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Research Article

Artificial Neural Network Modelling for Biodiesel Production Using Waste Camel Bone based Heterogenous Catalyst

Jevita Khoo Suk Kim[1], Senthil Kumar Arumugasamy[2*], Mani Jayakumar[3,4], Tesfaye Kassaw Bedru[4]

[1] Department of Chemical and Environmental Engineering, University of Nottingham Malaysia, Jalan Broga, 43500 Semenyih, Selangor Darul Ehsan, Malaysia

[2] Department of Biotechnology, Faculty of Engineering, Karpagam Academy of Higher Education, Coimbatore - 641 021, Tamilnadu, India

[3] Centre for Natural Products and Functional Foods, Karpagam Academy of Higher Education, Coimbatore - 641 021, Tamilnadu, India

[4] Department of Chemical Engineering, Kombolcha Institute of Technology, Wollo University, P.O. Box 208, Kombolcha, Ethiopia.

[*]Corresponding Author: Senthil.Arumugasamy@nottingham.edu.my

Abstract: In recent scientific findings, utilizing solid wastes, especially biowastes from animal bones, as heterogeneous catalysts for biofuel production has gained attention in shifting from first- to third-generation feedstocks for a more environmentally friendly and sustainable transition from petroleum diesel to biodiesel. However, commercialization is still far off, as challenges and limitations demand further technological advancements to achieve a holistic production process with bearable costs to support the economy. Modeling studies have always been essential to understanding the behaviour of process and reduce costs as they can predict experimental results for untested conditions. This study addresses the element of process modeling in biofuel production by targeting critical parameters such as catalyst loading rate, alcohol-to-oil molar ratio, reaction time, and temperature to maximize biodiesel yield from non-edible seed oil. Experimental study was carried out in which waste camel bone was utilized as a heterogeneous base catalyst for the conversion of non-edible Jatropha curcas seed oil to biodiesel. Three types of artificial neural networks were developed namely: feedforward (FFNN), cascade forward (CFNN), and patternet (PNN), applying various training algorithms. A comparison among them was made, and it is demonstrated that the FFNN performed better overall than the other networks in predicting oil yield. CFNN with Levenberg–Marquardt (LM) achieved perfect accuracy (R = 1.0) and outperformed FFNN under scaled conjugate gradient (0.9789 vs 0.9347), though its performance collapsed under Bayesian regularization (BR) (R = 0.04). FFNN demonstrated more stable performance across algorithms (R = 0.9961–1.0), while PNN also achieved near-perfect fits with LM (0.9999) and BR (1.0) but showed much weaker performance under gradient-based algorithms (R = 0.5664–0.6923). The results highlight the potential of integrating machine learning in biodiesel production to capture process patterns and improve yield prediction, offering a pathway to overcome current limitations and move closer to commercialization.

Keywords: Biodiesel production, Heterogeneous catalyst, Process modeling, Artificial neural networks, Feedforward neural network, Cascade forward neural network, Patternet.

1. Introduction

In the midst of the global energy transition in response to the ever-increasing demand for energy, among many initiatives and inventions, extraction of fuel from biomass has been explored over the past two decades. Global energy usage from renewable sources has been increasing steadily, driven by the need to decarbonize transportation, heating, and power sectors, which together contribute to more than two-thirds of global CO_2 emissions [4, 8]. Among these efforts, biodiesel, bioethanol, and other biofuels are among the most promising alternatives that show proven evidence of having similar characteristics to fossil-fuel-based oil [2]. Therefore, production of biofuel from biodegradable sources, especially biodiesel, is believed to be a promising alternative and sustainable source of energy, which initially challenged the food industry.

