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Review Paper on Microwave Aid Transesterification Process Parameters and Optimization Methods Applied

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Abstract- This review explores microwave-assisted biodiesel production, emphasizing advantages like direct energy transfer and shortened reaction times. Catalyst types, microwave power, reaction time, free fatty acid content, and temperature are discussed. The impact of different catalysts and optimal microwave power ranges for enhanced production are highlighted. Challenges related to free fatty acid content are addressed, and innovative methods are explored. The review emphasizes the crucial role of temperature in biodiesel production and its influence on reaction rates and yield. The impact of biodiesel on engine performance and emissions is investigated, focusing on studies involving waste cooking oil biodiesel in diesel engines. Optimization through Design of Experiments and response surface methodology is discussed, with a suggestion to integrate AI tools, particularly artificial neural networks and deep learning, for enhanced optimization and prediction accuracy. In conclusion, the review underscores microwave-assisted biodiesel production as efficient and environmentally friendly. The integration of AI tools is recommended for a more streamlined and data-driven approach in optimizing biodiesel synthesis parameters.

Keywords- Review, Optimization, Process Parameters, Transesterification, Microwave.

I. INTRODUCTION

Extensive research has been conducted on various techniques for biodiesel production, revealing that traditional heating methods often entail significant power consumption. A primary drawback of conventional approaches is their limited capacity to uniformly apply temperature, predominantly affecting the material surface. In contrast, microwave systems offer a distinct advantage by directly imparting thermal energy to the interior molecules of the reactants [1]. Without altering other parameters, the use of microwave radiation has proven effective in reducing reaction times from several hours to mere minutes, presenting a substantial improvement over conventional heating methods for accelerating the transesterification reaction [2].

However, the adoption of microwaves as a heating source does pose challenges due to elevated costs [3]. To address this issue, researchers have explored modifications to domestic microwave ovens. For instance, in a notable study, Teflon hoses were introduced to create helixes within the microwave, necessitating the incorporation of two openings in the oven for material input and output [4]. This innovative system prioritized microwave safety to prevent material boiling and spillage within the oven. With its enclosed design, the system effectively managed the concern of material dissolution (see Figure 1).

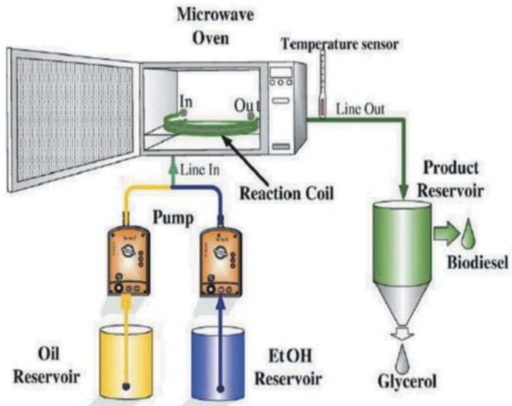

Figure 1: Modified microwave system [4].

Microwave radiation offers several advantages over conventional methods [5], including:

- Energy transfer directly to the material, utilizing diffusional radiation rather than heat transfer.
- Controlled and precise heating, allowing instantaneous activation and deactivation of heat.
- Selective heating capabilities, enabling targeted treatment of specific components or areas within the material.
- Significantly shortened reaction times, accelerating processes that traditionally took hours.
- Improvement in quality and properties of the final product.
- Facilitation of the synthesis of new materials.
- Execution of reactions that are impossible with conventional tools.
- Reduction in adverse emissions during the process.
- Increased overall efficiency of the product.
- Environmental compatibility, characterized by low noise and absence of specific contamination.
- Utilization of clean energy with a reaction trend that produces heat through molecular-level interactions with materials without inducing any changes in them.

In summary, these advantages contribute to more efficient and rapid heating of reactants, reduced instrument size, enhanced temperature control, quicker installation, increased production, and a streamlined process with fewer stages, collectively fostering improved productivity [6].

II. EFFECTIVE PARAMETERS ON THE BIODIESEL PRODUCTION BY MICROWAVE

1. Catalyst

Transesterification, a slow equilibrium reaction in nature, is catalyzed to expedite the process and reduce reaction time. Catalysts play a crucial role in enhancing reactivity between alcohol and oil, which otherwise exhibit low reactivity. Catalysts for transesterification are categorized as homogeneous, heterogeneous, or biological. Currently, the prevalent method for biodiesel production involves homogeneous catalysts, particularly alkaline catalysts. This approach accelerates the reaction rate through efficient mass transfer, with catalyst effectiveness influenced by oil water and free fatty acid content [7, 8].

