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Statistical Analysis of Biofuel Production from Waste Cooking Oil: Optimizing Process Efficiency and Fuel Quality

***M. Mohamed Althaf, M. A. Rifayathali, R. Mohamed Sameer**

Jamal Mohamed College (Autonomous), Tiruchirappalli, Tamil Nadu, India.

*Corresponding Author Email: althaf2maths@gmail.com

Abstract: *The increasing need for energy, alongside the diminishing resources of non-renewable fossil fuels and environmental worries, has spurred the exploration of sustainable alternatives such as biofuels. Waste cooking oil (WCO) has emerged as a promising source for making biodiesel, providing a renewable and environmentally friendly energy option while addressing waste management issues. This research offers a thorough statistical examination of biofuel production from WCO, covering various factors including biofuel output, ester content, acid level, flash point, cetane number, density, viscosity, calorific value, CO2 reduction, energy usage, production expenses, and profit margins. The analysis employs descriptive statistics, correlation studies, regression models, and ANOVA to clarify the connections between these variables and their influence on production effectiveness, fuel quality, environmental sustainability, and economic feasibility. The findings demonstrate strong correlations between biofuel yield and parameters such as ester content, flash point, cetane number, and calorific value, highlighting their interdependence in optimising fuel properties. Negative correlations were identified between biofuel yield and factors like glycerol yield, acid value, and production cost, indicating potential trade-offs in process optimisation. Regression models and ANOVA analyses confirmed the statistical significance of the independent variables in explaining the observed variance in biofuel production parameters. The study emphasises the importance of statistical tools like SPSS for conducting rigorous data analysis and facilitating informed decision-making. The insights obtained from this research can guide process optimisation, fuel quality improvement, and economic viability assessments, ultimately promoting the widespread adoption of biofuels derived from WCO as a sustainable and environmentally friendly energy source.*

Keywords: *Biofuel, Waste cooking oil, Statistical analysis, Process optimization, Fuel quality and Economic viability.*

1. INTRODUCTION

The ongoing growth of the global population is fuelling a swift escalation in the need for energy, with forecasts suggesting a notable 53% surge by 2030 in contrast to levels recorded in 2001. This upsurge in demand coincides with the rapid depletion of non-renewable fossil fuels like coal, oil, and gas. These finite resources are anticipated to endure for approximately another 200, 40, and 70 years respectively, based on present rates of consumption. Nonetheless, the combustion of fossil fuels in vital sectors such as transportation, manufacturing, and electricity generation is exacerbating environmental concerns such as carbon emissions and the broader issue of global climate change [1]. In light of these challenges, there's an increasing imperative to investigate alternative, more environmentally friendly energy sources. Solar, wind, nuclear, hydro, and biofuels have emerged as potential alternatives. Among these options, biofuels, such as biodiesel, show potential as renewable energy sources with reduced carbon emissions. Biodiesel, especially when produced from non-edible feedstocks, offers a feasible substitute for traditional diesel fuel [2]. The upsurge in fossil fuel usage propelled by economic globalization, population expansion, and industrialization has played a part in greenhouse gas emissions and notable carbon accumulation in the atmosphere, resulting in global climate change. To tackle these issues and bolster energy security, countries are progressively broadening their energy portfolios. Biofuels, sourced from sustainable origins with appropriate chemical attributes, have emerged as a practical substitute for fossil fuels [3]. Concerns about food security have arisen with first-generation biofuels, which are derived from edible oils, prompting the energy industry to seek alternative fuel sources. The second generation of biofuels prioritizes the use of residual biomass and waste, including waste cooking oil (WCO). WCO, obtained from cooking processes, contains accumulated free fatty acids, rendering it a technically feasible feedstock for biofuel conversion. Its widespread availability and affordability, sourced from various establishments such as restaurants, food processing industries, fast-food outlets, and households, render it an appealing option [4]. Waste cooking oil (WCO), sourced from households, restaurants, hotels, and food processing enterprises, plays a notable role in global biodiesel production, comprising around 10% of the total output. Despite being abundant and cost-effective, converting WCO into biodiesel poses economic challenges due to its elevated free fatty acid levels. Moreover, technical hurdles such as shortages of raw feedstock and collection complexities impede its widespread adoption. Thus, the recycling of WCO into potential renewable resources and advancements in conversion technology are crucial [5]. Data from various countries underscore the scale of waste cooking oil (WCO) production, with estimates indicating substantial volumes generated each year. In Canada, annual WCO production is estimated at around 135,000 tons, while in the UK and European Union countries, figures range from 200,000 to 1,000,000 tons per year. The situation is even more pronounced in Asia, where approximately 5.5 million tons of WCO are produced annually, with Thailand alone disposing of 117,000 tons per year without proper treatment. Such significant quantities of WCO present challenges concerning collection, treatment, and disposal, emphasising the pressing need