However, this issue can be resolved by converting from first-generation sources of oil to third-generation. The first generation comes from edible food sources that have the potential to interfere with the raw material supply for food production when this approach is scaled up globally to support alternative energy sources significantly. Meanwhile, the second-generation source is waste from the food industry, whereas the third generation is algae-based [4]. The use of edible oils such as soybean and palm oil previously led to the "food versus fuel" conflict, hence shifting the research focus to non-edible oils such as *Jatropha curcas* and waste cooking oils, both of which exhibit good conversion potential and do not compete with food supply chains [2, 7]. *Jatropha curcas* in particular, a drought-resistant plant with 40–50% oil content, has been widely tested as a sustainable biodiesel source requiring no engine modification [7].

Since waste from the food industry and food product end users demands attention for proper management, the second-generation source of oil created a path for repurposing some of the food and biowaste into catalysts that enhance the transesterification process. In this process, triglycerides in vegetable oils or animal fats react with a short-chain alcohol (commonly methanol) in the presence of a catalyst to form fatty acid alkyl esters (biodiesel) and glycerol as a by-product. For feedstocks with high free fatty acid (FFA) content, a preliminary esterification step is often carried out to reduce FFA levels and prevent soap formation during the reaction [2,4]. The need for such a greener and sustainable method arises due to the limitations posed by homogeneous catalysts, leading to the use of heterogeneous catalysts such as bones, nanoparticles, and activated carbon [8]. Homogeneous catalysts such as NaOH can only be used once and also form soap when water is added, which makes the process expensive.

However, the ability to use bones makes it attractive, as billions of kilograms of bone waste are generated from slaughterhouses and disposed of in landfills. The bone source is considered because of the presence of calcium and phosphorus elements [6]. The pores on the bone can be calcined and reduced in size with appropriate temperature rise, transforming into active catalysts containing hydroxyapatite (HAp) and β-tricalcium phosphate with high basicity and reusability [4]. These biocatalysts are cheap and recyclable; thus, this field has begun to be explored to test and enhance biocatalyst efficiency using various types of bones from cow, camel, duck, fish, etc. For instance, Alsaiari et al. [2] reported biodiesel production from date seed oil using camel bone-derived HAp catalyst achieving up to 89 wt.% yield at 75°C, 180 min, with a 7:1 ethanol–oil molar ratio and 4 wt.% catalyst loading, all within ASTM fuel quality standards.

The process of producing biodiesel from non-edible oil is still in the initial transition phase from pilot plant to actual industrial process. Many studies have been performed using different non-edible sources and suitable catalysts to make the production feasible, with low operating cost and environmental sustainability [4]. To further enhance the industrialisation of this process, artificial intelligence (AI) and machine learning (ML) are increasingly being used for process model development and optimisation to ensure its feasibility to operate within safe margins while meeting product quality requirements [5,8].

Particularly, the Artificial Neural Network (ANN) approach is popular in processing and learning from experimental data to connect causal relationships between input and output variables, mimicking how the human brain works [11]. The recent trend of using ANN has shown strong potential in handling highly non-linear biodiesel systems, especially when the reaction behaviour is influenced by kinetics, thermodynamics and transport effects [5,12]. They focus on ANN application for catalyst-based transesterification. For instance, Suleyman et al. (2020) used a heterogeneous CaO catalyst for biodiesel production from waste cooking oil and achieved around 99.48% conversion, while Arif et al. (2024) reviewed ANN performance across systems using KOH, H_2SO_4, CaO, alumina-doped CaO and enzyme catalysts, all reporting R^2 values above 0.95 for predicting biodiesel yield and key reaction parameters.

Kumar et al. (2024) also highlighted ANN models reaching $R^2 \approx 0.9976$, showing that ANN can predict biodiesel performance with high accuracy.

However, these studies also show several drawbacks. Firstly, the catalysts used in those works (CaO, KOH, acids, enzymes) are different from camel-bone-derived catalysts, so there is still a clear gap in ANN development for low-cost bio-waste catalysts. Secondly, most ANN models depend on having large and clean datasets, which is difficult when working with new catalysts, where data availability is limited. Lastly, ANN still behaves like a "black box", which offers accurate predictions but not much understanding of how the catalyst properties influence the reaction behaviour. These limitations support the need to develop an ANN model specifically for camel-bone catalyst systems, especially to handle the strong non-linearities and limited experimental data in this research.