A high fatty acid methyl ester (FAME) content of 99.4% was produced in one study by optimizing conditions at 1 weight percent catalyst content, a 12:1 alcohol-to-oil molar ratio, 400 W microwave energy, and a temperature for the reaction of 27°C. NaOH and continuous microwaves were also used in this study [9]. Using a 3 weight percent catalyst concentration, an 800 W microwave power, a 30 second material retention time, a 12:1 molar ratio, and a reaction temperature of 78°C, researchers in another study produced biodiesel from palm oil wastes with a 97% production efficiency [10].

SrO and nano SrO catalysts were applied in a different study to produce biodiesel from edible oil waste using microwaves. The results showed exceptional performance, reaching 99.2% efficiency in approximately 8.2 minutes [10]. Employing traditional and microwave heat sources, the generation of biodiesel from camelina oil and methanol was investigated utilizing metallic catalysts (BaO, SrO, CaO, and MgO). According to the study, using microwaves accelerated the manufacture of biodiesel in less time, with BaO and CaO showing the highest activity and producing yields of 80% and 94%, respectively [11].

In a different study, beta aluminum zeolite was used as a catalyst in the transesterification processes. The catalyst's stability across eight cycles was demonstrated, and 90% of the production efficiency was achieved using microwaves [12]. However, there are drawbacks to using heterogeneous catalysts, including complicated synthesis, consumption of energy, high prices, and the development of a hazardous environment [13].

The growing popularity of enzyme catalysts, especially Novozym 435, has drawn notice because to its resistance to oils that include high levels of water and free fatty acids (FFAs). Under ideal circumstances, microwave assisted transesterification using Novozym 435 enzyme and methanol produced a 95% conversion rate in a study on the synthesis of biodiesel from yellow horn oil [20]. In a different study, the generation of biodiesel from Macoda oil using Lipozyme IM and Novozyme 435 in combination with methanol was found to be more efficient when enzymes and microwaves were used instead of traditional heating techniques [21].

2. Microwave Power

The transesterification reaction's performance and cost in the process of producing biodiesel are significantly influenced by the amount of microwave power used. While increasing the microwave power can boost the production of biodiesel, going beyond a specific threshold can have negative consequences on triglyceride molecular structure [21].

A study that looked at using microwaves to produce biodiesel from waste oil looked at two different kinds of oils: those with a high and low fatty acid content.

The results showed that up to 500 W of microwave power, biodiesel synthesis increased. Nevertheless, the generation of biodiesel was reduced when increasing the power to 700 W. Notably, oils high in free fatty acids (FFAs) showed less of an effect from power enhancement, with the best production rate being reached at 600 W. Overpowering the system also might cause alcohol to evaporate, which would lower the amount of biodiesel produced [22].

A different study looked at the ethanol-to-oil molar ratio, temperature, stirring rate, microwave energy, and reaction time in order to produce biodiesel from cottonseed oil. The optimal variables, which included a molar ratio of 17:1, temperature of 70 °C, stirring rate of 380 rpm, reaction time of 12 min, and microwave power of 270 W, were determined by utilizing Response Surface Methodology (RSM). A remarkable 99.5% biodiesel generation efficiency was attained in these circumstances [24].

3. Reaction Time

Reaction speeds are greatly accelerated by microwave heating, which is caused by electromagnetic interactions created by microwaves. Several reaction parameters, such as catalyst quantity, methanol-to-oil ratio, reaction time, and temperatures, were examined in a study on the generation of biodiesel from micro-algae oil.

The utilization of semi-continuous microwave application resulted in an impressive 84.01% output efficiency. At 60°C, a methanol-to-oil ratio of 1:10, a catalyst concentration of 1.5 weight percent, and a reaction duration of 15 minutes, this efficiency was attained [25].

An innovative method of producing biodiesel involved pre-mixing reactants with several mixers before using microwaves. To provide specific conditions for material flow, coiled reactors were added (refer to Figure 1). This technology met worldwide ASTM criteria for biodiesel in just 5 minutes, achieving an astounding 99.8% efficiency utilizing NaOH and palm oil [26].

As depicted in Figure 2, there is a notable increase in biodiesel production efficiency with the extension of reaction time, reaching a peak before the curve shows a diminishing slope. Beyond a certain point, specifically in the transition from 90 to 120 minutes, there is a decrease in biodiesel production efficiency.

