

The Scope of Integrating Artificial Intelligence on the Evaporation Traits of Additive Blended Fuels

R. Vasudevan¹, J. Sathik Basha¹, T. Thevaisanthi^{2*}



¹Faculty of Science Cluster, National University of Science & Technology - IMCO, Sohar, Oman

¹Science Cluster, National University of Science & Technology - IMCO, Sohar, Oman

²Kalasalingam Academy of Research and Education, Krishnankoil, Tamil Nadu, India



ABSTRACT: Nanoparticles and oxygenated additives significantly enhance fuel properties when blended with diesel or biodiesel, leading to improved engine performance and reduced harmful emissions. These additives influence ignition delay, a crucial factor in combustion. This study critically reviews the hot plate evaporation technique to evaluate the ignition delay of various blended fuels meticulously calibrated in diverse proportions and incorporated with cutting-edge additives, including nanoparticles (viz., CNT, CeO₂, Al₂O₃), oxy-additives (viz., DEE, Ethylene glycol, Ethanol), and water emulsions to enhance the combustion, emission and performance characteristics of diesel engines. This fascinating research area has captured researchers' keen interest, marking it as an extensively explored scientific domain. This paper also explores the potential of integrating AI tools, such as artificial neural networks (ANN) and various algorithms, with the above technique to forecast combustion behaviour, enhance efficiency, and refine the emission characteristics of advanced fuels as a future scope of study.

KEYWORDS: Ignition delay, evaporation, artificial intelligence, machine learning, artificial neural network (ANN).

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I. INTRODUCTION

Fuel droplet evaporation has become a prominent research area in fuel engineering science. The evaporation of fuel droplets over a hot plate signifies the quality and ignition properties of the concerned fuels. In the recent developments with the research community, numerous efforts have been made to investigate the quality and ignition attributes of various fuels such as diesel, water-diesel emulsion fuels, nanoparticles and oxy additives blended diesel and biodiesel fuels. The hotplate evaporation characteristics outcomes reveal the physical significance of the ignition delay (Abu-Zaid, 2003; Basha and Anand, 2010b). Ignition is the time interval between the start of fuel injection into the combustion chamber and the onset of the combustion (Miron et al., 2021).

The ignition delay of the fuel reveals the ignition quality and the combustion nature of the fuels when subjected to internal combustion engines. Ignition delay consists of two stages: physical delay (the period between the fuel injection and the start of combustion inside the engine cylinder) and chemical delay (the proceedings after the combustion process). During the physical delay period, the fuel gets atomized, vaporized, and mixed with air to enhance the temperature inside the engine cylinder. Meanwhile, in the chemical delay period, the preflame reaction starts and slowly accelerates until complete combustion occurs. If the ignition delay is too long, it affects the combustion, and hence, there are chances of inferior performance and enhanced harmful emissions from diesel engines (Abdelaal et al., 2013).

Many researchers have conducted hotplate evaporation of fuel characteristics to predict the ignition delay's significance before the engine cylinder's actual combustion process (Ahmed et al., 2023; Oo et al., 2015; Basha and Anand, 2010 ; Abu-Zaid, 2003).The hotplate evaporation characteristics predict the importance of ignition delay by studying the evaporation time versus hotplate surface temperatures and determining the critical surface temperature. The critical surface temperature represents the minimum temperature at which these fuels start evaporating on a hot surface, providing insights into their vaporization behaviour (Mohaddes et al., 2021). This method is currently of technological importance for its applicability to droplet combustion, particularly in the case of compression ignition engines.

The experimental setup includes a steel metallic plate, an electrical heater, a variac, k-type thermocouples, a glass burette, a digital camera, and a rigid support for the hotplate evaporation experimental setup described by Basha and Anand (2012). The hot plate is heated to a predefined temperature using an electrical heater. Insulation is placed around the hot plate to reduce heat loss. As the heater turns on, the temperature of the hot plate increases. A variac keeps the hotplate temperature set at a constant value. The fuel droplets impinge onto the hot plate when the surface temperature reaches a predetermined value (100°C). Simultaneously, a digital timer records the time (until the fuel droplet entirely vanishes on the heated surface). Many researchers conducted several experiments following a similar procedure and at other higher temperatures, such as 110, 120, and 130 upto 400°C (Wang et al., 2020; Basha & Anand, 2010; Tyagi et al., 2008).

*Corresponding author: t.theivasanthi@klu.ac.in

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In this paper, the experimental outcome of numerous research works over the hotplate evaporation characteristics has been reviewed critically for different fuels (viz., diesel, water-diesel emulsion fuel, nanoparticles blended water-diesel emulsion fuel, water-biodiesel emulsion fuel, nanoparticles blended water-biodiesel emulsion fuels). Using Artificial Intelligence (AI) in the biodiesel industry offers a favourable opportunity to transform several facets of production, optimization, and sustainability, thereby advancing biodiesel research, particularly considering the growing global demand for clean, renewable energy sources. AI offers a flexible toolkit for academics and businesspeople, covering feedstock selection, process optimization, quality control, and environmental effect assessment. AI integration can result in more environmentally friendly procedures, more productive manufacturing processes and a better comprehension of the complex factors involved in studying biodiesel. Artificial neural networks (ANNs) have become more prevalent in solving complicated nonlinear real-world engineering and scientific problems due to their tremendous capacity for generalization (Talari et al., 2018; Qiao & Chandra, 1996), as shown in Fig 1.