This study presents research on different types of ANN models, such as Feedforward Neural Network (FFNN), Cascade Forward Neural Network (CFNN), and Pattern Neural Network (PNN), implemented on the pilot process of biodiesel production from Jatropha curcas seed oil using camel bone-derived catalyst performed. The subsequent section outlines the ANN implementation methodology, followed by the presentation of results and a brief discussion prior to the conclusion.

2. Materials and Methods

An experimental study utilizing waste camel bone as a green heterogeneous catalyst for biodiesel production from non-edible *Jatropha curcas* seed oil was conducted to compare the performance of different types of neural networks using various training algorithms. Before delving into the methodology, a brief explanation of how the experimental study was executed is provided to gain a more holistic understanding of the model developed with the assistance of machine learning techniques.

Prior to the transesterification of *Jatropha curcas* seed oil, the heterogeneous camel bone-based catalyst was prepared. The raw material, waste camel bones were purchased from a local meat store and all necessary laboratory-grade chemical reagents were used without additional separation or purification. The bones were first repeatedly washed with tap water, hot water and finally distilled water remove cartilage, dirt and residual meat. The cleaned bones were dried overnight, then crushed using a hammer mill and sieved to obtain a particle size in the range of 100–500 μm. The powdered bone was first calcined at 600°C for 2 hours in an electric furnace with calcium carbonate as a support material. The calcined powder was further ground and sieved to ensure a uniform particle size. Then, the bone powder was soaked in 12% potassium hydroxide at 90°C for 5 hours to enhance its basicity and to eliminate any residual organic matter and finally recalcined at 900°C for 3 hours. The final product was a fine white powder, stored in an airtight desiccator to prevent moisture contamination before use in subsequent procedures. Catalyst characterization was performed using FTIR, XRD, and TGA to examine functional groups, crystalline structure, and thermal stability, respectively, while titration was used to determine catalyst basicity.

Biodiesel synthesis follows a three-step conversion pathway where triglycerides gradually break down into diglycerides and monoglycerides before finally forming glycerol. In this work, the reaction was initiated by dispersing the catalyst powder into methanol (99.8%) inside a 500 mL three-neck round-bottom flask fitted with a condenser and magnetic stirrer. This mixture was kept at 40 °C and stirred for 40 minutes to form the methoxide species. After that, 50 mL of pre-heated Jatropha curcas (JC) oil was added under continuous stirring (500 rpm) at atmospheric pressure, and the transesterification reaction was allowed to run for 3 hours. Once completed, the mixture was centrifuged at 5000 rpm for 8 minutes and washed three times with deionised water to remove any remaining methanol. The final biodiesel product was then analysed for FAME yield using gas chromatography.

To control variables such as methanol-to-oil ratio, catalyst concentration, and reaction time, an Artificial Neural Network (ANN) was used because it can learn complex, nonlinear relationships between multiple inputs and outputs. The ANN structure consisted of an input layer, hidden layer(s), and an output layer, with each neuron connected through weighted links that determine how strongly information is passed forward. These neurons process incoming signals using activation functions, such as the sigmoid (tansig), and generate outputs based on continuously updated weights during training [8,13]. As the learning progresses, the network reduces the difference between predicted and actual values by adjusting these weights through backpropagation, often using the Levenberg–Marquardt algorithm to achieve faster convergence and minimise residual error [14].

All experimental data were pre-processed and normalised using min–max scaling within the range [0,1] to ensure stable training and prevent any single variable from dominating the model [12]. The ANN followed a feedforward multilayer perceptron (MLP) structure, where information moves only from the

input layer towards the output. The model was trained and tested in MATLAB™ to determine the best number of hidden neurons that would give low mean square error (MSE) and high correlation values (R and R^2). The hidden layer size was tuned through trial and error to reach a balance between accuracy and overfitting, which happens when the model learns the training data too closely. The final ANN model was evaluated using MAE, MAPE, MSE, and RMSE, confirming its reliability and strength in predicting and optimising biodiesel production performance.