for sustainable solutions [6]. Recent research has delved into the utilisation of diverse ash materials, including peanut shell ash, coal fly ash, and banana peel ash, as catalysts for biodiesel production. These materials demonstrate catalytic activity and present a sustainable method for waste utilisation. Expanding upon prior investigations, this study delves into the potential of wheat shell ash and water scale as sources of calcium oxide for biodiesel production. The objective is to refine reaction conditions utilising methanol and waste cooking oil (WCO) as reactants [7]. Biofuels, including biodiesel and bioethanol, present promising alternatives for reducing carbon emissions in the transport industry. Biodiesel, in particular, is highly regarded as a replacement for petroleum diesel, constituting nearly 80% of total biofuel production in the EU. Biodiesel sourced from used cooking oil (UCO) or waste cooking oil (WCO) represents a second-generation biofuel, derived from non-crop feedstock, and demonstrates potential in terms of quality and production cost [8]. In nations like Greece, where there's an abundance of used cooking oil (UCO) owing to high vegetable oil consumption, recycling UCO into biodiesel offers a sustainable resolution to waste management and energy requirements. Nonetheless, the improper disposal of UCO into sewage systems poses notable environmental and economic hurdles, including water contamination and escalated costs for wastewater treatment facilities. Recycling UCO into biodiesel emerges as a viable strategy for its sustainable management, mitigating environmental repercussions and bolstering energy security [9]. India, as one of the largest consumers of cooking oil worldwide, generates a considerable volume of waste cooking oil each year. Biodiesel production from this waste not only tackles the challenge of waste disposal but also fosters the notion of "waste to wealth" and facilitates intelligent waste management practices. Through coordinated initiatives, India stands poised to recover a substantial amount of waste cooking oil for biodiesel production, thereby advancing its energy security objectives [10]. The economic feasibility of biodiesel production can be significantly bolstered by employing efficient heterogeneous catalysts, which provide benefits like recyclability and diminished environmental footprint compared to homogeneous catalysts. Numerous studies have highlighted the effectiveness of heterogeneous catalysts, such as barium oxide (BaO) supported on various substrates, in transesterification reactions for biodiesel production. Furthermore, catalysts supported by tin oxide (SnO2) have exhibited promising catalytic activity, rendering them suitable options for synthesising biodiesel from waste cooking oil [11]. Non-edible oils, such as jatropha oil, castor oil, and waste cooking oil (WCO), are attracting increasing interest as biodiesel feedstocks. WCO, in particular, is promising because of its affordability, avoidance of competition with edible oils, and its ability to mitigate disposal challenges. Life Cycle Assessment (LCA) studies have demonstrated the environmental benefits of utilising WCO for biodiesel production, stimulating further investigation into its economic feasibility [12]. Assessing the economic viability of WCO biodiesel production entails examining factors like catalyst expenses and process streamlining. While homogeneous catalysts are prevalent, there's a burgeoning interest in CaO-based catalysts due to their simplicity and robust catalytic performance. Simulation tools like Aspen Plus play a pivotal role in refining biodiesel production processes and evaluating technical feasibility [13]. Response Surface Methodology (RSM) has become an invaluable tool for fine-tuning biodiesel production parameters, assisting in the maximisation of yield while minimising operating costs. Numerous studies have showcased the efficacy of RSM in optimising process parameters and ensuring biodiesel quality meets fuel standards. Additionally, research endeavours have explored the kinetics and thermodynamics of biodiesel production from WCO, emphasising its potential to lower production expenses compared to alternative feedstocks. The integration of RSM with the desirability function approach presents a novel methodology for optimising biodiesel production and deepening comprehension of reaction mechanisms and dynamics [14]. Waste biomass sourced from diverse outlets such as agriculture, sewage, and mining, notably residues from the iron and steel industry, offers plentiful resources for catalyst production. Employing agricultural waste, such as rice straw, for catalyst synthesis not only repurposes materials that would otherwise be discarded but also tackles environmental issues linked to their disposal. The trend towards solid acid catalysts, derived from carbon-based sources like sulfonated cellulose or glucose, underscores a preference for reusable and environmentally benign alternatives to liquid acids [15]. In biodiesel production, the selection of catalyst is contingent upon the free fatty acid (FFA) content of the feedstock. Alkaline catalysts are suitable for low FFA content, but high FFA content requires alternative catalysts to prevent saponification. Enzyme catalysts provide a non-polluting option but are often economically prohibitive. Concentrated sulfuric acid can catalyze both esterification and transesterification processes, yet it poses challenges like equipment corrosion and wastewater generation, underscoring the demand for heterogeneous acid catalysts [16]. Waste cooking oil (WCO) has emerged as an economically feasible feedstock for biodiesel production, helping to alleviate environmental risks linked with improper disposal. Through the repurposing of WCO, environmental pollution can be mitigated, thereby benefiting human health and aquatic ecosystems, while simultaneously lowering the expenses associated with waste treatment [17].