In one such recent study, Sahin used AI tools such as artificial neural network (ANN), support vector machine (SVM), and extreme gradient boosting (XGBoost) to examine engine performance and exhaust emissions for various types of fuel blends (Seda Şahin, 2023). The results depicted that the ANN model was the most accurate in predicting engine performance and emissions, while the SVM model was the best in predicting exhaust gas temperature. Tuan et al. (2023) compared the efficiencies of both ANN and SVN models. The results show that both models matched precise results with lower error rates in determining the ignition delay. The linear Regression (LR) model used by Kumar (2019) noted that the precision of the biodiesel yield estimate is lower than that of ANN. More surprisingly, a few researchers have applied ANN and other methods to enhance the predictive performance of blended fuels. A multiple input multiple output (MIMO)-ANN was designed to model different engine performance parameters for diesel-biodiesel-gasoline blends (Zandie et al., 2022). Rao et al. (2023) conducted a study on linseed-based biodiesel, evaluating the effects of 5% graphene NPs dosed in linseed biodiesel with various proportions on engine performance and emissions. The dosing of nano additives to B10, B20, and B30 blends with diesel using multiple methods to create B10G5, B20G5, and B30G5. B20G5 overcame the diesel in terms of better brake thermal efficiency (BTE) and reduced CO and HC emissions. When comparing ANN with RSM, the former proved more accurate in predicting engine performance

factors. Sharma (2021) compared the predictive powers of ANN with gene expression programming (GEP) to predict the engine's performance and emissions characteristics in a stationary diesel engine. Sixty experimental test results were incorporated to develop a predictive model with the help of artificial intelligence (ANN) and the GEP algorithm. The ANN model proved marginally more accurate when comparing the two models across the same parametric range. Additional work by Ramachandran et al. (2023) examined the impacts on performance and emissions in reactive controlled compression ignition combustion mode of different CNG energy shares. Compared to conventional biodiesel combustion, the results showed that a 30% CNG share decreased NO_x and smoke emissions by 25-31% and increased thermal efficiency by 4.35%. Two machine learning models - the Gradient Boosting Regressor (GBR) and LASSO (Least Absolute Shrinkage and Selection Operator) Regression predicted the results. admirably in accuracy with R² values ranging from 0.98 to 0.99 and comparatively modest root mean square error (RMSE) values. Hossain et al. (2022) investigated the application of super learner methods such as hybrid Bayesian Optimization Algorithm-Support Vector Regression (BOA-SVR) and Bayesian Optimization Algorithm-Boosted Regression Tree (BOA-BRT). The study combines BOA with AI approaches, creating the BOA-SVR and BOA-BRT models. The BOA-SVR model achieved a maximum biodiesel yield of 91.35% with a KOH dose of 0.6 wt per cent and a Methanol: Oil ratio of 7:1, and its performance improved as the accuracy increased. In another study, biodiesel production conditions were determined by hybridizing ANN and Genetic Algorithm (Treve et al., 2022).

We chose ANN for this study because it can predict various biodiesel properties and engine characteristics. In engine behaviour prediction, ANN recognizes an accuracy rate of greater or equal to 95% (Hoang et al., 2021), while biodiesel fuel properties such as the cetane number, flash point, kinematic viscosity, density, and cetane index of ABE-diesel blends are studied by Veza et al., (2020) and Giwa et al., (2015).

The ANN model predicts multivariables outputs based on various input variables. Unlike the traditional modelling methodologies, it is different as they can be used to learn about a system even if the process flows are not predefined. Predictions made by a well-trained artificial neural network (ANN) are much faster than those produced by conventional simulation programs or mathematical models, as iterative calculations are not required. However, choosing the correct neural network topology is critical for accuracy and simplicity.