An artificial neural network model was developed in MATLAB™ (R2023a) to forecast biodiesel yield from the process variables. The data set comprised three inputs which are methanol to oil molar ratio, catalyst concentration and reaction time, alongside the biodiesel yield as the output. The three inputs were chosen as the key control parameters that determine biodiesel yield. This allows the correct ratio of catalyst and methanol for a given amount of seed oil, as well as the identification of the peak of the reaction yielding the highest biodiesel output to meet the required production amount and quality. Control of the raw material proportions, with sufficient reaction time for maximum conversion, saves raw materials and energy, and maximizes the yield. The experimental data can be considered refined from the second-stage experiment, where optimisation of the manipulated variables was performed to determine the optimal ranges used for robust and targeted ANN modelling. As a result, the variable ranges were narrowed beyond the initial functional testing ranges, as shown in Table 1 by the minimum and maximum values of the variables.

Table 1. Experimental data input and output variable ranges.

	Methanol to oil ratios	**Catalyst concentration**	**Reaction time**	**Yield**
Minimum value	9.582	2.844	2.529	96.015
Maximum value	11.962	3.595	3.802	97.121

To bolster the data set's robustness the rows were replicated fivefold using MATLAB's repmat function (duplication factor = 5). A modest random jitter of ±1 % was introduced so that no two samples were exact duplicates. Before feeding the data to the network both the predictors and the targets were scaled to the oto1 range, a step that generally speeds up convergence and improves training efficiency. The resulting normalized set was then randomly split into three portions: 70 %, for training 15 % for validation and the remaining 15 %, for testing. A feedforward multilayer perceptron (MLP), with a hidden layer was used. Hidden neuron counts were swept from 1 up to 35 in order to pinpoint the configuration that drove the mean square error (MSE) to its lowest while boosting the correlation coefficient (R^2) as possible. Training was carried out with the LM backpropagation algorithm, chosen for its convergence and strong accuracy, in handling models. In the hidden layer a tangential sigmoid (tansig) activation function was employed, while the output layer used a linear (purelin) transfer function. The training regime was set to run for 1,000 epochs target an error of 1×10^{-6} and report performance feedback every fifty iterations. After the training phase wrapped up the model's forecasts were put to the test, on both the validation and test sets. To bring those predictions back into real-world units the inverse mapminmax routine was applied, allowing a comparison with the biodiesel yields. Accuracy was then gauged with a toolbox of error metrics: (1) Mean Square Error (MSE), (2) Root Mean Square Error (RMSE), and (3) Mean Absolute Error (MAE), (4) Mean Absolute Percentage Error (MAPE) and (5) he coefficient of determination (R^2). Finally, performance and regression plots were drawn to evaluate the network's prediction quality.

To ensure a comprehensive performance evaluation, the ANN model was trained using ten different training algorithms available in MATLAB:

- Levenberg–Marquardt (LM)
- Conjugate Gradient Backpropagation with Powell–Beale Restarts (CGB)
- Conjugate Gradient Backpropagation with Fletcher–Reeves Updates (CGF)
- Bayesian Regularization Backpropagation (BR)
- Conjugate Gradient Backpropagation with Polak–Ribiére Updates (CGP)
- Gradient Descent (GD)
- Gradient Descent with Adaptive Learning Rate (GDA)
- Gradient Descent with Momentum and Adaptive Learning Rate (GDX)
- Resilient Backpropagation (RP)
- Scaled Conjugate Gradient (SCG)

Each algorithm was tested under identical data conditions, and network parameters such as the number of hidden neurons, iteration limits, and error tolerances were systematically adjusted to achieve optimal convergence and minimise prediction error.

