performance and emissions of a diesel engine when kerosene is added to the diesel fuel has been assessed. Engine tests are performed in accordance with the testing protocol outlined in ISO 8178 [3] mode five-D2. The study discovered three different fuel mixtures: pure diesel, and volumetric combinations of 5%, 10%, and 15% diesel/kerosene, referred to as K5D, K10D, and K15D, respectively [4]. It has been discovered that as the mixture exceeds 15%, the viscosity and density decrease, leading to wear issues in the injection pump and injectors. Furthermore, it has been

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024

established that the K5D mixture is the most appropriate choice as it effectively decreases the degree of opacity, NOx emissions, and specific fuel consumption [4, 5, 6].

Additional study has created a strong and efficient simulation mechanism that accurately models the combustion of a diesel-kerosene mixture in a diesel engine. The system comprises a total of 48 distinct species and 152 individual responses [7]. In order to verify the mechanism, a simpler version of the kerosene sub-mechanism is employed. This simplified version is confirmed by comparing its ignition delay times, which are measured in both a constant volume combustion chamber and an optical engine [8]. Nevertheless, it is important to note that this model does not replicate the harmful emissions of the mixture [9].

A study was conducted to experimentally investigate the effects of blending three oxygenated chemicals, namely diethyl ether (DEE), kerosene, and diesel, on the combustion characteristics, performance, and emissions of a direct injection diesel engine. The study initially experimented with various volumetric ratios of DEE, ranging from 2% to 25%, mixed with diesel fuel. The objective was to find the ideal blend that achieves a balance between performance and emissions. The results showed that DE15D, a mixture containing 15% DEE, was the most effective.

Later on, a blend of kerosene and DE15D was produced by combining kerosene in ratios of 5%, 10%, and 15% with diesel. Engine tests were conducted under different load circumstances, spanning from 10% to 100% of the overall load, for all fuel variations [11]. The experimental tests showed that the combination of electric kerosene and diesel generally decreased brake thermal efficiency and specific fuel consumption. However, it resulted in lower gas emissions, minimal levels of NOx, similar levels of CO production, and reduced HC emissions at partial loads compared to the combination of DE15D and pure diesel [12].

Previous studies have concentrated on investigating the consequences of blending diesel with kerosene. These studies explicitly analyzed the changes in density, kinematic viscosity, and exhaust gas emission parameters, such as opacity, in six light automobiles. The researchers conducted experiments using five distinct mixtures with variable volume ratios (85:15, 75:25, 65:35, 50:50, and 25:75) in addition to pure diesel at a ratio of 100:75 [13]. Based on their investigations, it was noted that the density remained rather consistent even when increasing amounts of kerosene were added. However, the kinematic viscosity exhibited a downward trend as the levels of adulteration grew. In addition, the study findings showed that even with minor adulteration, the opacity percentage value (% k value) dropped, suggesting a potential beneficial impact on emissions [14].

To assess the effectiveness of using kerosene as an additive in diesel injection engines for improving lubrication efficiency [15]. The HFRR test findings revealed that the combination of diesel and kerosene did not provide enough lubrication, which might potentially cause damage to the injection system and fuel delivery pump. In order to resolve this problem, the industry decided to implement a wear limit of 460 microns, as recommended by CEN, to guarantee satisfactory performance. In order to improve lubrication and prevent excessive wear in these engine systems, it is advisable to add additives such as monocarboxylic acid ester, tetradecyl, or hexadecyl acetate, as suggested by [15].

Engine performance evaluation entails a thorough examination of specific fuel consumption and fuel energy efficiency. Meanwhile, emissions analysis aims to quantify the levels of detrimental gases, such as carbon monoxide (CO), hydrocarbons (HC), and nitrogen oxides (NOx), found in engine exhaust emissions [16]. The study findings demonstrate that the addition of kerosene to biodiesel blends results in a significant decrease in NOx emissions across all load circumstances, as well as a reduction in HC emissions, particularly at full load conditions.

Furthermore, it should be mentioned that the effectiveness of this blend diminishes as the proportion of kerosene increases. Hence, it is advisable to restrict the inclusion of kerosene to a maximum of K20 in order to attain a substantial decrease in specific fuel consumption and enhance fuel efficiency [17]. The research seeks to conduct a multivariate analysis to comprehend the rheological properties of diesel and kerosene blends, thereby enhancing our grasp of the fuel's features and performance.