2. METHODOLOGY

Statistical software plays a pivotal role as an analytical tool, ensuring precise data analysis and error prevention. Researchers must align their choice of statistical software with their research objectives. SPSS, or Statistical Package for the Social Sciences, is a widely utilised software among researchers for statistical data analysis [18]. SPSS provides a wide array of analysis capabilities, encompassing data transformation, regression analysis, analysis of variance, multivariate analysis, t-tests, time series analysis, design and analysis of experiments, among others. Its versatility enables researchers to perform both parametric and non-parametric comparison analyses effortlessly. Furthermore, SPSS facilitates the verification of test assumptions and enables precise frequency analysis [19]. With SPSS, researchers can confidently delve into their data, conduct a myriad of statistical analyses, and extract meaningful insights to bolster their research objectives. Its user-friendly interface and comprehensive analytical capabilities render SPSS an invaluable tool in the research community, facilitating the execution of rigorous and dependable statistical analyses [20]. SPSS, or Statistical Package for the Social Sciences, stands as a versatile application employed for an extensive spectrum of statistical analysis tasks, encompassing advanced statistical analysis, machine learning algorithms, string analysis, and big data analysis. Serving as a comprehensive data analysis platform, it aids researchers in organising and scrutinising data in accordance with established methodologies. With its 25th version introduced in 2019, SPSS continues to maintain its position as one of the most extensively utilised software for quantitative research [21]. In the field of education, SPSS finds extensive use in numerous research studies aimed at analysing data and deriving insights. For instance, research conducted by ebjan, U., & Tominc, P. (2015) delves into the impact of teacher support and conformity with learning needs on students' utilisation of SPSS. Similarly, Murtiningsih, M., Kristiawan, M., & Lian, B. (2019) explore the correlation between principal supervision and interpersonal communication with teacher work ethic. Other studies, such as those by Espelage, DL, Polanin, JR, & Low, SK (2014) and Chong, W. H., Klassen, R. M., Huan, V. S., Wong, I., & Kates, A. D. (2010), investigate various facets of education utilising SPSS for data analysis [22]. The integration of SPSS (Statistical Product and Service Solution) into data analysis has become increasingly widespread, providing access to diverse data types and functioning as a sophisticated spreadsheet software. Recognised for its utility in data analysis, mathematics, statistics, and data visualisation, SPSS plays a pivotal role in comprehending mathematical concepts and conducting research in mathematics education. Its adaptability and advanced capabilities in data management render it invaluable for both educators and students [23]. SPSS software emerges as a viable tool for swiftly and accurately processing statistical data, providing diverse outputs crucial for decision-makers. By utilising SPSS software, students can enhance their comprehension of the material and streamline statistical data analysis, while also developing their skills in SPSS usage. Furthermore, the chosen learning model to facilitate student knowledge-building is the TPS (Think-Pair-Share) cooperative learning model. In this model, students collaborate in pairs within their teams, initially reflecting on individual answers to posed questions before engaging in group discussions and sharing their insights with other teams. Through this process, students actively participate in knowledge construction and exchange, fostering a deeper understanding of the subject matter [24]. To optimally utilise SPSS for data processing and analysis, it's crucial to prepare the data beforehand. SPSS for Windows operates through six types of windows: the SPSS Data Editor, Output Window, Syntax Window, Chart Carousel, Chart Window, and Help Window. Each window serves distinct functions, ranging from entering and manipulating data to generating outputs and visualisations, as well as offering assistance and guidance throughout the analytical process [25]. The existing SPSS macros offer limited functionalities for conducting analyses, primarily centred on main analyses such as mean effect size, subgroup analyses, and meta-regression. However, they lack features for addressing publication bias and providing graphical options like forest plots and funnel plots. Additionally, utilising SPSS macros necessitates researchers to write SPSS syntax, which can prove cumbersome for many practitioners. IBM SPSS recently introduced a point-and-click meta-analysis menu with Version 28, catering to the preferences of researchers accustomed to using SPSS. Despite the availability of other programs in the literature, SPSS remains a popular choice. However, until now, there hasn't been a study specifically focusing on conducting meta-analysis using IBM SPSS [26]. IBM SPSS Statistics Version 28 provides the necessary functionalities for conducting most analyses required in meta-analysis studies. The trial version can be downloaded from the official website, and after registration, users can obtain an IBMid and code to set up the software. The trial period lasts for 30 days, after which users may choose to purchase the full version. Whether using the trial or full version of SPSS 28, researchers have access to procedures for calculating mean effect size, heterogeneity statistics, assessing publication bias, and conducting moderator analyses [27]. In the domain of biofuel production, several input parameters profoundly influence the process's outcome and efficiency. Oil quality parameters, such as Free Fatty Acid (FFA) content, moisture content, and viscosity, are pivotal, affecting the oil's suitability for transesterification. Higher FFA content may require more catalyst, while excess moisture can lead to undesirable soap formation, ultimately reducing yield. Viscosity, indicating oil flow properties, directly impacts processing efficiency. Catalyst parameters also demand attention, as the type and concentration of catalyst employed influence reaction kinetics and product purity. Various catalysts, ranging from NaOH and KOH to enzymes, exhibit different effects on reaction rates and yields. The concentration of catalyst relative to the oil weight further dictates reaction efficiency and the purity of the resulting biofuel. Reaction conditions, encompassing temperature, duration, and methanol-to-oil molar ratio, intricately shape transesterification outcomes. Temperature governs reaction rates and conversion efficiency, while reaction time determines reactant contact duration, impacting yield. The methanol-to-oil ratio influences reaction completeness and glycerol separation, a crucial byproduct. Pre-treatment methods, such as filtration and degumming processes, are essential for impurity removal and phospholipid elimination, respectively. The selection of cooking oil as the primary source adds complexity, as different oils have diverse compositions and properties, ultimately affecting the final biofuel quality. In assessing biofuel production efficacy, various evaluation parameters are considered. Yield parameters, encompassing biofuel yield and glycerol byproduct yield, provide insights into process efficiency and resource utilisation. Fuel quality parameters, including ester content, acid value, flash point, and cetane number, offer crucial information on product purity, safety, and combustion properties. Moreover, physical and chemical properties like density, viscosity, and calorific value influence energy content, combustion characteristics, and operational feasibility. Environmental impact indicators, such as CO2 emissions reduction and energy consumption during production, evaluate sustainability and eco-friendliness. Lastly, economic factors like production cost per litre and profit margin assess financial viability and competitiveness.

3. ANALYSIS AND DISCUSSION

TABLE 1. Reliability Statistics

Cronbach's Alpha	N of Items
.757	**13**

Table 1 shows that the reliability of the 13-item scale was assessed using Cronbach's Alpha, resulting in a coefficient of 0.757. This indicates a satisfactory level of internal consistency, suggesting that the items on the scale are relatively homogeneous and measure the same underlying construct. In social sciences, a Cronbach's Alpha above 0.7 is generally considered acceptable, implying that the scale is reliable for research purposes. This result suggests that the 13 items are well-suited to be used together in a single scale, providing dependable and consistent results when applied to the same sample under similar conditions.

TABLE 2. Descriptives Statistics

	N	Range	Minimum	Maximum	Sum	Variance	Skewness	Kurtosis
Biofuel Yield (%)	50	10.5	78.5	89	4191.5	11.557	-0.136	-1.327
Glycerol Yield (%)	50	4.2	8.5	12.7	530.9	1.713	0.09	-1.266
Ester Content (%)	50	3	94	98	4808	1.165	-0.075	-1.352
Acid Value (mg KOH/g)	50	0.4	0.3	0.7	25.5	0.013	0.151	-0.709
Flash Point (°C)	50	9	154	163	7925	8.622	-0.244	-1.317
Cetane Number	50	9	50	59	2712	8.839	-0.093	-1.308
Density (g/cm³)	50	0.05	0.84	0.89	43.25	0	0.191	-1.209
Viscosity (mm²/s)	50	0.6	4.2	4.8	226.2	0.034	-0.044	-1.09
Calorific Value (MJ/kg)	50	2	38	40	1961	0.37	0.092	-1.366
CO2 Reduction (%)	50	6	67	73	3481	3.22	0.094	-0.99
Energy Consumption (kWh)	50	1	2	2	104	0.059	0.443	-0.912
Production Cost (currency/unit)	50	0.13	0.7	0.83	38.07	0.002	-0.025	-1.162
Profit Margin (%)	50	6	15	21	906	3.7	-0.285	-1.136
Valid N (listwise)	50							

The descriptive statistics for 50 samples across various biofuel production parameters reveal notable insights in table 2. The biofuel yield ranges from 78.5% to 89%, with a total sum of 4191.5 and a variance of 11.557, indicating moderate variability. The skewness of -0.136 points to a slight left skew. Glycerol yield spans from 8.5% to 12.7%, with a sum of 530.9 and a variance of 1.713, showing slight positive skewness (0.09). Ester content, an essential quality measure, ranges from 94% to 98%, with minimal variability (variance 1.165) and slight negative skewness (-0.075). The acid value ranges from 0.3 to 0.7 mg KOH/g, with a variance of 0.013 and slight positive skewness (0.151). Flash point and cetane number show negative skewness, indicating that most values are higher within their ranges. Density, viscosity, and calorific value exhibit low variance and slight negative skewness, indicating consistency. CO2 reduction and energy consumption have minor positive skewness, suggesting a few higher values. Production cost and profit margin display minimal skewness and variance, indicating stability in financial metrics.