The same procedure was subsequently applied to develop Feedforward Neural Network (FFNN) and Patternet Neural Network (PNN) models, to perform a comparison among the three networks to find the best network for biodiesel production.

3. Results and Discussion

FFNN, DFNN, PNN model performances were evaluated through error values obtained with the determination of MSE, RMSE, MAE, MAPE and R^2 and compared with different training algorithms in Table 1-3.

Table 2. Comparison of FFNN performance across 10 training algorithms for training, validation, and testing phases.

Error Values	**Feedforward Neural Network**														
Learning Phases	Train					Validation					Testing				
Training Algorithm	MSE	RMSE	MAE T	MAPE	R2	MSE	RMSE	MAE	MAPE	R2	MSE	RMSE	MAE	MAPE	R2
LM	0.000	0.007	0.006	0.010	1.000	0.001	0.023	0.016	0.020	0.996	0.001	0.033	0.021	0.020	0.998
CGB	0.009	0.093	0.073	0.080	0.903	0.012	0.111	0.089	0.090	0.877	0.016	0.125	0.095	0.100	0.871
CGF	0.003	0.056	0.041	0.040	0.962	0.008	0.090	0.070	0.070	0.937	0.007	0.084	0.063	0.070	0.929
BR	0.099	0.315	0.273	0.280	0.002	0.098	0.314	0.268	0.280	0.012	0.073	0.271	0.228	0.240	0.118
CGP	0.001	0.034	0.028	0.030	0.989	0.002	0.043	0.036	0.040	0.976	0.006	0.079	0.059	0.060	0.909
GD	0.001	0.038	0.028	0.030	0.986	0.002	0.045	0.037	0.040	0.972	0.003	0.051	0.039	0.040	0.962
GDA	0.008	0.091	0.069	0.070	0.914	0.028	0.168	0.144	0.150	0.727	0.023	0.153	0.132	0.140	0.734
GDX	0.035	0.188	0.152	0.160	0.647	0.041	0.202	0.168	0.170	0.516	0.023	0.150	0.126	0.130	0.723
RP	0.004	0.064	0.049	0.050	0.956	0.023	0.150	0.115	0.120	0.722	0.013	0.112	0.079	0.080	0.872
SCG	0.001	0.029	0.023	0.020	0.991	0.008	0.090	0.061	0.060	0.935	0.005	0.071	0.048	0.050	0.929

Table 3. Comparison of CFNN performance across 10 training algorithms for training, validation, and testing phases.

Error Values	**Cascaded Neural Network**														
Learning Phases	Train					Validation					Testing				
Training Algorithm	MSE	RMSE	MAE T	MAPE (%)	R2	MSE	RMSE	MAE	MAPE	R2	MSE	RMSE	MAE	MAPE	R2
LM	0.000	0.001	0.001	0.000	1.000	0.000	0.002	0.001	0.000	1.000	0.000	0.002	0.002	0.000	1.000
CGB	0.008	0.089	0.069	0.070	0.911	0.009	0.093	0.074	0.080	0.910	0.019	0.136	0.100	0.100	0.793
CGF	0.005	0.071	0.057	0.060	0.947	0.008	0.090	0.077	0.080	0.904	0.007	0.083	0.066	0.070	0.933
BR	0.104	0.322	0.276	0.290	0.015	0.052	0.227	0.185	0.190	0.045	0.087	0.295	0.267	0.280	0.027
CGP	0.003	0.054	0.046	0.050	0.968	0.009	0.097	0.077	0.080	0.922	0.012	0.108	0.091	0.090	0.852
GD	0.008	0.088	0.069	0.070	0.920	0.016	0.127	0.097	0.100	0.823	0.013	0.113	0.080	0.080	0.865
GDA	0.016	0.125	0.103	0.110	0.838	0.017	0.129	0.114	0.120	0.763	0.027	0.164	0.129	0.130	0.755
GDX	0.018	0.132	0.106	0.110	0.831	0.024	0.154	0.119	0.120	0.768	0.015	0.123	0.104	0.110	0.668
RP	0.015	0.124	0.094	0.100	0.790	0.025	0.157	0.117	0.120	0.828	0.037	0.191	0.157	0.160	0.716
SCG	0.006	0.076	0.061	0.060	0.933	0.009	0.096	0.075	0.080	0.924	0.006	0.079	0.066	0.070	0.935

Table 4. Comparison of PNN performance across 10 training algorithms for training, validation, and testing phases.