2. Methodology

The beginning of this study starts with examining the qualities of the two types of fuel and their six combinations known as D5K, D10K, D15K, D20K, D25K, and D30K, with varying proportions of kerosene in diesel: 5%, 10%, 15%, 20%, 25%, and 30%, respectively. The selection of physical and

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024

chemical attributes to evaluate is based on the assessments to be carried out on the experimental vehicle, acquired through standardized procedures performed in the Petroleum and Thermodynamics Laboratory of the Faculty of Chemical Engineering at the National Polytechnic School. These evaluations provide valuable information about the behavior and performance of the fuel mixes, which helps to comprehensively understand their characteristics and potential applications in different operational environments. Table 1 lists the physical and chemical properties analyzed with the respective test standards.

Table 1: Tested Physicochemical Properties.

	Properties	**Standard**
Physical Properties	Relative Density at 15.6 ºC /15.6 ºC	ASTM D-1298
	Calculated Cetane Index	INEN1495:2013(R)
	Distillation: 90% Temperature	INEN –ISO 3405: 2014 (1R)
	Kinematic Viscosity 40 ºC	INEN 810:2013(1R)
Chemical properties	Sulfur content	ASTM D-4294
	Higher caloric value	ASTMD-240
	Flashpoint	INEN 1493:2013

Source: own elaboration.

- Utilized Equipment

The Technology Transfer Center for Training and Research in Vehicle Emission Controls (CCICEV) utilizes its available equipment and resources to collect experimental data on pollutant emissions, torque, and power for each fuel mix. The following is an elucidation of these:

The external fuel tank

In order to accommodate the testing of various fuel blends, it is imperative to implement an external fuel storage system that facilitates seamless fuel changeover without the requirement of emptying the vehicle's tank. This system has a reservoir, a gasoline outlet for engine feed, and a return inlet.

The Chassis Dynamometer LPS 3000 is a device used to measure the power and performance of a vehicle's chassis.

This apparatus was employed to ascertain the utmost power and torque of the engine across various fuel compositions.

- Meter for measuring fine particulate matter

The MAHA MP4 particle meter is the device utilized for measuring particulate matter during the tests. This device provides continuous measurements of the concentration of particulate matter, which are visually presented in milligrams per cubic meter (mg/m3) over time using a computer interface.

An opacimeter is a device used to measure the opacity or degree of opacity of a substance, such as smoke or exhaust gases.

The opacimeter currently in stock is the MAHA MDO2, which comprises of two primary components: the opacimeter itself (a measuring instrument) and a portable terminal equipped with a data printer for recording the measurement results in both graphical and numerical formats. The measurement is conducted by employing a partial discharge sample process within an enclosed chamber to assess the level of opacity of the exhaust gases.

- Examinations Conducted

In order to assess the mechanical efficiency of the engine, as well as the amount of particulate matter and the level of opacity in the gases generated during combustion, each tested mixture was analyzed. Below are descriptions of some tests:

- Torque and Power Evaluation

The evaluation of the engine's torque and power performance is carried out using the LPS 3000 chassis dynamometer. Discrete measurement is conducted for diesel engines. The performance of these

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024

vehicles is evaluated by measuring the power and torque applied to the wheels during acceleration, as well as the power and torque lost during deceleration.

- Test for Particulate Matter PM2.5 and Opacity

The contemporaneous measurement of PM2.5 particles and the percentage of Opacity is conducted in a static test.

3. Multivariate analysis

Multivariate data analysis[18, 19] was conducted using the Statistica software. This involves the statistical study of several variables measured in elements of a population, with the following objectives:

1) Summarize the data using a small set of new variables, constructed as transformations of the original ones, with minimal loss of information.

2) Find groups in the data, if they exist.

3) Classify new observations into defined groups; and

4) Relate two sets of variables.