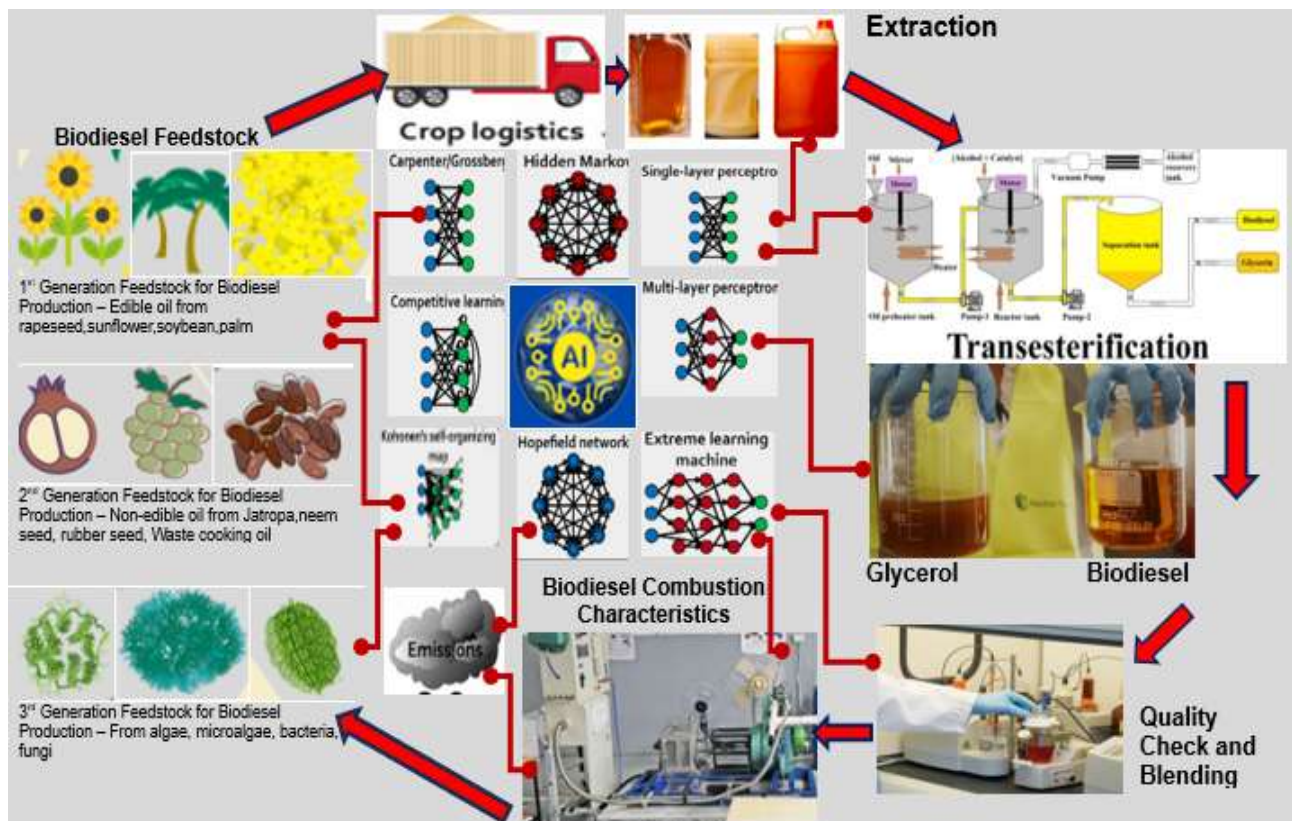


Figure 1. Machine Learning Technology's application to various branches of Biodiesel engineering

The general structure of the ANN models shows the connections among the various parameter nodes in the three layers—input, hidden, and output.

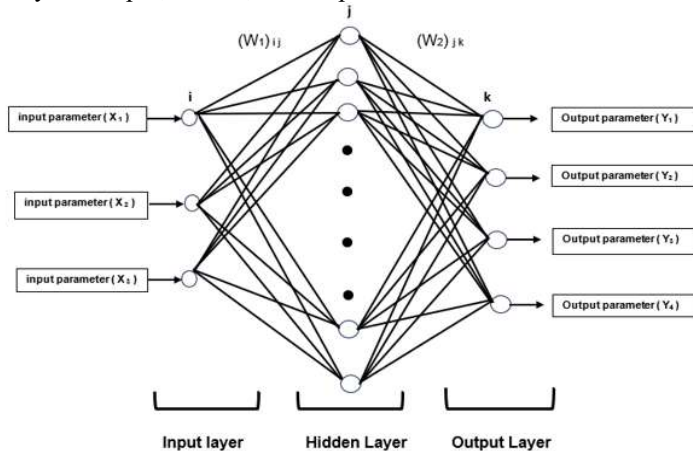


Figure 2. Depicts the general structure of an ANN.

There must be an input layer within a network, and the output layer can follow up by one or more hidden layers. As for each layer, neurons, known as nodes, are connected. Weights connect each layer's neurons, passing messages between the networks. Alongside the output signal, each neuron produces an output signal and receives inputs from other neurons.

Based on structure, ANN models are classified as feed forward or feed backward recall systems and, on learning mode, into

supervised or unsupervised models. Data is passed one way in feedforward ANN models from inputs to outputs while data can pass to and from between input and output in feed backward ANN models.

However, in supervised mode, learning involves using a data pattern with specific input and output, while unsupervised models have only input values for learning. The use of feedback networks is informative because they possess bidirectional data flow whereby neurons can send info to superior layers and accept feedback from inferior layers.

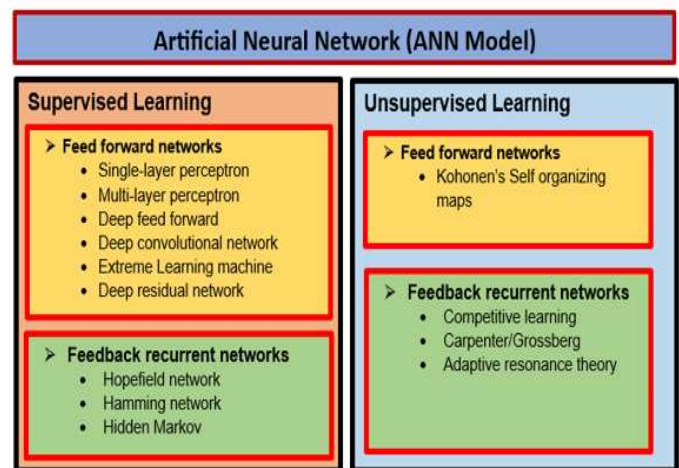


Figure 3. A general taxonomy of ANN models

Among the neural models presented above in the figure, the most used are MLPNN (Multi-Layer perceptron neural network), ELM (Extreme learning machine), and SOM (Self-organizing maps) methods. Recently, many other models, such as ANFIS, KELM, SVM, LS-SVM, RBFNN, GP, GRNN, BRNN, SGB, CFNN, PNN, AMT, and RT models, have also been used by researchers in the biodiesel research discipline (Sun et al., 2022), (Awogbemi & Kallon, 2023). ANN and machine learning algorithms for biodiesel-related feedstock assessment, property evaluation, and process control and improvement. Several investigations have shown the suitability of these approaches in modelling biodiesel characteristics and enhancing the manufacturing processes (Bukkarapu & Krishnasamy, 2024; Giwa et al., 2015; Rocabrundo-Valdés et al., 2015). When selecting efficient feedstock, the ability to announce fuel properties from the fatty acid composition has been paramount for ANNs. Previous research has demonstrated satisfactory prediction of cetane number, viscosity, flash point and density of biodiesel from numerous feedstock (Al-Shanableh et al., 2016; Giwa et al.,

2015). This approach enables the researchers to assess the prospects of candidate feedstocks before investing in experimental research on biodiesel, which may lead to much time and expense when hashing out biodiesel prospects (Khan et al., 2022).