The frequency statistics for various biofuel production parameters offer detailed insights into their distribution in table 3. The average biofuel yield is 83.83%, with a standard deviation of 3.3996%, indicating some variability. The median and mode are 84.5% and 88%, respectively, with 75% of values below 87.125%. Glycerol yield has an average of 10.618% and a standard deviation of 1.3088%, with a median of 10.5% and a mode of 9.0%, showing slight variability and multiple modes. Ester content is highly consistent, with an average of 96.16%, a low standard deviation of 1.079, and a median matching the mean at 96.2%. The acid value is closely grouped around the mean of 0.51 mg KOH/g, with a low standard deviation of 0.1129. Flash point and cetane number show

TABLE 3. Descriptive Statistics of Biofuel Properties and Economic Indicators

	Mean	Median	Mode	Percentiles		
				25	50	75
Biofuel Yield (%)	83.83	84.5	88	80	84.5	87.125
Glycerol Yield (%)	10.618	10.5	9.0[a]	9.425	10.5	12
Ester Content (%)	96.16	96.2	98	95	96.2	97.18
Acid Value (mg KOH/g)	0.51	0.5	0.5	0.4	0.5	0.6
Flash Point (°C)	158.5	159	160	155	159	161
Cetane Number	54.24	55	55	51	55	57
Density (g/cm³)	0.865	0.86	0.86	0.85	0.86	0.88
Viscosity (mm²/s)	4.524	4.5	4.5	4.375	4.5	4.7
Calorific Value (MJ/kg)	39.22	39.15	40	38.68	39.15	39.82
CO_2 Reduction (%)	69.62	70	70	68	70	71
Energy Consumption (kWh)	2.08	2	2	1.9	2	2.3
Production Cost (currency/unit)	0.7614	0.76	0.7	0.72	0.76	0.8
Profit Margin (%)	18.12	18	20	16	18	20

moderate variability, with averages of 158.5°C and 54.24, respectively. Density and viscosity display low variability, indicating consistency. Calorific value, CO2 reduction, and energy consumption are relatively consistent, with slight variability around their averages. Production cost and profit margin exhibit minimal variability, suggesting financial stability. Overall, the dataset reflects a mix of high consistency and moderate variability across various parameters.

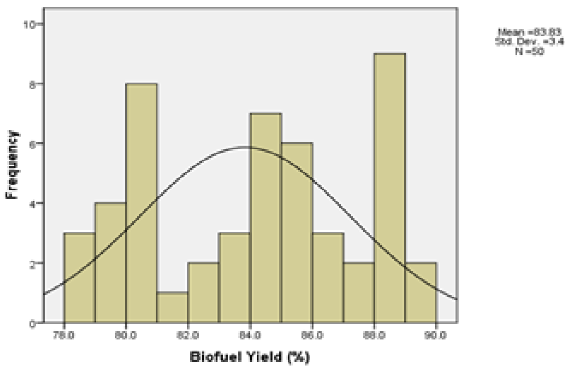

FIGURE 1. Biofuel Yield (%)

Graph 1 illustrates the yield of biofuel produced from used cooking oil. The horizontal axis represents the yield percentage, ranging from 78% to 90%. The vertical axis indicates the frequency of each yield range. The graph exhibits a bell-shaped curve, with the most frequent yield around 84%. The data distribution has a standard deviation of 3.4, indicating that most biofuel yields cluster near 84%.

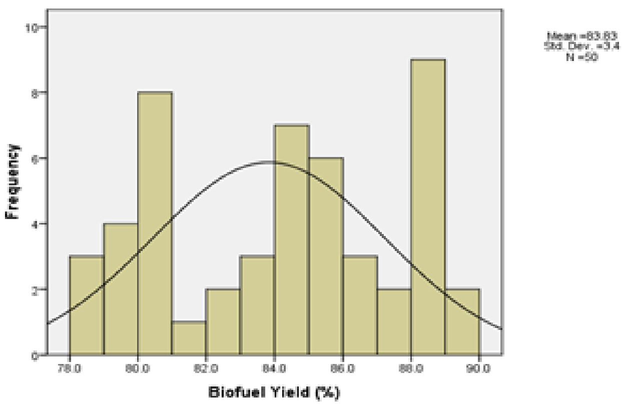

FIGURE 2. Glycerol Yield (%)

Figure 2 displays a histogram showing the distribution of glycerol yield percentages. The x-axis represents the glycerol yield percentage, ranging from 8.0% to 14.0%, while the y-axis indicates the frequency or number of occurrences for each glycerol yield percentage bin. The histogram exhibits a roughly normal distribution shape, with the highest frequency occurring around the mean value of 10.63%. The standard deviation is 1.59, suggesting a relatively narrow spread of data around the mean. This distribution implies that most glycerol yields from the process fall within a concentrated range centred around 10.63%, with fewer occurrences deviating significantly from the mean value.

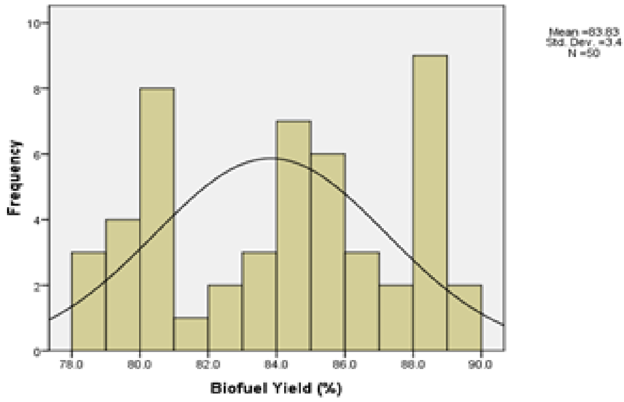

FIGURE 3. Ester Content (%)

Histogram 3 depicts the distribution of ester content percentages for a given dataset. The x-axis represents ester content ranging from approximately 54% to 88%, while the y-axis shows the frequency of occurrences. The distribution appears roughly normal or bell-shaped, with the highest frequency around the mean value of approximately 95.18%, as indicated by the curve superimposed on the histogram bars. This shape suggests that most data points cluster around the central ester content values, with fewer observations at the lower and higher extremes.