- Correlation Matrix

The correlation matrix R is used to assess the pairwise dependence among the variables. It is a square and symmetric matrix with ones on its major diagonal, and the coefficients of linear correlation between pairs of variables outside the diagonal. The calculation of this matrix can be expressed in matrix form as follows:

$$R = D - \frac{1}{2} SD - \frac{1}{2} \qquad (1)$$

Where D corresponds to the diagonal matrix formed by the elements of the main diagonal of the VarCov matrix Principal Component Analysis (PCA) is a commonly employed technique in multivariate data analysis, which enables the examination of multidimensional data sets containing quantitative variables. It is extensively utilized in the domains of biostatistics, marketing, sociology, and numerous other disciplines.

The approach is a projection technique that maps observations from a space with p variables to a lower-dimensional space with k variables (where k is less than p). The goal is to retain the highest possible amount of information, which is quantified by the total variance of the dataset. The dimensions of Principal Component Analysis (PCA) are commonly referred to as axes or factors. If the data captured by the first 2 or 3 axes accounts for a significant portion of the overall variability in the scatter plot, it is possible to show the observations in a 2 or 3-dimensional graph, which would make their understanding easier.

PCA is a data mining technique that facilitates the extraction of information from huge data sets. It serves multiple purposes, such as studying and displaying the relationships between variables in order to reduce the number of variables that need to be measured later on.

The process of acquiring uncorrelated factors that are formed by linear combinations of the original variables, which can then be utilized in modeling techniques such as linear regression, logistic regression, or discriminant analysis.

Utilizing two-dimensional or three-dimensional visualization techniques to detect clusters of similar observations or outliers.

Factor analysis approaches encompass a range of methodologies, such as maximum likelihood (the most well-known and informed), unweighted least squares, generalized least squares, principal axis factor, alpha factor, and image factor. Contrary to the principal components method, these approaches begin with a pre-established hypothesis on the number of aspects to be taken into account in the analytical model and presume that there is interdependence among them. There is a scarcity of

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024

reputable references discussing the pros and disadvantages of these strategies. This approach relies on the similarity values associated with each item.

The consistency observed here can be attributed to the variability of each item, which is influenced by both its distinctiveness and random mistake. Therefore, these methods are recommended for doing Confirmatory Factor Analysis (CFA) or when there is a desire to redefine or enhance the quality of a scale.

Cluster Analysis refers to a broad range of techniques that can be employed to establish a classification. To be more precise, a clustering approach is a statistical technique that takes a dataset with information about a group of entities and aims to rearrange them into clusters, which are relatively homogeneous groups.

Cluster Analysis is a method that is distinct from multivariate assignment and discriminating methods since it operates without prior knowledge of the structure of the categories. The only information we have is a set of observations, and our objective is to determine the organization of the categories to which these observations belong. The objective is to categorize the observations in a manner that maximizes the level of inherent similarity within each group and minimizes the level of similarity between different groups. While the structure of the categories is largely unknown, there are usually some ideas about the favorable and unfavorable qualities when creating a specific classification system. The analyst have enough knowledge about the topic to effectively differentiate between favorable and unfavorable category structures upon encountering them.

Canonical Correlation Analysis (CCA) is a statistical technique for analyzing multiple variables simultaneously, which was devised by Harold Hotelling. The objective is to identify and validate any potential links between two sets of variables. Canonical correlation analysis distinguishes itself from multiple correlation analysis by its ability to predict many dependent variables from multiple independent factors, while the latter only predicts one dependent variable from multiple independent variables.

Hypercanonical correlation is a type of correlation that specifically focuses on linear correlations between variables. Therefore, in this analysis, linear combinations of the original variables are generated according to their correlation pattern. When planning the experiment, it is crucial to take into account the sample size, as it determines the minimum number of observations required for each variable in order to accurately represent the correlations in the analysis.

Ultimately, the significance of each variable in the canonical function must be deduced by interpreting the canonical loadings. The canonical loadings represent the amount of variance that the observed variable has in common with the canonical theoretical value. The eigenvalue of each axis represents the degree of multivariate correlation between the newly derived linear variables resulting from the analysis.