This observation underscores the critical role of time in biodiesel production, emphasizing that while an initial increase in reaction time enhances efficiency, prolonged durations may lead to a decline in overall reaction efficiency.

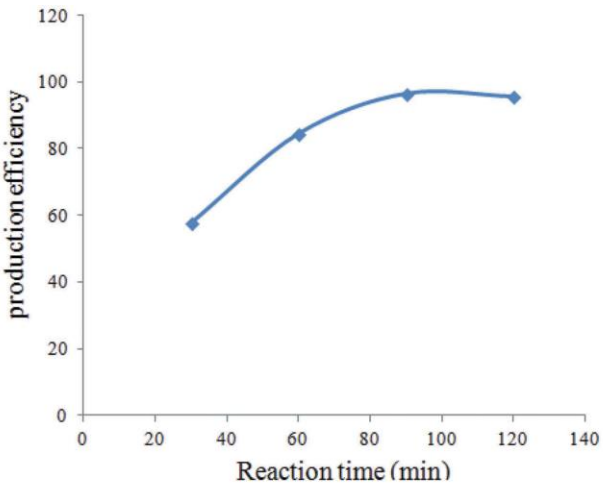

Figure 2: Biodiesel production efficiency vs. reaction time.

4. FFA Contents of Oil

Homogeneous alkaline catalysts, such as KOH and NaOH, are cost-effective and commonly utilized in industrial FAME procedures due to their short reaction times and ease of transport and maintenance [27]. However, the existence of FFAs in oil might affect transesterification events, resulting in the creation of undesired soap. High FFA concentrations, common in vegetable waste oils, can pose challenges and increase production costs [28]. A study on biodiesel production from high FFA content Nag Champa oil employed a two-step procedure involving successive microwave and ultra-sonication applications. The combined method reduced reaction times compared to individual use of microwave, ultra-sonication, and conventional methods, enhancing efficiency [29].

In a different study, a two-stage procedure was used to reduce the FFA level from 14% to 1% using microwave-assisted production of biodiesel from Jatropha curcas L. seeds. First, esterification was carried out utilizing H as an acid catalyst. Next, ethanol, KOH, and microwave energies were used for transesterification. Optimized parameters resulted in a maximum conversion yield of 97.29% [30]. Additionally, the use of aminophosphonic acid resin D418 (heterogeneous) with microwave radiation achieved a 90% conversion efficiency of FFA to fatty acid ethyl ester in 7 hours, outperforming normal heating conditions [31].

5. Effect of Temperature

The reaction's temperature also affects the amount of biodiesel produced. It has been observed that raising the temperature accelerates the reaction and increases yield. This could be because the oil's viscosity decreases with temperature, improving oil-alcohol mixing and facilitating the quicker process of separating glycerol from biodiesel. Nevertheless, a considerable decrease in biodiesel yield was seen with each temperature rise. This may be because, in contrast to the transesterification reaction, side reactions (such as the hydrolysis of methyl esters of fatty acids to homologous acid and alcohol) occur more quickly at higher temperatures, which leads to a lower yield of biodiesel. Noureddini [32] conducted research on soybean biodiesel made using methanol, varying the temperature between 30 and 70 °C while maintaining constant other parameters and observing the rate of reaction. Among the various temperature settings, it was found that 70 °C was the most favorable temperature for the best biodiesel output and reaction rate. Based on published research, Table 1 shows how temperature affects biodiesel production.

Table 1: Effect of temperature on Biodiesel production

Feed Stock Used	Temp. Range (°C)	References
Linseed oil	40–60 (increment of 10 °C)	[33]
Spirulina platensis algae	35–75	[34]
Sunflower oil	60–120 (increment of 20 °C)	[35]
Palm oil	70–110	[36]
	50–65	[37]
Pongamia oil	30–60	[38]
Canola oil	25–45	[39]