Error Values	**Patternet Neural Network**														
Learning Phases	Train					Validation					Testing				
Training Algorithm	MSE	RMSE	MAE T	MAPE (%)	R2	MSE	RMSE	MAE	MAPE	R2	MSE	RMSE	MAE	MAPE	R2
LM	0.000	0.001	0.000	0.000	1.000	0.000	0.002	0.002	0.000	1.000	0.000	0.008	0.003	0.000	0.999
CGB	0.008	0.092	0.070	0.070	0.899	0.011	0.106	0.085	0.090	0.898	0.006	0.079	0.063	0.060	0.951
CGF	0.008	0.088	0.068	0.070	0.919	0.011	0.106	0.097	0.100	0.758	0.016	0.125	0.102	0.110	0.865
BR	0.000	0.001	0.001	0.000	1.000	0.000	0.002	0.001	0.000	1.000	0.000	0.003	0.002	0.000	1.000
CGP	0.006	0.080	0.061	0.060	0.934	0.011	0.107	0.082	0.080	0.915	0.011	0.106	0.084	0.090	0.792
GD	0.008	0.087	0.070	0.070	0.926	0.027	0.163	0.122	0.130	0.692	0.035	0.187	0.153	0.160	0.418
GDA	0.026	0.162	0.128	0.130	0.766	0.027	0.163	0.120	0.130	0.617	0.012	0.109	0.091	0.090	0.742
GDX	0.028	0.168	0.137	0.140	0.713	0.024	0.156	0.123	0.130	0.566	0.044	0.210	0.171	0.180	0.581
RP	0.011	0.105	0.082	0.090	0.884	0.012	0.109	0.082	0.090	0.838	0.007	0.083	0.071	0.070	0.916
SCG	0.006	0.080	0.060	0.060	0.931	0.007	0.083	0.071	0.070	0.922	0.016	0.128	0.079	0.080	0.829

Table 2 summarises the performance of the feedforward neural network across different training algorithms. The Levenberg–Marquardt (LM) algorithm clearly gave the best results, with R^2 values almost equal to 1 and extremely low MSE (0.000–0.001) for training, validation and testing. This shows that LM is very effective for capturing the nonlinear behaviour of biodiesel yield. A few other algorithms like CGP, CGF, DG and SCG also performed well ($R^2 > 0.9$), meaning they could still learn the process–yield relationship quite efficiently. On the other hand, BR struggled producing $R^2 = 0.118$, likely due to over-smoothing, and the gradient-based methods (GDX, GDa) only reached moderate accuracy of $R^2 \approx$

0.65–0.73. Overall, LM stood out as the most reliable option for this network, giving accurate predictions without showing signs of overfitting.

Table 3 presents the results for the Cascade Forward Neural Network. Similar to FFNN, LM again produced almost perfect accuracy (R^2 = 1, MSE near zero) across all phases. CFNN tends to converge faster because of its extra connections from the input to the hidden layers, and this is reflected in its stable and precise performance. Algorithms like CGF, CGP and SCG also worked well (R^2 > 0.9), offering good accuracy at a lower computational cost. Meanwhile, BR performed poorly again in this architecture with R^2 < 0.05, and gradient-based methods (GDa, GDX) remained only moderately accurate with R^2 around 0.75–0.83. From these results, CFNN combined with LM appears to be a very strong modelling setup for biodiesel yield.