4. Results and discussion

The resultant cetane index value of 49.5 was obtained from the D25K mix, as shown in Table 2. This value exceeds the minimal threshold required by the NTE INEN 1495 requirements. The kinematic viscosity tests conducted at the standard temperature of 40°C conform to the prescribed limitations outlined in NTE INEN 810. The acceptable range is defined as $2 \leq$ kinematic viscosity in $mm^2/s \leq 5$. An inverse link between the proportion of kerosene in the mix and the calorific value is seen, with the calorific value decreasing as the proportion of kerosene increases.

In contrast, the sulfur content exhibits a positive correlation with the increasing volumetric proportion of kerosene in the mixture. Regarding the D20K fuel composition, the sulfur content is precisely measured at 436 parts per million (ppm) by weight percent. This value adheres to the regulatory criteria and does not surpass the upper limit specified by NTE INEN 1490, which is set at 500 ppm. This report provides a detailed examination of the complex relationship between various fuel qualities and their effects on performance and adherence to industry requirements.

The density of the mixture decreases as the proportion of kerosene increases, in line with the lower density of kerosene relative to diesel.

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024

- The cetane index decreases when there is a higher concentration of kerosene, which may suggest a deterioration in ignition quality.

- The distillation temperature falls significantly when more kerosene is added, which can impact the volatility of the fuel.

- Viscosity: The viscosity of different mixtures varies, with pure kerosene having the lowest viscosity. This can potentially affect engine lubrication.

- The sulfur content of kerosene increases as more of it is used, which can have environmental consequences and impact engine emissions.

- Calorific Power: Diminishes marginally with increased kerosene content, potentially impacting energy efficiency.

- The flash point of kerosene decreases as its quantity increases, which indicates a greater likelihood of it catching fire.

Table 2: Average descriptive values observed in each treatment.

Properties	**Unit**	**Diesel**	**D5K**	**D10K**	**D15K**	**D20K**	**D25K**	**D30K**	**Kerosene**
Relative density	g/cm^3	0.845	0.844	0.842	0.840	0.838	0.840	0.838	0.808
Calculated cetane number	--	52.3	52.5	52.4	51.7	51.1	49.5	49.8	40.6
Distillation: 90% temperature	ºC	349	3. 4. 5	340	336	333	329	325	242
Kinematic viscosity	mm^2/s	3,973	3,519	3,473	3,134	3,029	3,626	3,596	1,481
Sulfur content	% w	274	340	378	383	436	511	546	943
Higher caloric value	MJ/kg	44.53	44.41	44.36	44.20	44.03	43.97	43.82	43.57
Flashpoint	ºC	63.0	58.0	57.0	56.0	54.0	50.5	48.0	39.0

Source: own elaboration.

Figure 1 depicts the relationships between several chemical and physical characteristics of the fuel blends. Several noteworthy observations include:

- Distillation Temperature and Flash Point: These two variables exhibit a negative link, as the drop in the temperature at which 90% of the fuel has distilled is accompanied by a decrease in the ignition point of the fuel.
- Viscosity and density exhibit a link, suggesting that fuels with greater density generally possess higher viscosity.
- Cetane Index and Calorific Power: A moderate connection indicates that mixes with higher igniting capacity also tend to yield more energy output per unit mass.

These connections are essential for comprehending how changes in fuel composition impact its performance in internal combustion engine applications. The correlation analysis is useful for identifying significant associations that are essential for fuel formulation and the development of engines tailored for various fuel types.

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024

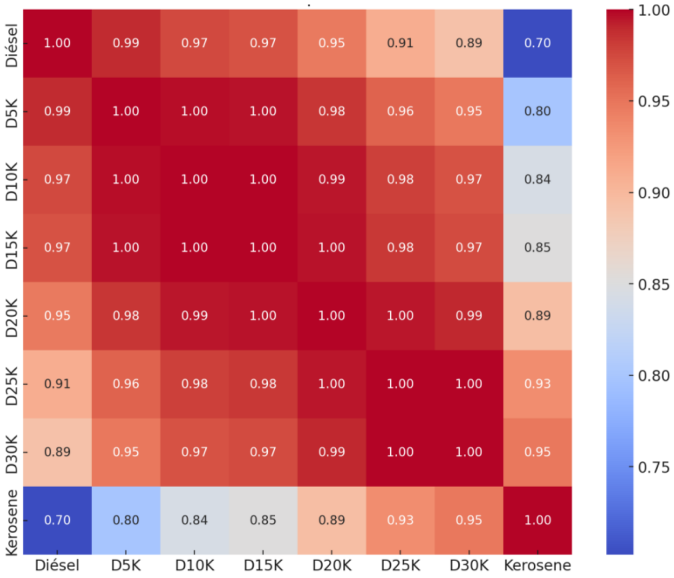

Figure 1: Correlation matrix of fuel properties. Source: own elaboration.