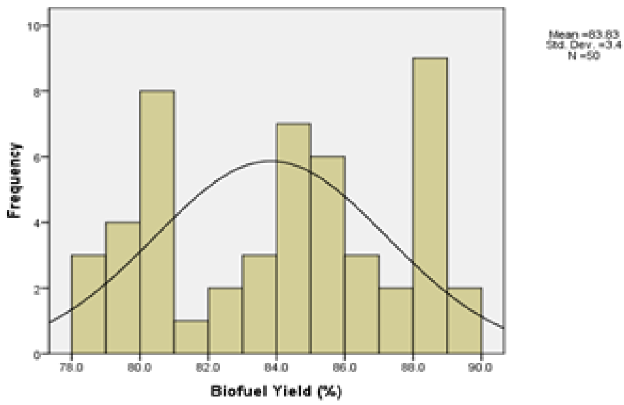

FIGURE 4. Acid Value (mg KOH/g)

Histogram 4 illustrates the distribution of acid values (measured in mg KOH/g) for a set of biofuel samples derived from cooked oils. The x-axis represents the acid value range, while the y-axis shows the frequency of samples within each acid value bin. The distribution appears roughly bell-shaped or normal, with the highest frequency around the mean acid value of 0.51 mg KOH/g, as indicated by the superimposed curve. The standard deviation is 0.113, indicating a relatively narrow spread of data points around the mean. Most samples have acid values clustering around the central region, with fewer samples exhibiting extremely low or high acid values. This distribution suggests that the majority of biofuel samples from cooked oils have acid values close to the average, with outliers being less common.

The histogram 5 displays the distribution of flash points (in degrees Celsius) for a set of biofuel samples derived from cooked oils. The x-axis represents the range of flash point temperatures, while the y-axis shows the frequency or number of samples within each temperature bin. The distribution appears roughly bell-shaped or normal, with the highest frequency observed around the mean flash point of 158.5°C, as indicated by the superimposed curve. The standard deviation is 2.936°C, suggesting a relatively tight spread of data points around the mean value. Most of the samples have flash points clustered near the central region, with fewer samples exhibiting flash points at the lower and higher extremes of the temperature range. This distribution implies that the majority of the biofuel samples from cooked oils have flash points close to the average value, while outliers with significantly higher or lower flash points are less common.

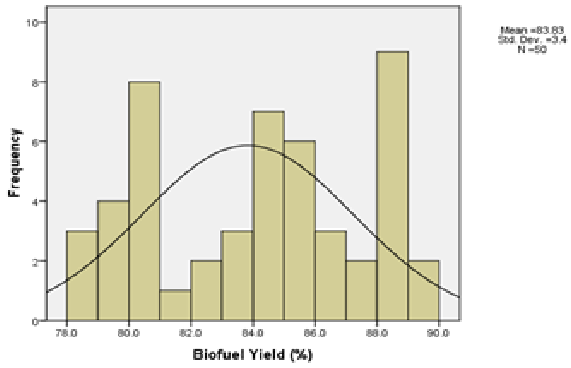

FIGURE 5. Flash Point (°C)

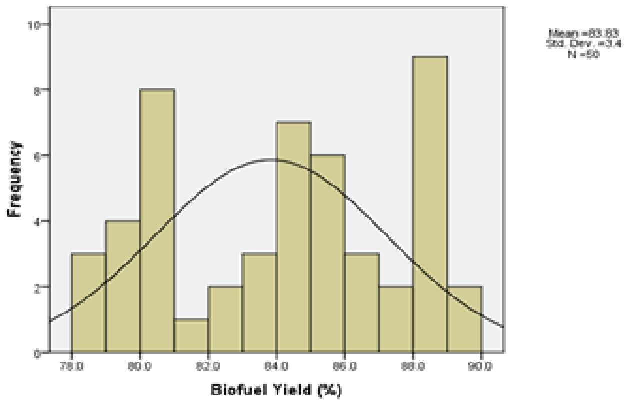

FIGURE 6. Cetane Number

The histogram 6 shows the distribution of cetane numbers for a set of biofuel samples derived from cooked oils. The x-axis represents the range of cetane numbers, while the y-axis displays the frequency of samples within each cetane number bin. The distribution appears approximately bell-shaped or normal, with the highest frequency around the mean cetane number of 54.24, as indicated by the superimposed curve. The standard deviation is 2.973, suggesting a moderate spread of data points around the mean. Most biofuel samples have cetane numbers clustered near the central region, with fewer samples exhibiting cetane numbers at the lower and higher extremes. This distribution implies that the majority of samples have cetane numbers close to the average, with outliers being less common. The cetane number is an important parameter for evaluating the ignition quality of diesel fuels, with higher values generally indicating better ignition properties.

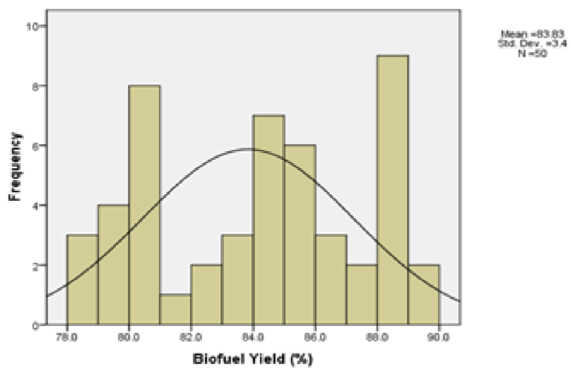

FIGURE 7. Density (g/cm³)

The histogram 7 displays the distribution of densities (in g/cm³) for a set of biofuel samples derived from cooked oils. The x-axis represents the range of density values, while the y-axis shows the frequency or number of samples within each density bin. The distribution appears roughly bell-shaped or normal, with the highest frequency observed around the mean density of 0.86 g/cm³, as indicated by the superimposed curve. The standard deviation is 0.016 g/cm³, suggesting a relatively tight spread of data points around the mean value. Most of the biofuel samples have densities clustered near the central region, with fewer samples exhibiting densities at the lower and higher extremes of the range. This distribution implies that the majority of the samples have densities close to the average value, while outliers with significantly higher or lower densities are less common. Density is an important property that affects the combustion characteristics and energy content of biofuels, with higher densities generally associated with better fuel quality.