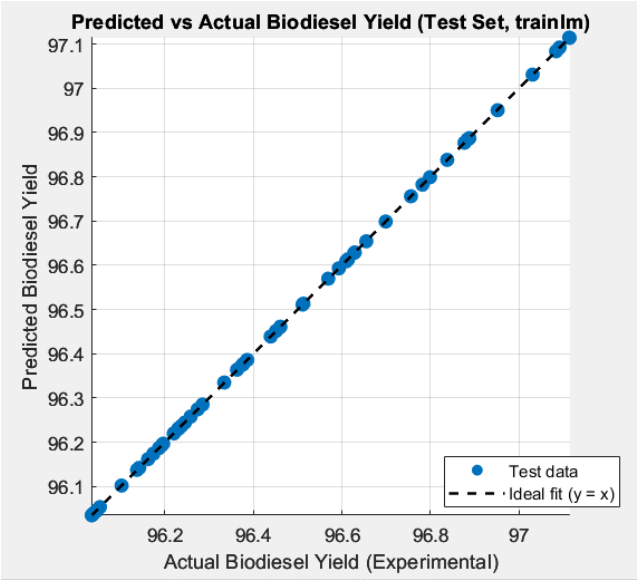

Figure 1: Comparison of best ANN model predicted results and experimental data.

Table 4 shows the Patternet Neural Network's performance. Here, both BR and LM achieved almost perfect accuracy (R^2 ≈ 1), indicating that this architecture works surprisingly well for regression, even though it was originally designed for pattern recognition tasks. BR performed much better in this network compared to the previous two, suggesting that Patternet's structure balances the regularisation effect without over-smoothing. LM also remained highly effective as usual. Other algorithms like CGB, RP and SCG performed reasonably well (R^2 > 0.8), while the gradient-based methods (GD, GDa, GDX) showed weaker fits (R^2 in the range of 0.4–0.7), mostly due to slow convergence and getting stuck at local minima. When comparing all three networks, the Cascade Forward Neural Network trained with LM gave the best overall performance, reaching R^2 = 1 across all stages with very low error values. The additional input-to-hidden connections in CFNN seemed to help the network learn faster and more accurately than the FFNN. This statement is further supported by Figure 1, in which the predicted results from the best ANN model are plotted against the experimental data, producing points that lie on the ideal fit line. Patternet also performed extremely well with LM and BR, showing that it can adapt effectively to nonlinear biodiesel data despite not being a traditional regression model. Across all networks, LM consistently produced the lowest error (MSE ≈ 0.000–0.002) and the highest accuracy, making it the most suitable algorithm for this type of system. Conjugate-gradient methods (CGP, CGF, SCG) were also strong alternatives when lower computational load is needed. BR was unstable in FFNN and CFNN but worked very well for Patternet. Meanwhile, gradient-descent algorithms (GD, GDa, GDX) showed the weakest performance overall. In summary, the CFNN with LM combination emerged as the most reliable and accurate model for predicting biodiesel yield.

4. Conclusions

This study compared three neural network models FFNN, CFNN and PNN using ten different training algorithms to predict biodiesel yield based on key process parameters. Overall, the LM algorithm consistently produced the best results, with very low errors (MSE < 0.002) and R^2 values almost equal to 1 across training, validation and testing. Among the three architectures, the CFNN showed the strongest performance, achieving R^2 = 1.000 in all phases, which reflects excellent generalisation and prediction accuracy. The Patternet network also performed extremely well, especially when trained with BR or LM, showing that it can adapt effectively even though it was originally designed for classification tasks. These findings highlight that both the choice of network architecture and the

training algorithm play an important role in how well the model learns and predicts biodiesel yield. Overall, the combination of CFNN with the LM algorithm proved to be the most reliable and accurate setup. This optimised ANN framework can support process optimisation and control in biodiesel production, leading to more efficient, data-driven decision-making within the biofuel industry.

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