Factorial loads quantify the extent to which each variable contributes to the factors. Factor 1 likely accounts for much of the variation in the overall physical and chemical properties of the fuels. It has high values in almost all samples, except for Kerosene, indicating a significant impact on the typical features of fuels. In contrast, Factor 2 exhibits substantial variability and appears to more successfully separate the features that differentiate Kerosene from the mixtures and pure diesel. This factor likely captures factors related to volatility or flammability. Finally, Factor 3 and Factor 4 exhibit much reduced loads and could capture more nuanced differences within the blends.

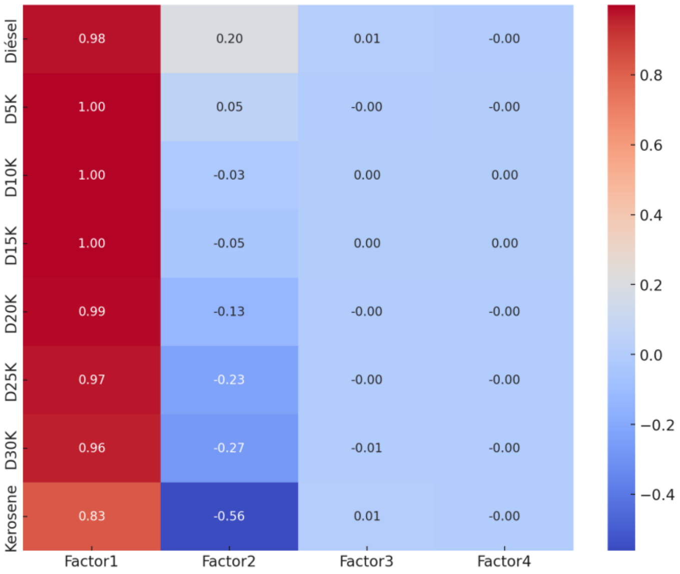

Figure 2: Factorial Loads Analysis. Source: Own elaboration.

The principal component analysis is shown in Figure 3. Here, the first principal component (PC1) captures the majority of the variance, followed by subsequent components. The cumulative explained variance reaches nearly 100% with the first four components.

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024

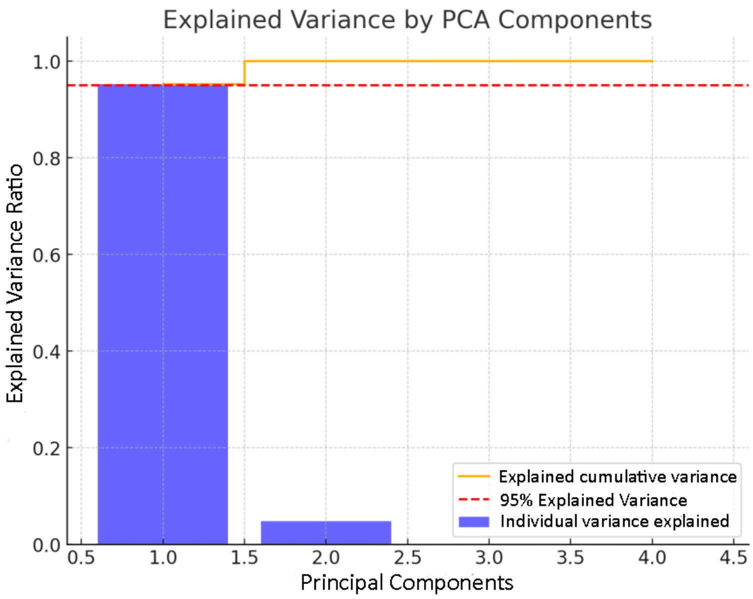

Figure 3: Principal Component Analysis. Source: Own elaboration.