Surprisingly, despite the outperforming of many problems by ANNs, some comparative relative studies have been conducted using other techniques as well. For example, Garg and Jain (2020), conducting a comparative analysis of modelling biodiesel yield and process parameters using Response Surface Methodology (RSM) and Artificial Neural Network (ANN), declared the latter as more predictable. Furthermore, Bukkarapu and Krishnasamy (2024) compared and analyzed various machine learning techniques, such as Support Vector Machines and Random Forests, for screening biodiesel properties and setting the composition. A summary of some of the recent works involving the AI tools integrated is listed in Table 1.

Table 1: Some recent work from the literature depicting the relation between the biodiesel fuel domain, ignition delay and AI integration.

S.No	Feedstock	Description	AI integration	References
1	Crude Palm Kernel Oil	Analysis of crude palm kernel oil (CPKO) biodiesel production, using KOH and NaOH	Response surface methodology (RSM) and Artificial neural network (ANN)	Ayoola et al. (2020)
2	Jatropha Biodiesel blends	Preparation of biodiesel from jatropha oil through transesterification process and analysis of performance and emission analyses using CuO nanoparticles.	RSM and ANN	Ramachandran et al. (2023)
3	Castor Oil	Synthesis of Castor oil biodiesel using Mn Doped ZnO particles	—	Zahid et al. (2023)
4	Waste-derived biogas and third-generation algal biodiesel	Predict and optimize the combustion and exhaust emission characteristics of a variable compression dual-fuel combustion engine	Multi-layer perceptron network (MLPN) was employed to develop an Artificial Neural Network (ANN) based prognostic model	Sharma et al. (2022)
5	Rapeseed Oil	A statistical approach to the probability density of ignition delay of B7 and B20 Rapeseed biodiesel for or full load and different engine speeds as tested operating conditions	Arrhenius equation with and without the Livengood-Wu integral	Sakane et al. (2023), Miron et al. (2021)
6	Linseed Oil	Optimize biodiesel production from linseed oil using a novel ultrasonic cavitation reactor.	RSM, GA and PSO	Ahmad et al. (2023)
7	Refined canola oil (RCO) and waste frying oil (WFO)	Estimate CP, PP and CFPP of biodiesel samples using nine FA components as input data of 103 biodiesel study	9-6-3 back-propagation ANN architecture	Al-Shanableh et al. (2016)
8	Jatropha Biodiesel, Water-Diesel Emulsion,	Emission, Combustion Characteristics Study using hot plate evaporation	—	Sadhik Basha (2018), Basha & Balushi (2020, Basha & Anand, (2020)

Overall, using ANNs and other MLAs has enhanced biodiesel research, specifically regarding feedstock choice and biodiesel properties. Such techniques are practical in minimizing experimental work, speeding up processes in the biodiesel industry, and developing sustainable methodology (Fahmi & Cremaschi, 2012; Sewsynker-Sukai et al., 2016).

This paper summarizes the evaporating characteristics on hot plates of several blended fuels. The authors analyzed the ignition delay using the hot surfaces' critical surface temperature for each fuel. Nevertheless, this study also enhances the knowledge of fuel behaviour and emission during combustion in CI engines. It opens up new directions in advancing renewable fuels that foster the growth and advancement of the energy sector. We analyze numerous studies that utilize different AI tools and methods currently employed in biodiesel research as a novel approach to incorporating ANN. We aim to integrate it with the hot plate evaporation characteristic set up to study the physical significance of ignition delay, which has not been explored so far by implementing the .

II. BLENDED FUEL EVAPORATION STUDIES USING HOT PLATE SURFACE METHODOLOGY - EVAPORATION CHARACTERISTICS STUDIES ON WATER-DIESEL EMULSION DIESEL FUELS

Recent fuel-evaporation studies investigated the relationship between hot plate surface temperature and evaporation time, concentrating on fuels emulsified with water and diesel. Abu-Zaid (2003) analyzed the evaporation rate of water-diesel emulsion fuels with various water concentrations (viz., 10, 20, 30 and 40% by vol.) on both stainless steel and aluminium hotplate surfaces. The water content of the emulsion fuel accelerates the evaporation process. Basha and Anand (2011) developed emulsion fuel by systematically incorporating diesel, water, surfactant, and alumina nano additives. The fuels with higher dosages of alumina nanoparticles exhibited an improved evaporation rate than those of neat diesel and neat emulsion fuel, as shown in Figures 4 a) and 4 b).

The evaporation time–surface temperature plot shows the critical temperature, which signifies the attribute of the enhanced igniting fuel (Basha & Anand, 2011). In fuel engineering, fuel with a low evaporation time improves the ignition characteristics and a shorter ignition delay (Javed et al., 2017). Fig 4 a) shows that the D2S5W100A fuel has a substantially lower critical surface temperature than the neat diesel and water diesel emulsion fuels. The D2S5W100A fuel had a vital surface temperature of 340 °C, while the neat diesel had 371 °C (Basha & Anand, 2012).

Thus, increasing nano-additive dosage in base fuel reduces evaporation time, enhancing ignition qualities and shortening ignition delay. The reduced evaporation time could be due to nanoparticles' surface area/volume ratio characteristics in water-diesel emulsion.