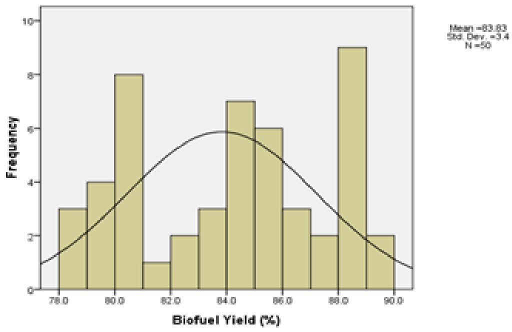

FIGURE 8. Viscosity (mm²/s)

Image 8 shows a histogram depicting the distribution of viscosity (measured in mm²/s) for a given dataset. The x-axis represents the viscosity values, while the y-axis shows the frequency or count of observations within each viscosity range. The histogram follows a bell-shaped curve, indicating a normal or near-normal distribution. The mean viscosity value is 4.52 mm²/s, with a standard deviation of 0.185 mm²/s. The sample size (N) is 50. This distribution suggests that most viscosity measurements are concentrated around the mean value, with fewer observations at the lower and higher ends of the range. The relatively low standard deviation indicates that the data points are closely clustered around the mean, reflecting consistent viscosity values within the dataset.

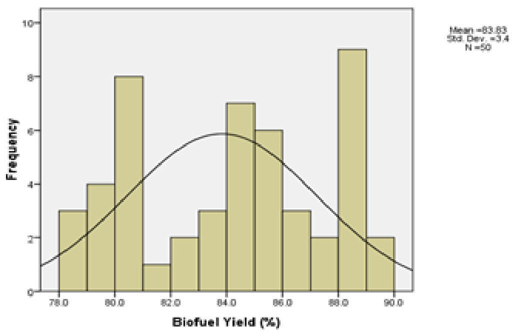

FIGURE 9. Calorific Value (MJ/kg)

Image 9 displays a histogram representing the distribution of calorific values (measured in MJ/kg) for a dataset, likely related to biofuel derived from cooked oil. The x-axis shows the calorific value ranges, while the y-axis represents the frequency or count of observations within each range. The histogram appears to follow a roughly normal distribution, with a mean calorific value of 39.22 MJ/kg and a standard deviation of 0.608. The sample size (N) is 50.

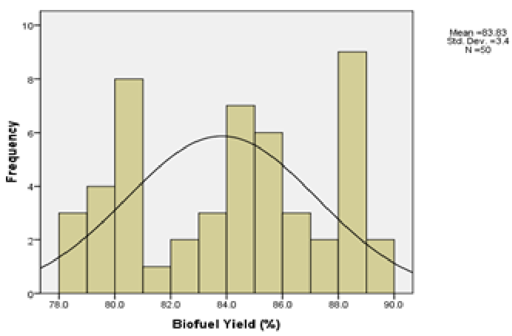

FIGURE 10. CO2 Reduction (%)

Figure 10 displays a histogram of CO2 reduction percentages achieved using biofuel from cooked oil. The data shows a mean CO2 reduction of 69.62% with a standard deviation of 1.794%. The sample size (N) is 50.

The histogram reveals that most reductions fall between 68% and 72%, with the highest frequency around 70%. The distribution appears roughly normal but slightly left-skewed, indicating a tendency for more frequent lower reduction percentages within the range.

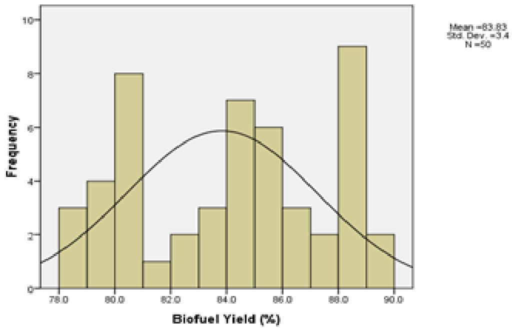

FIGURE 11. Energy Consumption (kWh)

Figure 11 presents a histogram of energy consumption (in kWh) for producing biofuel from cooked oil. The data has a mean energy consumption of 2.08 kWh with a standard deviation of 0.243 kWh and a sample size (N) of 50. The histogram shows that energy consumption values are mostly concentrated between 1.8 kWh and 2.4 kWh, with the highest frequency around 2.0 kWh. The distribution is roughly normal and centered around the mean, but slightly right-skewed, indicating a slight tendency for higher energy consumption values within the measured range.

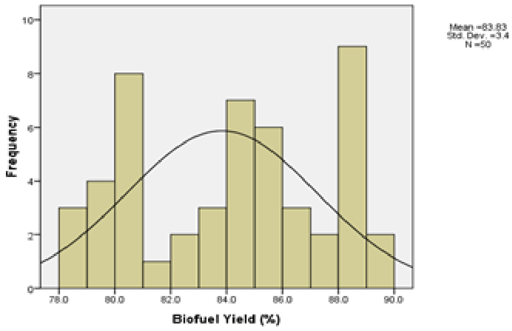

FIGURE 12. Production Cost (currency/unit)

Figure 12 shows a histogram of production costs (in currency per unit) for biofuel made from cooked oil. The mean production cost is 0.76 currency/unit, with a standard deviation of 0.042 and a sample size of 50. The histogram reveals that production costs predominantly range from 0.70 to 0.825 currency/unit. The highest frequencies are observed at approximately 0.70 and 0.80 currency/unit, indicating a bimodal distribution. This distribution suggests two common cost clusters around these values, with fewer instances in the mid-range, creating a gap around the mean. This bimodal distribution may imply that there are two distinct groups or processes influencing the production costs, each leading to different cost outcomes. Understanding these clusters can help in identifying the factors contributing to the cost variations and potentially optimizing production processes to reduce overall costs.