Compared to the previous analysis, the factors also identify important directions in the data space, though they are aimed at capturing the underlying influence of latent variables, not simply variance. The factorial load for each property shows how each contributes to the factors. These loads are similar in structure to the principal component vectors in PCA but are designed to capture underlying sources of covariance instead of direct variance.

The cluster analysis using the principal components obtained from the PCA has been completed, and the results have been visualized in the space of the first two principal components (PC1 and PC2) (Figure 4).

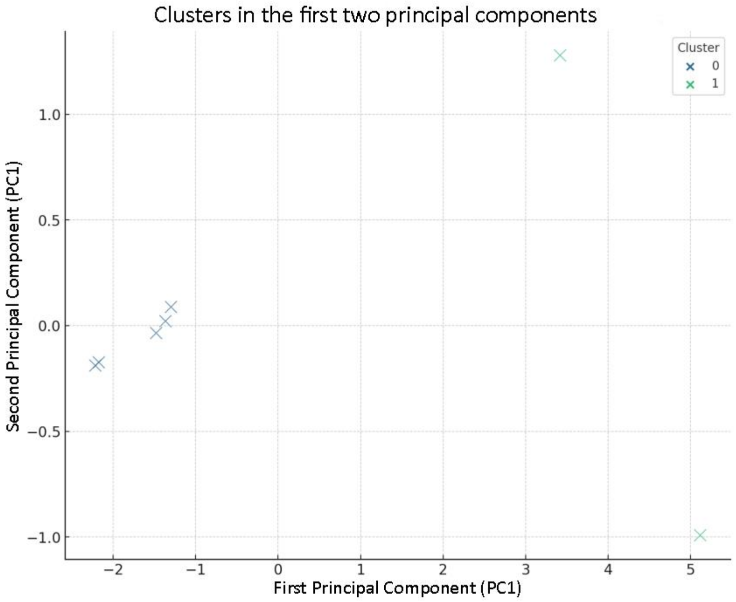

Figure 4: Cluster analysis. Source: own elaboration.

The clusters have been formed based on the characteristics captured by the first two principal components. The visualization shows how the samples are grouped into two distinct clusters:

- Cluster 0: Represents the majority of the samples, concentrating near the origin in the PC1 and PC2 space.

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024

- Cluster 1: Includes samples that are more dispersed and tend to have higher values on PC1 and varied values on PC2.

PC1 appears to capture the majority of the variability among the samples, leading to a clear separation into two groups based on this component. This suggests significant differences in the characteristics of the fuel mixes that are primarily captured by PC1. While PC2 provides further separation within the space, it is less significant in terms of forming clusters compared to PC1.

Canonical Correlation Analysis (CCA) is a statistical method employed to analyze the associations between two sets of multivariate data. This method aims to identify pairs of linear combinations of variables from two sets that have the highest possible correlation with each other. The graph displays each sample as a point, projected onto the space defined by the first two canonical components derived from the analysis.

- Canonical Correlation 1 (blue): Shows how the first pair of linear combinations maximize the correlation between the datasets. This correlation appears to capture the principal variability among the sets of features.

- Canonical Correlation 2 (red): Represents the second pair of linear combinations that maximize the correlation, after removing the influence of the first pair.