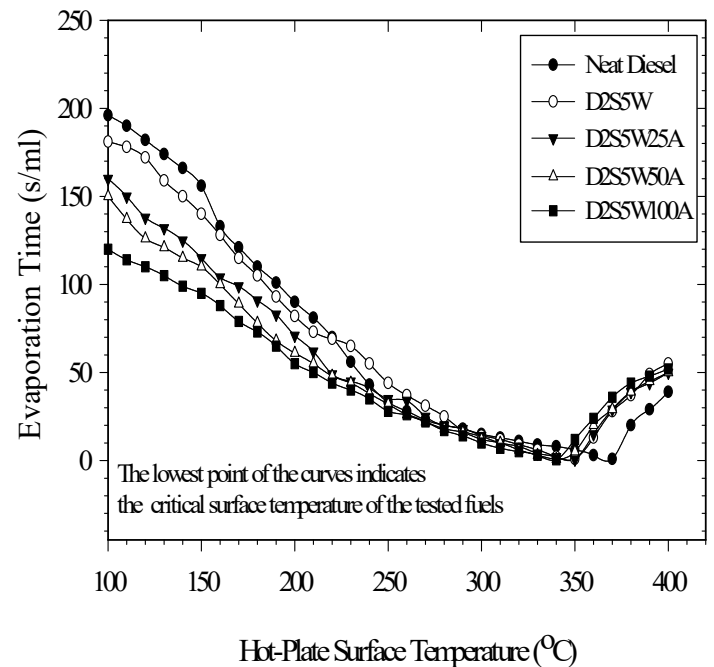


Figure 4a). Evaporation Time – Surface Temperature Curve comparing the critical surface temperature for Alumina nano additive (A 25, 50 and 100 ppm) blended diesel, water (5%) and surfactants (50 ml) emulsion fuels and neat diesel (Basha & Anand, 2012).

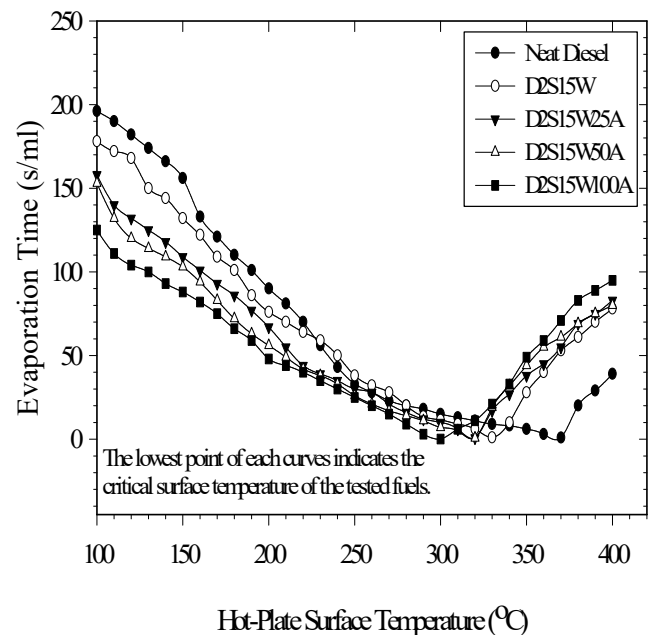


Figure 4b). Evaporation Time - Surface Temperature Curve for neat diesel and diesel-water emulsion – Diesel, surfactants (span 80 + tween 80) and water (5%) with alumina additives(25, 50 and 100 ppm) showing the critical surface temperature (Basha & Anand, 2011).

The excellent heat conduction characteristics and large surface area to volume ratio make them an ideal solution to any base fluid, including water, which speeds up the heat transfer rate (Das et al., 2007). The researchers affirmed that emulsion fuels also have longer ignition delays in the diesel engine combustion characteristics. Jeong et al.(2008) examined the auto-ignition features and combustion behaviour of a water-diesel fuel droplet to investigate the evaporation lifetime of emulsion fuels at different temperatures.

III. BLENDED FUEL EVAPORATION STUDIES USING HOT PLATE SURFACE METHODOLOGY - EVAPORATION CHARACTERISTICS STUDIES ON ADDITIVE BLENDED DIESEL FUELS

In recent methodologies about the evaporation attributes of fuel, some researchers incorporated nano-additives with diesel fuel to achieve some critical results in fuel characteristics and experimented with aluminium and Alumina nano-additives blended with diesel fuels to determine ignition delay. Their experimental results showed that the improved ignition probability of nano-additives blended diesel fuels and improved the ignition delay characteristics during combustion in the engine cylinder. Tyagi *et al.* (2008) discussed research attempts using nano additives blended with diesel fuels for power generation applications. Wang et al. (2020) studied the evaporation features of ceria blended nanofluids (with some concentrations of 0.05%, 0.25%, 1.25%, & 5% by weight) conducted at predetermined ambient temperatures (viz., 673 K & 873 K). Results indicate an improvement in evaporation time for the ceria fluid fuel droplets for 0.25% to 1.25% ceria concentrations. Diesel blended with alumina nanoparticles (25, 50 and 100 ppm) doped using an ultrasonicator was conducted to study the evaporation characteristics and the results shown in Fig 5 a) and Fig 5 b) (Basha, 2014).