III. EMISSION AND PERFORMANCE OF ENGINE

Numerous studies on waste cooking oil biodiesel's performance, emission, and combustion characteristics and highlights about the fuel tested, engine used, and trends observed by different investigators are as depicted below in detail. Due to its sufficient oil content, palm kernel oil (PKO) is a good feedstock for the manufacturing of biodiesel. As a result, the effectiveness of its conversion of PKO to biodiesel using microwave and traditional heating systems was first evaluated in the diesel engine. Ten weight percent oil with a high FFA level was found in the palm seed (Zahidi type). PKO was trans-esterified using both conventional and microwave methods after its FFA content was reduced by an esterification process [40]. Muralidharan et al. [41] used waste cooking oil and its mixes with regular diesel under various loading circumstances to perform research on a single-cylinder, four-stroke variable compression ratio CI engine. With a larger load, the B40 blend showed improved brake thermal efficiency while exhaust gas temperature dropped. Using Canola Oil Methyl Esters (COME) and Waste Palm Oil Methyl Esters (WPOME) in a 6-cylinder diesel engine, Ozsezen and Canakci [42] discovered that WPOME and COME had less braking power at full load than Petroleum-Based Diesel Fuel (PBDF). NOx emissions rose while HC, CO, CO2, and smoke opacity decreased. Exhaust gas temperature and emissions were found to be condition-dependent on the engine, but unburned hydrocarbon emissions were shown to be fuel-dependent on two DI four-stroke diesel engine generators [43]. Increased NOx emissions in WCOME-fueled CI engines are frequently seen as compared to Petro diesel. Due to advanced injection time brought on by the processed waste cooking oil blend's larger bulk modulus, external EGR [44] reduced NOx emissions in waste cooking oil combined with regular diesel. Studies using methyl esters from used cooking oil are usually carried out in steady-state environments. The US-HDD transient cycle was used by Lin et al. [45] to investigate the use of Waste Cooking Oil Methyl Esters (WCOME) in Ultra Low Sulfur Diesel (ULSD) on a Heavy Duty Diesel Engine (HDDE). There was a decrease in PAH emissions of 7.53%–37.5%, HC emissions of 10.5%–36.0%, and PM emissions of 5.29%–8.32%. There was a decrease in CO emissions of 3.33–13.1%. In a multi-cylinder vertical diesel engine, waste cooking oil from coconut and palm oils was combined with pure diesel at a ratio of 5% WCOME to 95% pure diesel [46]. In comparison to pure diesel, the lower heating values of palm and coconut oils led to a 0.7% and 1.2% decrease in brake power for C5 and P5 blends, respectively. For the P5 and C5, the exhaust temperature rose by 1.12% and 1.58%, respectively. While C5 had lower HC emissions, P5 mixes showed greater CO2 and lower CO emissions. For C5, NOx emissions went down by 1%, but for P5, they were up by 2%.Blends of Waste Fried Oil Methyl Esters (WFOME) were studied by Hirkude and Padalkar [47] using a single-cylinder, four-stroke DI diesel engine. For the B50 blend at rated output, they saw a 6.89% rise in BSFC and a 6.5% drop in BTE. For various mixes, there were decreases in CO emissions ranging from 21% to 45% and in particulate matter from 23% to 47%. Experiments were carried out on a EURO IV Diesel Engine using mixes of waste cooking oil (WCO) biodiesel and pure diesel under different loading scenarios by An et al. [48]. Blends using biodiesel were shown to have lower emissions of NOx and HC. While BTE was higher for 50% and 100% loads and lower for the 25% loading condition, higher BSFC was observed at low speeds and partial loads. An examination was conducted on two types of biodiesels using a four-cylinder, four-stroke, water-cooled, turbocharged DI engine: virgin vegetable oil biodiesel and waste oil biodiesel [49]. In addition to a 15% increase in BSFC, biodiesel produced somewhat greater in-cylinder pressure and heat release rates. Using several mixes of leftover cooking oil methyl esters as fuel, Nantha Gopal et al. [50] published on the performance, emission, and combustion characteristics of a constant speed single-cylinder 4-stroke air-cooled DI diesel engine. Tests using blends of Waste Cooking Oil Methyl Ester (WCOME) in percentages of 20%, 40%, 80%, and 100% were contrasted with blends using mineral diesel. When compared to diesel, the results indicated that WCOME had higher specific fuel consumption, lower CO and HC emissions, lower brake thermal efficiency (BTE), and higher NOx emissions.