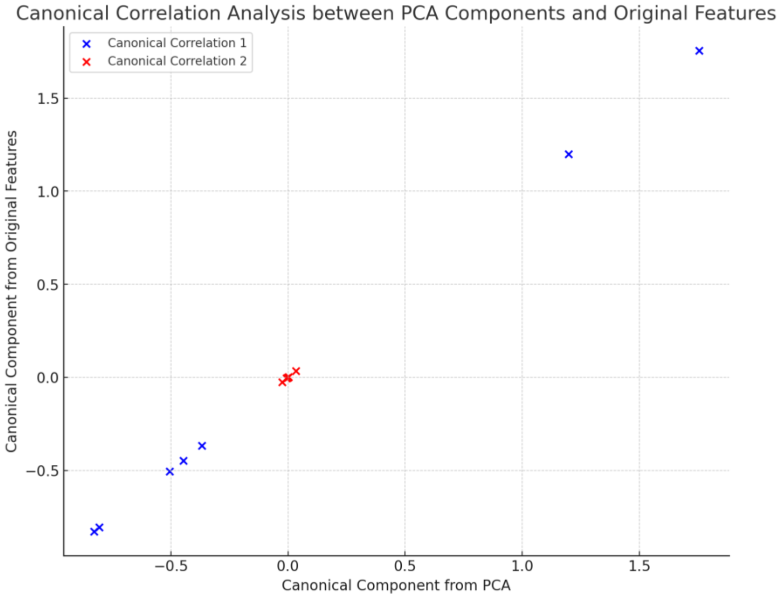

Figure 5: Canonical Correlation Analysis. Source: Own elaboration.

The canonical correlations indicate that there is a significant linear relationship between the transformed datasets, suggesting that the linear transformations of the principal components reflect or are significantly related to the linear transformations of the original fuel properties.

This may imply that the main variations captured by the PCA components are closely related to specific variations in the physicochemical properties, which can be valuable for understanding how different combinations of properties affect the behavior of the fuel in more general terms.

In Canonical Correlation Analysis, the resulting equations come from the linear combinations of the sets of variables that maximize the correlation between these two sets. These combinations are represented by the canonical loadings (coefficients) of each variable in the two datasets.

Canonical Equations for the Original Variables:

- Canonical Correlation 1:

$$0.965 \times Diésel + 0.116 \times D5K + 0.099 \times D10K - 0.089 \times D15K - 0.057 \times D20K + 0.120 \times D25K - 0.138 \times D30K + 0.018 \times Kerosene$$

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024

- Canonical Correlation 2:

$$-0.133 \times \mathrm{D15K} + 0.832 \times \mathrm{D20K} + 0.225 \times \mathrm{D25K} - 0.387 \times \mathrm{D30K} - 0.088 \times \mathrm{Kerosene}$$

These equations represent the optimal combinations of variables in each set that maximize the correlation between them. The first canonical correlation captures the greatest common variability among the sets, while the second captures the next greatest variability orthogonal to the first. These results allow for a precise understanding of how each variable in one set linearly relates to variables in the other set, which can be useful for identifying significant underlying relationships between different types of data or features in your analyses.

In this research, the production of biodiesel is briefly described, followed by a discussion on the properties of biodiesel fuel and the influence of different fatty acid profiles and raw materials. It is shown that the properties of biodiesel least influenced by minor components can be determined through a simple equation where the properties of biodiesel fuel are calculated based on the amounts of fatty acid esters from individual components and their properties. The optimization of biodiesel composition is also addressed [20].

5. Conclusions

The research revealed that the mix containing 5% kerosene stands out as the most suitable, offering an improvement in performance and a reduction in emissions without significantly compromising lubrication and engine longevity. This finding is supported by the observed values of relative density and kinematic viscosity, which remain within the limits specified by NTE INEN standards, ensuring compliance with fuel quality standards. Additionally, the calculated cetane index for this mix is favorable, suggesting good ignition capability and efficient engine performance.

However, multivariate analyses indicate that there are limitations regarding kerosene content. Mixes with more than 20% kerosene showed decreases in density and viscosity, which can negatively affect engine performance and increase wear. These results suggest limiting kerosene content to 20% in diesel mixes and considering the use of additives to offset potential negative effects on lubrication and other critical engine parameters. It is recommended to explore other mixes and additives that can provide similar benefits without the identified challenges, using multivariate approaches for more rigorous evaluation.

Funding: “This research received no external funding”

Conflicts of Interest: “The authors declare no conflict of interest.”

References

[1] Zhen X, Wang Y, Liu D. Bio-butanol as a new generation of clean alternative fuel for SI (spark ignition) and CI (compression ignition) engines. Renew Energy [Internet]. 2020;147:2494–521.

[2] Dunn RO, Knothe G. Alternative diesel fuels from vegetable oils and animal fats. Journal of oleo science. 2001;50(5):415–26.

[3] Balcerski A, Kropiwnicki J. Remarks upon adequacy of conditions of ISO 8178 emission tests with regards to real operation conditions of marine engines. Journal of KONES. 2008;15(4):23–30.