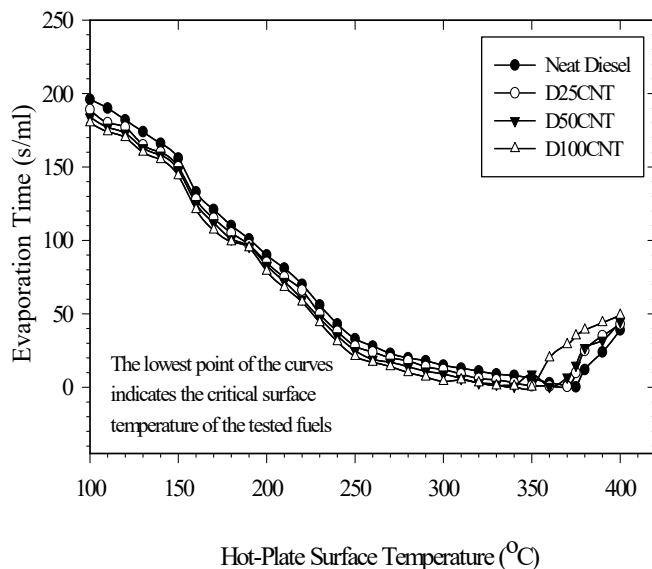


Figure 2a). Evaporation Time vs Temperature Curve for neat diesel (100%) and Diesel with Alumina Nano additives (25, 50 and 100 ppm) concentration blended to determine the critical surface temperature (Basha, 2014).

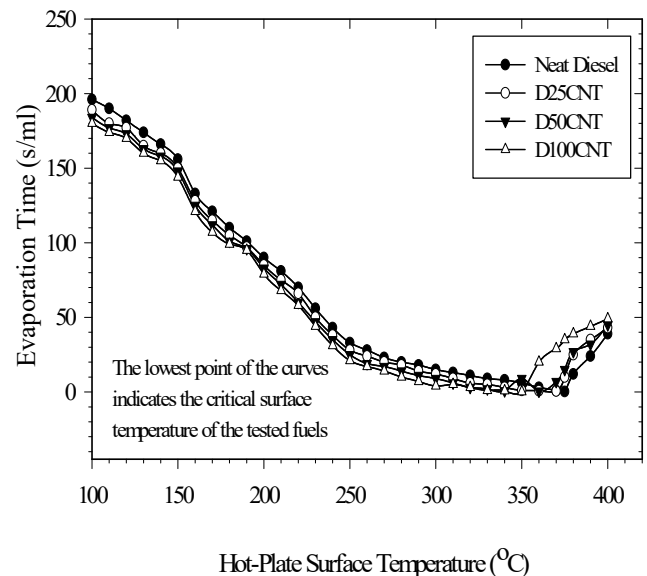


Figure 3a). Evaporation Time vs Temperature Curve for neat diesel (100%) and Diesel with CNT (25, 50 and 100 ppm) concentration blended to determine the critical surface temperature (Basha, 2014).

IV. BLENDED FUEL EVAPORATION STUDIES USING HOT PLATE SURFACE METHODOLOGY - EVAPORATION CHARACTERISTICS STUDIES ON ADDITIVE BLENDED BIODIESEL FUELS

Biodiesel fuels have recently been considered alternatives for power generation sectors (viz., diesel engine power plants, gas turbine power plants, combined cycle power plants, and transportation). Due to its wide acceptance worldwide by researchers, engineering professionals, and environmentalists, biodiesel is essential in these sectors. However, biodiesel fuels are not considered alternative fuels due to their inferior calorific value, high viscosity and burning qualities. Based on the evaporation time results, Basha and Anand (2011) performed hotplate studies to determine the combustion characteristics of additive blended biodiesel fuels. These biodiesel fuels blend with nano-additives like ceria, alumina, CNT, copper oxide and oxygenated additives like diethyl ether ethylene glycol (Basha & Anand, 2011; Basha, 2014; Basha, 2018). Wang et al. (2020) studied the evaporation attributes of CNT + ceria blended jatropha biodiesel fuels (50 ppm of CNT+50 ppm of ceria, 100 ppm of CNT+100 ppm of ceria, 250 ppm of CNT+250 ppm of ceria, 500 ppm of CNT+500 ppm of ceria by weight) at predetermined ambient temperatures (say 873 K & 673 K). The nanoparticles caused an acceleration in micro-explosions at 873K, and the evaporation time was accelerated. Henceforth, the burning quality of the same was enhanced compared to that of neat biodiesel. Sadhik Basha

& Anand (2011) conducted experiments utilizing several additives such as alumina nanoparticles, CNTs, and Di-Ethyl Ether with biodiesel fuels to examine the evaporation characteristics features on the hotplate evaporation setup. The additive blended diesel fuels exhibited advanced critical surface temperature and accelerated evaporation time compared to neat biodiesel fuels, as shown in Fig 6a, Fig 6b and Fig 6c.

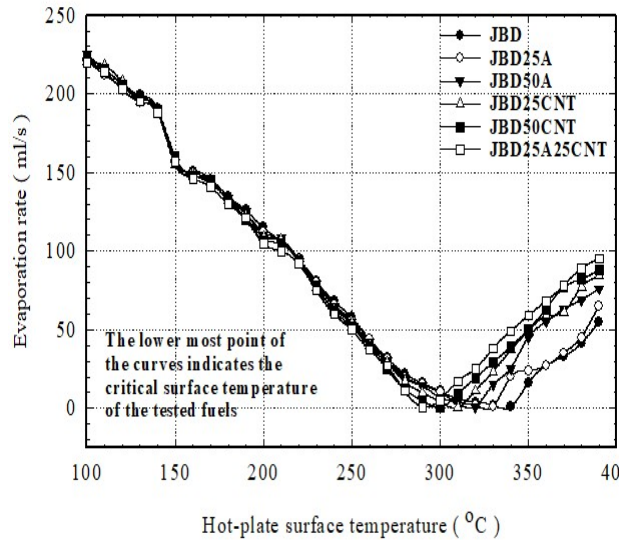


Figure 6a). Evaporation Time vs Temperature Curve for Jatropa Biodiesel (JBD) blended with Alumina (A 25 and 50 ppm) and CNT nanoparticle (25 and 50 ppm) showing the critical surface temperature (Sadhik Basha & Anand, 2011).