A Waste Cooking Oil (WCO) emulsion made up of 70% WCO, 15% water, 10% ethanol, and 5% surfactant was another option investigated [51]. In comparison to diesel, plain WCO produced more smoke, hydrocarbon, and carbon monoxide emissions during tests on a Kirloskar AVI CI engine. With increased cylinder peak pressure and maximum rate of pressure rise at high power outputs, WCO emulsions dramatically decreased all emissions. Without any changes, the performance of diesel engines running on WCO emulsion was on par with standard diesel engines. Ahmed et al. [52] examined

WCOME made from mustard oil using gas chromatography and tested it in a Mitsubishi Pajero engine. Among the several biodiesels, Mustard Oil biodiesel (MB) showed the highest calorific value and the best oxidation stability. When compared to pure diesel, the test fuel demonstrated appreciable decreases in noise levels and considerable reductions in HC and CO emissions. Chuah et al. combined pure diesel with waste cooking oil methyl esters made using hydrodynamic cavitation technology [53]. In comparison to pure diesel, the mixes of WCOME demonstrated 1.9%–8.4% poorer brake thermal efficiency, 0.6%–5.2% lower torque, and 1.6%–6.7% lower braking power. Because biodiesel has a higher oxygen content, it burns more efficiently, producing relatively more carbon dioxide emissions and less carbon monoxide emissions.

IV. INVESTIGATION INTO THE ENGINE'S OPERATING PARAMETER VARIATIONS

More frequently, the properties of Petroleum-based Diesel fuel dictate Diesel engine design and development. Recently, biodiesels from various vegetable oil sources are being utilized in Diesel engines. Therefore, understanding the optimal operating parameters for Diesel engines using biodiesel becomes crucial. Transesterification technologies, widely employed for biodiesel production, induce significant changes in oil properties, impacting engine operating parameters such as injection pressure and timing. Researchers globally have extensively worked on this aspect, as summarized in Table 2, which outlines studies where engine parameters like compression ratio, injection pressure, or timing were varied to analyze engine characteristics. Muralidharan and Vasudevan [54] investigated a variable compression ratio CI engine using waste cooking oil methyl esters. They varied compression ratios (18, 19, 20, 21, and 22) and found that the blend B40 demonstrated superior brake thermal efficiency at a compression ratio of 21. Kannan and Anand [55] varied injection pressure (220 to 300 bar) and timing (23°, 25.5°, 28° bTDC) for a single-cylinder 4-stroke DI KIRLOSKAR diesel engine with Waste Cooking Oil (WCO) as fuel. An optimal setting of 280 bar injection pressure and 25.5° bTDC timing resulted in increased Brake Thermal Efficiency (BTE), reduced emissions, and higher cylinder gas pressure.

Table 2: Details of engines and fuels used in various studies

Engine	Parameters analyzed	References
Four stroke (4S) water cooled vapor CR compression ignition engine	CR: 18-22	[41]
Single cylinder 4 stroke DI	IP: 220-300 bar, IT: 23-28 °bTDC	[55]
4S, single cylinder direct injection variable CRDI	CR: 14-18	[56]
Single cylinder 4 stroke DI	IP: 80-160 MPa, IT: -25 to 0 CAD aTDC by 5 CAD	[57]

IP: Injection pressure, IT: injection timing, DI: direct ignition; CR: compression ratio, 4S: 4 stroke

Using various mixes of WCO biodiesel and diesel, El-Kassaby and Nemit Allah [56] investigated the effects of compression ratio and blending ratio on a single-cylinder variable compression ratio diesel engine. They found that while HC and CO emissions reduced with an increase in compression ratio, brake thermal efficiency increased along with CO2 and NOx emissions. A single-cylinder DI diesel engine with a common rail injection system was the subject of an analysis by Hwang et al. [57] about the effects of injection parameters (varying injection timings from -25 to 0 CAD after TDC and 80 and 160 MPa injection pressures). Waste Cooking Oil (WCO) reduced emissions of HC, CO, and smoke, but NOx increased under all tested circumstances. Salmani et al.'s study [58] looked at the characteristics of ignition delay at high pressure and temperature levels. They discovered identical combustion properties at 25 bar ambient air pressure when comparing pure diesel and micro-emulsion of coconut oil. This suggests equivalent ignition latencies at fixed injection pressure.

V. RESEARCH ON USING ANN MODELING TO FORECAST IMPORTANT ENGINE CHARACTERISTICS

Researchers may now use sophisticated tools and computationally efficient numerical approaches to forecast and optimize operational parameters, thanks to advancements in computer capacity [59–