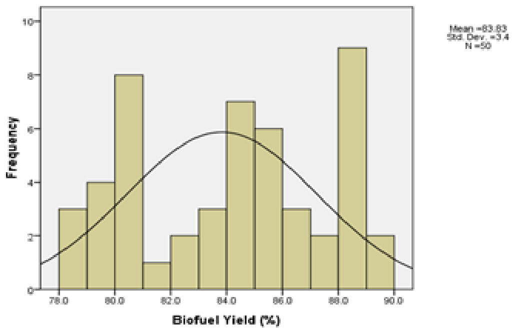

FIGURE 13. Profit Margin (%)

Figure 13 displays a histogram representing the distribution of profit margins in percentage terms for biofuel production from cooked oil. The x-axis represents the profit margin percentage, while the y-axis shows the frequency or number of occurrences for each profit margin bin. The distribution exhibits a bell-shaped curve, characteristic of a normal distribution. Bell curves are symmetrical, with the highest frequency occurring at the mean or central value. In this case, the mean profit margin is 18.12%, with a standard deviation of 1.923%. This distribution indicates that most profit margins are clustered around the mean value, with fewer instances at the lower and higher ends of the range. The relatively low standard deviation suggests that the profit margins are closely grouped around the mean, reflecting consistent profitability within the dataset.

TABLE 4. Pearson Correlation Matrix of Biofuel Properties and Economic Indicators

	Biofuel Yield (%)	Glycerol Yield (%)	Ester Content (%)	Acid Value (mg KOH/g)	Flash Point (°C)	Cetane Number	Density (g/cm³)	Viscosity (mm²/s)	Calorific Value (MJ/kg)	CO_2 Reduction (%)	Energy Consumption (kWh)	Production Cost	Profit Margin (%)
Biofuel Yield (%)	1	-.987	.971	-.958	.992	.978	-.943	-.978	.945	.979	-.942	-.982	0.251
Glycerol Yield (%)	-.987	1	-.976	.954	-.976	-.968	.924	.973	-.963	-.980	.926	.970	-0.262
Ester Content (%)	.971	-.976	1	-.956	.956	.962	-.937	-.967	.972	.957	-.925	-.960	.325*
Acid Value (mg KOH/g)	-.958	.954	-.956	1	-.945	-.913	.925	.967	-.912	-.938	.857	.932	-.316*
Flash Point (°C)	.992	-.976	.956	-.945	1	.972	-.922	-.963	.918	.970	-.941	-.971	0.184
Cetane Number	.978	-.968	.962	-.913	.972	1	-.913	-.947	.958	.958	-.981	-.957	.284*
Density (g/cm³)	-.943	.924	-.937	.925	-.922	-.913	1	.921	-.899	-.902	.875	.927	-0.215
Viscosity (mm²/s)	-.978	.973	-.967	.967	-.963	-.947	.921	1	-.929	-.976	.905	.969	-.324*
Calorific Value (MJ/kg)	.945	-.963	.972	-.912	.918	.958	-.899	-.929	1	.931	-.925	-.935	.408
CO_2 Reduction (%)	.979	-.980	.957	-.938	.970	.958	-.902	-.976	.931	1	-.906	-.978	0.268
Energy Consumption (kWh)	-.942	.926	-.925	.857	-.941	-.981	.875	.905	-.925	-.906	1	.903	-0.234
Production Cost	-.982	.970	-.960	.932	-.971	-.957	.927	.969	-.935	-.978	.903	1	-.289*
Profit Margin (%)	0.251	-0.262	.325*	-.316*	0.184	.284*	-0.215	-.324*	.408	0.268	-0.234	-.289*	1

Table 4 presents the Pearson correlation coefficients for various factors related to biofuel production and its economic implications. Each coefficient, ranging from -1 to 1, indicates the strength and direction of the association between two variables. Biofuel yield (%) shows substantial negative correlations with glycerol yield (-0.987), acid value (-0.958), and production cost (-0.982), indicating that as biofuel yield increases, glycerol yield and production expenses decrease. Conversely, it has significant positive correlations with ester content (0.971), flash point (0.992), cetane number (0.978), and calorific value (0.945), suggesting that higher biofuel yield correlates with elevated levels of ester content, flash point, cetane number, and calorific value. Glycerol yield (%) exhibits negative correlations with biofuel yield, ester content, and production cost, while positively correlating with viscosity (0.973) and profit margin (-0.262). Ester content (%) shows strong positive correlations with biofuel yield, flash point, cetane number, and calorific value, and negative correlations with acid value and viscosity. Additional noteworthy correlations include a significant negative association between energy consumption and biofuel yield (-0.942) and positive correlations between profit margin and ester content (0.325) and calorific value (0.408). The negative correlation between energy consumption and biofuel yield (-0.942) implies that as biofuel yield increases, energy consumption decreases, potentially indicating enhanced production efficiency. The strong positive correlation between ester content and both flash point (0.956) and calorific value (0.972) suggests that increased ester content corresponds to higher fuel stability and energy content, which are desirable attributes in biofuels. Conversely, the negative correlation between ester content and acid value (-0.956) indicates that as ester content in biofuel increases, acidity decreases, signifying superior fuel quality. The positive correlation between production cost and glycerol yield (0.970) implies that higher glycerol yield is associated with increased production costs, possibly due to the additional processing or purification steps required to manage excess glycerol.