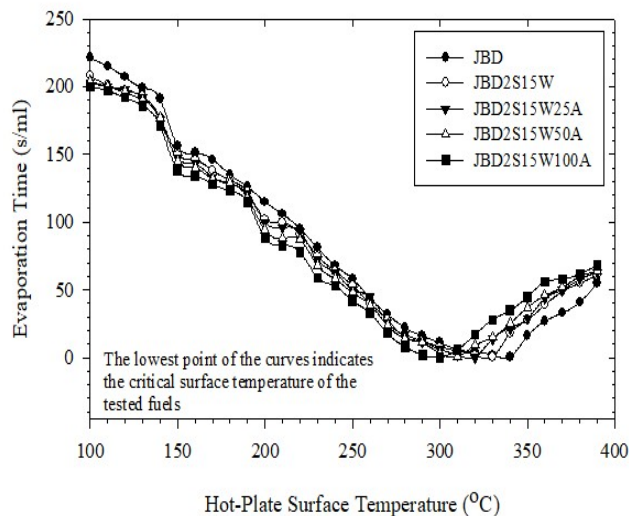


Figure 6b). Evaporation Time vs Temperature Curves for Jatropa Biodiesel (JBD), Water (W 5%), surfactant (S15 – 50ml) and Alumina nanoparticle (25, 50 and 100 ppm) blended fuels to determine the critical surface temperature (Basha, 2016).

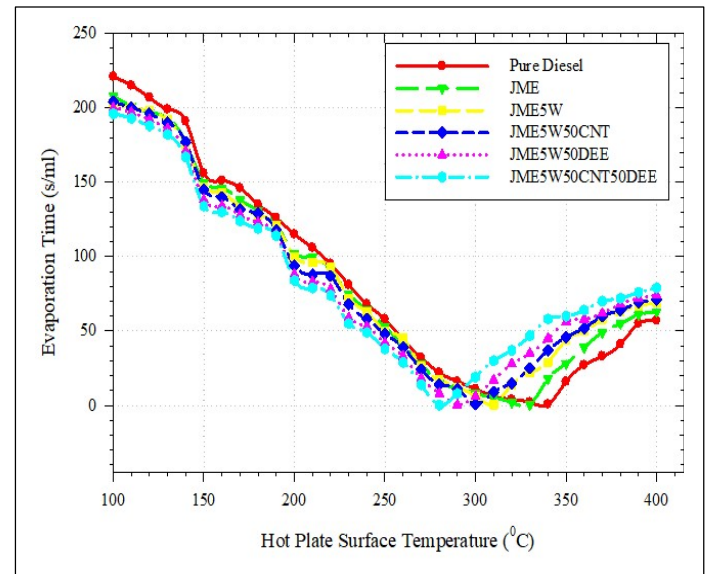


Figure 6c). The Evaporation Time-temperature Curve for additive—blend biodiesel fuels shows the evaporation rates of 5 different blended biodiesel fuels: Jatropa Methyl esters (JME), water (5%), CNT (50 ppm), and Di-ethyl ether (DEE - 50 ppm) compared with pure diesel for their critical surface temperature (Basha, 2018).

V. ARTIFICIAL INTELLIGENCE AND ADVANCED FUEL COMBUSTION DOMAIN

Artificial intelligence, the trending digitalization technology, has impacted all fields for the past few years- IT, medicine, academics, arts, music, environmental science, and engineering. The energy engineering field has seen a genuine transformation with the advent of AI technologies, which have added innovation to every aspect. AI technology is an intelligent assistant for combustion dynamics, performing magic to optimize fuel injection, increasing combustion efficiency and reducing environmental impact. Utilizing tools such as Machine Learning, Deep Learning, Superficial learning, and various Algorithm techniques, cleaner and more environmentally friendly fuel blends can be created by analyzing massive amounts of data to forecast how different fuels would behave within the combustion engine. Artificial intelligence goes one step ahead by using various models and simulation methodologies to predict complex chemical interactions in combustion in the CI engine and reveal hidden secrets. AI serves as a watchful steward in fuel production, monitoring procedures and guaranteeing that our fuels fulfil strict requirements. Integrating AI into the fuel engineering domain can support the traditionally existing knowledge, and cutting-edge technology always keeps us ahead of the curve. Researchers have relied extensively on various aspects of AI tools in recent years to substantiate and validate their experiments and predict future trends using the collected experimental data.

Using machine learning technology in biodiesel research offers several benefits, such as the capacity to automate biodiesel

facilities, streamline model structures, simulate lab-scale biodiesel systems, and verify biodiesel compliance with requirements. Additionally, it lowers the need for water chemicals, labour, and energy and optimizes engine settings. However, to accurately predict something, much data might not be appropriate for extrapolation. It also needs data to be normalized, may have trouble modelling extreme or irregular events, and relies on trial and error to determine the ideal specifications. Also, for every new fuel modelling, a specific algorithm must be chosen based on trial and error to determine its suitability. To overcome these, potential future applications or advancements in machine learning technology include real-time monitoring and control, hybrid machine learning schemes with high capabilities of interpolation and extrapolation, optimization of ML models and development of ML-based soft sensors.