63]. Artificial Neural Networks (ANN) are a cutting-edge modeling technology that reduces the need for a great deal of testing by speeding up the prediction of operational parameters. Such works are reviewed in this section and are included in Table 3. Canakci et al. [64] used the back-propagation technique to investigate in detail the prediction of emission parameters and performance using five distinct neural networks. With an astounding R^2 value of 0.99, the fifth network predicted flow rates, maximum injection pressure, emissions, engine load, maximum cylinder gas pressure, and thermal efficiency while taking into account input parameters including engine speed, fuel qualities, and environmental factors. In order to anticipate performance and emission characteristics, Shivakumar et al. [65] used Waste Cooking Oil (WCO) blends in their trials on a single-cylinder variable compression ratio DI diesel engine. They then used Artificial Neural Networks (ANN). For every category, two distinct models were created, and the predicted and experimental values exhibited a strong connection. The training and test data's Mean Relative Error (MRE) showed prediction accuracy. Ghobadian et al. [66] created an ANN model based on experimental data and used a two-cylinder diesel engine to assess performance and emission characteristics. The engine torque, specific fuel consumption, and CO and HC emissions were all precisely predicted by the model, which had correlation coefficients (R) ranging from 0.929 to 0.999.

Table 3: Details of Different input and output parameter control in various engines

Engine Type	Input variables	Output variables	Remarks	References
Water-cooled 4S and naturally aspirated, indirect injection, diesel engine	ES, fuel properties, environmental factors	Flow rate, IP, EL, BTE	5 ANN networks were used. One hidden layer network with back propagation algorithm used	[64]
Computerized 4S naturally aspirated, direct injection, variable CR, water cooled DETR	CR, IT, Fuel blend	BTE, BSFC, ET, NOx and UHC	Tan-sigmoid activation function with single hidden layer trained with backpropagation algorithm. Mean relative error is used as the performance evaluation model	[65]
2 Cylinder 4S DE	ES, Fuel blend	UHC, CO, BSFC, torque	Log-sigmoid activation function with single hidden layer trained with backpropagation algorithm.	[66]

DETR: diesel engine test rig, IT: injection timing, BTE, ES: engine speed, EL: engine load, BSFC: brake specific fuel consumption, ET, exhaust temperature, NOx: nitrous oxide, UHC: unburnt hydrocarbon, DE: diesel engine

Suhaiqah [67] has suggested a variety of factors for experiment design that make use of response surface technique and We spoke about variables such the ratio of methanol to oil, the concentration of NaOH, the reaction temperature (°C), and the reaction duration (min). Eqn. (1) [67] is used to compute the FAME yield throughout the Transesterification Reaction. Employing the response surface methodology and face-centered central composite design, Mahfud [68] optimized his study and found that yield raised as he improved reaction time and microwave power, with the best conditions being 50 minutes each and 440.53 watts. The highest yield, which was calculated using Equation (2), was achieved by using KOH catalysts at low concentrations of 2%. Mohammed et al.'s [69] application to examine how important operating factors affect the yield and conversion of Jatropha biodiesel was successful. According to ANOVA results, temperature had the greatest impact on FAME conversion and yield, with an ideal temperature of 60˚, a catalyst dosage of 4%, and a 6-hour reaction period. Furthermore, it was discovered that the interaction between catalyst loading and reaction duration had an incredibly large impact on both responses, comparable to Eqn. (2). Mohammed et al. have established an eqn. (3) to determine the yield.

$$Y_i = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X^2 + \sum_{i=1}^{k} \sum_{j=1}^{k} \beta_{ij} X_i X_j \text{ ---------------- (1) [67, 73, 74]}$$

$$Yield\ (\%) = \frac{Crude\ product\ mass \times Purity}{Lipid\ mass} \times 100 \text{ ------------(2) [68]}$$

$$Yield\ (\%) = \frac{Weight\ of\ the\ Bio-Diesel}{Weight\ of\ FEA} \times 100 \text{ --- -----------(3) [69, 72]}$$

Table 4: DOE Parameters opted by different researchers in different studies.

Control factors	References
M:O (w/w%), RT (°C), Rt (min)	[67]
Power, Rt	[68]
RT, CL (wt%), Rt	[69]
RT, Pressure, CL	[70]
RT , M:O, CL, CT (°C)	[71]
Rt, RT, CL, M:O	[72]
M:O, CL, RT	[73]
M:O, CL, Rt	[74]

M:O: Methanol to oil ratio NaOH concentration,
RT: Reaction temperature (°C), Rt: Reaction time (min),
CL: Catalyst loading (wt%), CT: Calcination temperature