Table 5 outlines the summary of regression models for various factors related to biofuel production. R Square values, ranging from 0.707 to 0.997, indicate the proportion of variance in the dependent variables explained by the independent variables. Adjusted R Square values, which account for the number of predictors, are slightly lower but still suggest substantial explanatory power. The standard error of the estimate, which measures prediction accuracy, ranges from 0.00448 to 1.197. Lower values indicate more precise predictions based on the independent variables. Change statistics, including R Square Change and F Change, assess model fit improvement with each additional independent variable. Significant F Change values ($p = 0$) indicate the models' statistical significance and the collective contribution of independent variables to explaining variance in the dependent variable. Regression models for biofuel yield, glycerol yield, ester content, acid value, flash point, cetane number, viscosity, calorific

TABLE 5. Regression - Model Summary

Dependent Variable	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
Biofuel Yield (%)	.999[a]	0.997	0.996	0.2039	0.997	1131.906	12	37	0
Glycerol Yield (%)	.996[a]	0.992	0.989	0.1346	0.992	382.726	12	37	0
Ester Content (%)	.993[a]	0.985	0.980	0.1510	0.985	206.099	12	37	0
Acid Value (mg KOH/g)	.991[a]	0.982	0.976	0.0175	0.982	166.298	12	37	0
Flash Point (°C)	.997[a]	0.995	0.993	0.2460	0.995	578.811	12	37	0
Cetane Number	.997[a]	0.995	0.993	0.2440	0.995	603.495	12	37	0
Density (g/cm³)	.971[a]	0.943	0.925	0.0045	0.943	51.010	12	37	0
Viscosity (mm²/s)	.994[a]	0.988	0.984	0.0233	0.988	253.628	12	37	0
Calorific Value (MJ/kg)	.994[a]	0.988	0.984	0.0780	0.988	247.707	12	37	0
CO_2 Reduction (%)	.993[a]	0.985	0.980	0.2510	0.985	205.050	12	37	0
Energy Consumption (kWh)	.995[a]	0.991	0.988	0.0270	0.991	338.231	12	37	0
Production Cost	.994[a]	0.989	0.985	0.0052	0.989	266.842	12	37	0
Profit Margin (%)	.841[a]	0.707	0.612	1.1970	0.707	7.454	12	37	0

value, CO2 reduction, energy consumption, and production cost show strong explanatory power and statistical significance. However, the profit margin model has lower R Square and Adjusted R Square values, indicating less explanatory capacity compared to the other dependent variables.

TABLE 6. ANOVA (regression)

Model	Sum of Squares	df	Mean Square	F	Sig.
Biofuel Yield (%)	564.77	12	47.064	1131.906	.000[a]
Glycerol Yield (%)	83.263	12	6.939	382.726	.000[a]
Ester Content (%)	56.239	12	4.687	206.099	.000[a]
Acid Value (mg KOH/g)	0.614	12	0.051	166.298	.000[a]
Flash Point (°C)	420.26	12	35.022	578.811	.000[a]
Cetane Number	430.92	12	35.91	603.495	.000[a]
Density (g/cm³)	0.012	12	0.001	51.01	.000[a]
Viscosity (mm²/s)	1.651	12	0.138	253.628	.000[a]
Calorific Value (MJ/kg)	17.897	12	1.491	247.707	.000[a]
CO2 Reduction (%)	155.44	12	12.954	205.05	.000[a]
Energy Consumption (kWh)	2.865	12	0.239	338.231	.000[a]
Production Cost (currency/unit)	0.086	12	0.007	266.842	.000[a]
Profit Margin (%)	128.24	12	10.686	7.454	.000[a]

Table 6 presents the analysis of variance (ANOVA) results for the regression models of various factors related to biofuel production. The ANOVA table assesses the significance of each independent variable's contribution to explaining the variance in the dependent variable. For biofuel yield (%), glycerol yield (%), ester content (%), acid value (mg KOH/g), flash point (°C), cetane number, density (g/cm³), viscosity (mm²/s), calorific value (MJ/kg), CO2 reduction (%), energy consumption (kWh), and production cost (currency/unit), the sum of squares, degrees of freedom, mean square, F-value, and significance level (Sig.) are reported. Significant F-values ($p = 0$) across all variables indicate that the regression models are statistically significant, implying that the independent variables collectively contribute to explaining the variance in the respective dependent variables. The sum of squares quantifies the variance explained by each independent variable, with higher values suggesting greater influence. Notably, the profit margin (%) model also shows significant results, indicating that the independent variables have a statistically significant effect on profit margin. However, the F-value and mean square for profit margin (%) are comparatively lower than those for other variables, suggesting a lesser degree of variance explained by the independent variables in relation to profit margin. Furthermore, the ANOVA results reveal the relative importance of each independent variable in explaining the variance in the dependent variables. Variables such as biofuel yield (%), glycerol yield (%), flash point (°C), cetane number, and calorific value (MJ/kg) exhibit particularly high F-values and mean square values, indicating substantial contributions to the regression models. Conversely, variables like density (g/cm³), production cost (currency/unit), and profit margin (%) show comparatively lower F-values and mean square values, suggesting a lesser impact on the dependent variables' variance. Despite this, all variables demonstrate statistical significance, reinforcing their relevance in the biofuel production process and economic analysis.

4. CONCLUSION

The analysis of biofuel production from waste cooking oil (WCO) and its associated parameters has revealed several significant insights. These findings underscore the viability of WCO as a feedstock for biodiesel synthesis, offering a sustainable solution to waste management while addressing energy security concerns. Statistical analysis unveiled strong correlations among various parameters, highlighting their interdependence in optimizing biofuel production efficiency and quality. Notably, biofuel yield displayed robust positive correlations with ester content, flash point, cetane number, and calorific value, indicating that higher yields correspond to improved fuel properties. Conversely, negative correlations were observed between biofuel yield and factors like glycerol yield, acid value, and production cost, suggesting potential trade-offs in process optimization. Regression models and ANOVA analyses further reinforced the statistical significance of the independent variables in explaining the variance observed in biofuel yield, glycerol yield, ester content, acid value, flash point, cetane number, density, viscosity, calorific value, CO2 reduction, energy consumption, and production cost. This underscores the importance of considering and fine-tuning these parameters to enhance process efficiency, fuel quality, environmental sustainability, and economic viability. While the profit margin model exhibited a lower explanatory capacity compared to other dependent variables, its statistical significance highlights the influence of the independent variables on profitability. Further research into optimizing these variables could potentially improve profit margins, thereby fostering the economic feasibility of biofuel production from WCO. The analysis also highlighted the importance of statistical tools like SPSS in facilitating rigorous data analysis and enabling informed decision-making. The reliability and validity of the data, as evidenced by the Cronbach's Alpha and descriptive statistics, lend credibility to the findings and provide a solid foundation for future research endeavours. The study emphasises the promising potential of WCO as a sustainable feedstock for biofuel production, offering a viable solution to waste management challenges while contributing to energy security and environmental sustainability goals. The insights gained from the statistical analysis can guide process optimisation, fuel quality enhancement, and economic viability assessments, paving the way for the widespread adoption of biofuels derived from waste cooking oil.

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