Applying AI technologies to hot plate evaporation characteristics provides a potential future for research. Blended fuel consists of a complex mixture of hydrocarbons and additives. Conventional methods are challenging to analyze regarding combustion characteristics (Aghbashlo et al., 2021). However, future ML tools can handle these intricate relationships and patterns within these blends, providing a more comprehensive understanding of these fuels' evaporation characteristics. Moreover, they are capable of handling large datasets. Hence, advanced models can be developed and trained with large data sets to predict the combustion behaviour for newly developed blends at faster rates. AI-based applications have not been applied to blended fuel's hot plate evaporation characteristics, providing a promising future scope in analyzing evaporation characteristics using ANN and other algorithms.

A recommended framework of combination which can be adopted for the future work may be tabulated as below:

Table 2: A recommended combination of AI Framework

Framework	Type	Input	Output	Role
MLP	Structured	Fuel Properties	Evaporation time	Baseline Prediction
CNN	Visual	Video Frames	Featuremap(like evaporation edge)	Frame-wise evaporation detection
LSTM/TCN	Temporal	Sequential features	Evaporation curve	Sequence modelling and prediction

The table shows a multi-model AI architecture that can quickly and accurately look at how fast additive-blended renewable energy fuels like biodiesel evaporate. In this system, the three separate deep learning algorithms MLP, CNN, and LSTM/TCN all work together. When studying the evaporation of fuels, each of them will be working with a different collection of facts and problems. The Multilayer Perceptron (MLP) is a basic model that can work with structured input data such fuel blend ratios, nanoparticle concentrations, environmental variables, and the physical properties of fuel, such as surface tension and viscosity. This makes it easier to guess when things will dissolve swiftly. But these old models, like MLPs, aren't as

accurate in real-world tests since they can't see changes and indications in pictures.

The Convolutional Neural Network (CNN) can fill in these gaps by taking high-resolution video frames and discovering spatial information in them. This framework takes pictures or recordings of the shape of droplets, how they spread across the surface, and the formation of a vapour halo. These things are impossible to measure by hand or with only statistics. This gets rid of the requirement to rely on manual observation or photo analysis based on thresholds.

Long Short-Term Memory (LSTM) or Temporal Convolutional Network (TCN) is the third part. It looks at how the droplet's look and actions change over time. This is especially important for studies where the rate of evaporation changes in a non-linear way since the two things affect each other. The LSTM/TCN fills in a lot of gaps in our knowledge of how blended fuel behaves over time when it is under thermal stress by employing memory and sequence models. Static models can't do this.

This three-layered model fills up a number of gaps in current studies on how gasoline evaporates:

- It does away with the need for separate models that can't handle complex relationships between time and place.
- It makes predictions more accurate by combining physical data, visual cues, and patterns that change over time.
- It gives you a way to look at evaporation traits in real time and after an experiment that can be scaled up and done automatically, which cuts down on mistakes and the time it takes to study them. This link makes it possible to simulate predictive combustion in new ways, make additives better, and undertake experimental diagnostics. It helps a lot with studies on combustion, better marine fuels, and systems that use renewable energy.

VI. CHALLENGES AND PROSPECTS

Components of blended biodiesel fuel include different feedstocks and related additives with different chemical characteristics. The physical properties of biodiesel blends change with temperature, pressure, and composition. Therefore, recording these dynamic behaviour needs elaborate experimental paradigms and complex modelling. Biodiesel additives that modify biodiesel properties may exhibit variability in their interactions under various conditions, threatening the stability and reliability of future evaporation experiments. Such behaviours must be characterized and modelled to a high degree to understand and predict them.

While developing models such as Artificial Neural Networks (ANN), there is often a lack of integrated or exhaustive, high-quality data sets for validation. This absence of data hampers the internal and external reliability of predictive models. Combining the hotplate evaporation studies with ANN and other models requires computational resources. These models tend to be high dimensional non-convex optimization problems, which are expensive and difficult to solve.

Using ANN, deep learning, and other tools further improves the predictive modelling of hotplate evaporation characteristics. All these techniques retain the complicated nonlinear features and give less biased predictions. AI models need vast and normalized databases on biodiesel blends and additives for better efficiency, which is why creating such databases is crucial. Such databases improve the training and validation of ANN and other models. Integrating AI techniques with the classic physical and chemical modelling of the evaporation characteristics provides a more comprehensive approach. In refined forms of the two models, methods draw on these features to deliver specific trends and accurate forecasting.

Real-time monitoring with integrated AI ensures a constant flow of data for analysis. This approach enables faster adjustments and enhances other biodiesel blending procedures and fuel quality. Using AI to model the biodiesel additive can help develop suitable formulations for different biodiesel blend ratios. In turn, it improves fuel performance, optimizes the evaporation characteristics, and, above all, reduces the environmental effects. There is a vast opportunity to optimize combustion efficiency, reduce emissions, and increase fuel economy by applying the results of hotplate evaporation and AI modelling. This expansion even strengthens biodiesel's position as an environmentally friendly fuel option.

VII. CONCLUSION

The evaporation characteristics of fuels play a crucial role in determining ignition delay, which impacts combustion quality and engine performance. Fuels that evaporate faster exhibit shorter ignition delays, enhancing combustion efficiency and reducing harmful emissions in diesel engines. Studies have focused on blended fuels with varying ratios, evaluating their performance and emission characteristics. AI-based tools have further advanced fuel synthesis and combustion research. However, a significant gap exists in exploring AI integration with evaporation on a hot plate. Future research could bridge this gap by using AI to improve experimental setups and deepen our understanding of the complex dynamics of evaporation and combustion processes.

AUTHOR CONTRIBUTIONS

Ranjit. Vasudevan: Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing. **J. Sathik Basha:** Supervision, Project administration, Writing – review & editing. **T. Theivasanthi:** Supervision, Writing – review & editing.

DISCLOSURE OF INTERESTS.

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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