Temperature, pressure, JOME:TMP molar ratio, and catalyst quantity are all thoroughly investigated in relation to their effects on the synthesis process using the Taguchi L9 experimental architecture. According to statistical analysis, the factors are ranked as follows: catalyst, JOME:TMP molar ratio, temperature, pressure, and catalyst. In the work by Kamil [70], the Taguchi parameter design effectively confirms the ideal process parameters using an empirical experiment for the synthesis of polyol ester. The YGME yield was estimated as a function of operational factors using the Taguchi optimization approach [71]. A YGME yield of 95.9 ± 0.94% was achieved by using the ideal methanolysis temperature, methanol/YG molar ratio, calcination temperature, and catalyst dose, which were 70 °C, 15:1, 700 °C, and 2.0 weight percent. Gouda et al. [72] chose a set of parameters that are shown in table 4 and came to the conclusion that, under optimal reaction conditions predicted by the RSM numerical optimization process under microwave irradiation, the prepared catalyst showed excellent activity for the transesterification of biodiesel with 98.03 ± 0.7% conversion and a yield of 97.22 ± 0.4%. With the use of a microwave-assisted process that uses CaO as a catalyst, waste cooking oil may be converted into biodiesel [73]. For both the FFD and CCD methods, the ideal biodiesel yield was determined to be 91.32% and 90.71% for M:O molar ratios of 9.6:1 and 9.61:1, CaO loading of 1.26 (w/w)% and 1.34 (w/w)%, and process times of 9.7 min and 9.89 min. The evaluation of response surface methodology (RSM) dependent optimization strategies for biodiesel synthesis from used or waste cooking oil via a CaO catalyzed microwave-irradiated process was the focus of Prajapati et al.'s study [74]. The following factors were used to maximize the biodiesel yield: reaction interval, CaO quantity (w/w%), and MeOH: oil molar ratio. These factors impact the production of biodiesel, which is examined using a variety of statistical graphs.

From the above studied it is very clear that, many parameters could be adopted to evaluated the yield and optimization of different oils such as waste food oil, seed oils, and other oils. This leads to many confusions and discrepancies while selecting the factors for the study and it is quite tedious to conclude the study. The solution for this kind of discrepancies is to opt for the AI based tools and prediction of AI based solution could help this kind of multiple parameter based studies.

VI. TOOLS FOR BETTER OPTIMIZATION

Gottfried Leibniz's theories and concepts are credited with introducing artificial intelligence (AI) to the world [75]. The field of artificial neural networks (ANNs) was introduced by McCulloch and Pitts in 1943 with their evolutionary representation of the human brain [76]. A vast variety of complicated issues may be learned, recognized, and solved by ANNs. ANNs and deep learning (DL) approaches are currently the most widely used and important machine learning (ML) algorithm techniques [77–84]. The accuracy of a deep neural network (DNN) and a standard machine learning method are contrasted in Figure 3. It is evident that DL techniques outperform traditional machine learning methods in terms of accuracy when sufficient data and processing capacity are available [76].

In machine learning, DL has gained popularity since 2006. Figure 4 [84] illustrates its place in data science and artificial intelligence. Because of the availability of data and the advancement of system processing capacity, DL approaches outperform classical ML algorithms [84, 85]. Traditional machine learning methods work effectively because they are simpler to build and work better in shorter databases and simpler applications. One of the main causes of the lack of early growth in neural networks and deep learning approaches is this [75, 76, 86]. Much quicker advancements in data gathering, storage, updating, and administration are now feasible with the arrival of the Big Data era. Furthermore, the advancement of GPU technology has enabled efficient handling of big data collections. Recent developments in DL approaches can be attributed to these remarkable advancements [76, 84]. These algorithms' popularity has also risen due to their ability to shorten calculation times and speed up the convergence process [77, 78].

Function approximation [87, 88], classification [89-94], feature selection [95, 96], medical image registration [80], pattern recognition [97–100], data mining [101], signal processing [102], nonlinear system identification [103, 104], speech processing [105], and other uses have all been applied to artificial neural networks (ANNs). Furthermore, several DL techniques have been applied to a range of tasks, such as handwritten digit identification [115–120], phoneme recognition [114], classification [106–110], prediction [111–113], etc.