[4] El-Sheekh MM, El-Nagar AA, Elkelawy M, Bastawissi HAE. Maximization of bioethanol productivity from wheat straw, performance and emission analysis of diesel engine running with a triple fuel blend through response surface methodology. Renewable Energy. 2023;211:706–22.

[5] Nayak SK, Le HS, Kowalski J, Deepanraj B, Duong XQ, Truong TH, et al. Performance and emission characteristics of diesel engines running on gaseous fuels in dual-fuel mode. International Journal of Hydrogen Energy. 2023;.

[6] Zhao Y, Li T, Niu T, Zheng W, Xie Y, E W. Performance and emissions of a diesel engine fueled by coal-based diesel fuels and their blends with polyoxymethylene dimethyl ethers. Scientific Reports. 2023;13(1).

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024

[7] Okumuş F, Sönmez Hİ, Safa A, Kaya C, Kökkülünk G. Gradient boosting machine for performance and emission investigation of diesel engine fueled with pyrolytic oil-biodiesel and 2-EHN additive. Sustainable Energy & Fuels. 2023;7(16):4002–18.

[8] Wang Z, Li X, Xiang L, Huang Y, Lang B, Cheng X, et al. Potential of kerosene-diesel blends as alternative fuels for diesel engines: Perspectives from spray combustion characteristics. Fuel. 2023;

[9] Zhao Y, Wang E, Shi Z. Effects of Hydrogen Addition on Premixed Combustion of Kerosene in SI Engine. Energies. 2023;16(10).

[10] Nobili A, Maffei LP, Pelucchi M, Mehl M, Frassoldati A, Comandini A, et al. Experimental and kinetic modeling study of α-methylnaphthalene laminar flame speeds. Proceedings of the Combustion Institute. 2023;39:243–51.

[11] Chaumeix N. Experimental and kinetic modeling study of α-methylnaphthalene laminar flame speeds. Proceedings of the Combustion Institute. 2023;39:243–51.

[12] Soca-Cabrera JR. Diesel engine emissions off road. Case Volskwagen ADG 1.9 L SDI. Revista Ciencias Técnicas Agropecuarias. 2020;29(2):15–22.

[13] Truong NP, Khoa NX, Van Tuan N. Building a research model for the combustion process of fuel in a constant volume combustion chamber. International Journal of Sustainable Engineering. 2024;17(1):1–15.

[14] Zangana LMK, Yaseen AH, Hassan QH, Mohammed MM, Mohammed MF, Alalwan HA. Investigated kerosene-diesel fuel performance in internal combustion engine. Cleaner Engineering and Technology. 2023;12.

[15] Cican G. Experimental Transient Process Analysis of Micro-Turbojet Aviation Engines: Comparing the Effects of Diesel and Kerosene Fuels at Different Ambient Temperatures. Energies. 2024;17.

[16] Alsulami RA, Windell B, Bartholet D, Windom B. Exploring the role of physical and chemical properties on the ignition and flame stability of liquid fuels with a spray burner and fuel ignition tester (FIT). En: 2018 AIAA Aerospace Sciences Meeting. 2018.

[17] Gülcan HE, Ciniviz M. The effect of pure methane energy fraction on combustion performance, energy analysis and environmental-economic cost indicators in a single-cylinder common rail methane-diesel dual fuel engine. Applied Thermal Engineering. 2023;230.

[18] Shi Y, Huang X, Liu H. A method for enhancing low-pressure ignition of n-decane based on increasing hydroxyl free radicals. En: Proceedings of International Conference on Aerospace System Science and Engineering. Singapore: Springer; 2018. p. 185–96.

[19] Gupta, S. K., & Krishnasamy, A. (2021). *Evaporation Characteristics of Fuels for Low Temperature Combustion Engine Applications* (No. 2021-01-1210). SAE Technical Paper.

[20] K. Upadyaya, M.Vartiainen, and K. Salmela-Aro, “From job demands and resources to work engagement, burnout, life satisfaction, depressive symptoms, and occupational health”, *Burnout research, 3*(4), 101-108, 2016.

Doi: https://doi.org/10.54216/FPA.160119
Received: July 11, 2023 Revised: November 15, 2023 Accepted: May 22, 2024