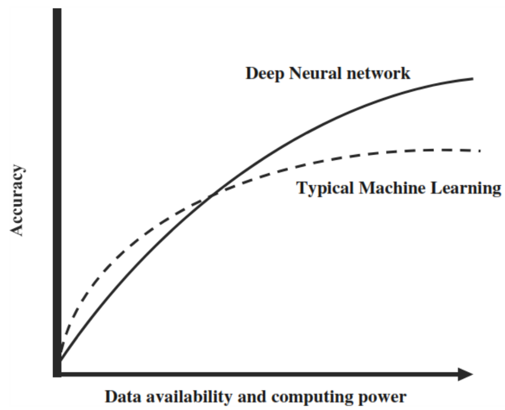

Figure 3: Comparison of the accuracy of a typical machine learning algorithm and a deep neural network [76]

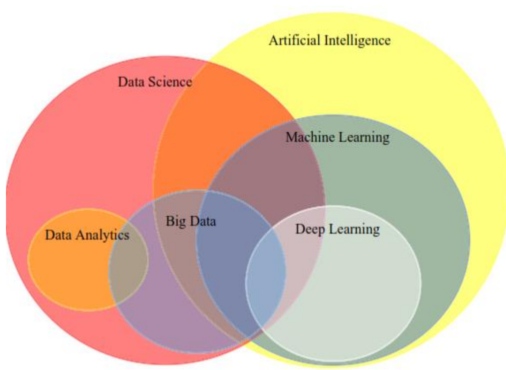

Figure 4: The position of deep learning in artificial intelligence and data science [84]

One of the main challenges in machine learning is discovering flaws and developing these algorithms, given the significance of employing ANNs and DL approaches in numerous applications. One of the hardest problems in machine learning is the process of ANNs and DL architectures learning. One of the primary goals of research over the last 20 years has been to optimize the parameters and structure of ANNs and DLs [82–84]. Numerous factors are frequently taken into account while optimizing ANNs and DLs, including weights, hyper-parameters, network architecture, activation nodes, learning parameters, learning algorithm, learning environment, etc. [83]. The most crucial aspects of neural networks and deep learning architectures are the optimization of weights, biases, and hyper-parameters. In actuality, the two pillars of structure and learning algorithm set ANNs and DLs apart. Gradient-based techniques have been utilized extensively in the past to teach architects. Nonetheless, it has been shown that optimization techniques are necessary due to the drawbacks of gradient-based algorithms [82–84]. For instance, the learning objective of the back propagation (BP) learning method is to minimize the cost function by optimizing the network's weights and thresholds. In order to apply BP in gradient-based learning methods, the cost function has to be derivative. This is another drawback of learning methods that use gradients. because the cost function and the activation function are frequently not derivatives. These algorithms often employ sigmoid activation functions. Numerous gradient-based techniques, including Levenberg Marquardt (LM) and Back Propagation (BP) approaches, have been developed in the literature to educate neural network-based systems [103]. In order to enhance gradient-based learning algorithms—which have superior generalizability and convergence than the BP algorithm—Conjugate Gradient Algorithm [121], Newton's Method [122], Stochastic Gradient Descent (SGD) [123], and Adaptive Moment Estimation (Adam) [124] were first created. Nevertheless, the DL structures and neural networks used in these techniques are regarded as "black boxes" [82]. because human intuition is incapable of interpreting it. A generalized and ideal network has been made possible by swarm intelligence and evolutionary algorithms [125–128]. The optimization of the ANNs and DLs' structure and parameters through the use of meta-heuristic (MH) methods has increased significantly since training them is an NP-hard optimization issue. The best estimate of DL components (hyper-parameter, weights, number of layers/neurons, learning rate) is formulated by MH algorithms as an optimization problem [82]. Multi-objective MH algorithms have become more necessary due to the presence of several purposes in optimizing ANNs and DLs, such as error reduction, network generalization, and model simplification. It is still difficult for optimizing ANNs and DL structures using MH methods, and further study is required. The learning process is enhanced when DLs are trained with MH algorithms. This shortens the algorithm's execution time and improves its accuracy.

VII. CONCLUSION

This review highlights the advantages of microwave-assisted biodiesel production, emphasizing reduced reaction times through direct thermal energy transfer. Innovative modifications, such as Teflon hoses in domestic microwave ovens, address cost challenges. Catalysts, including alkaline, metallic, and enzyme catalysts, play a crucial role in transesterification.

Microwave power optimization and innovative pre-mixing methods accelerate biodiesel synthesis. The review explores the impact of free fatty acid content and temperature on production, emphasizing the need for careful parameter optimization. Engine performance with waste cooking oil biodiesel is discussed, noting variations in operating parameters, biodiesel blend influence, and trends in efficiency, exhaust temperature, and emissions.

The effectiveness of Artificial Neural Networks (ANN) for predicting engine characteristics is highlighted, along with the application of Design of Experiments (DOE) and response surface methodology in biodiesel synthesis optimization. The role of AI, particularly ANNs, in streamlining complex parameter studies for biodiesel production and engine performance research is emphasized for enhanced efficiency.

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