

Prediction of Pyrolysis Oil Yield from Plastic Waste using Artificial Neural Network (ANN)

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Abstract

Plastic pollution has various negative effects, including significant ecological disruptions and the degradation of landscapes. An alternative to managing plastic waste (PW) is pyrolysis. In this study, the application of artificial neural network (ANN) for the pyrolysis of PW was investigated. The amount of pyrolysis oil yield (POY) from 0.5 kg to 5 kg of PW were determined. The Levenberg-Marquardt back propagation training algorithm (trainlm) was used to train the ANN using MATLAB R2022b ANN Toolbox. The POY is the output, and the input sets were temperature (T), pressure (P), particle sizes (PS), flow rate (FR), residence time (RT), heating rate (HR), and PW. The usefulness of the model for POY was demonstrated by the study effort, which verified the performance of the developed ANN models. The best validation performance's mean squared error (MSE) was 0.0060125. The ANN regression plots with an R^2 of more than 0.998 also demonstrates excellent results. The suitability of the ANN model for precise estimation of POY from PW is shown by the high values of the coefficient of determination (R^2). The study demonstrates that ANN is a versatile and effective technique for deciphering intricate pyrolysis data and maximizing the output of high value oil by optimizing operating conditions.

Keywords: Pyrolysis, Plastic Waste, Artificial Neural Network; Modeling; Pyrolysis Oil Yield.

Introduction

Plastics are used because of their advantageous qualities, which include being affordable, lightweight, and long-lasting (Wojnowska-Baryła *et al.*, 2020; Pal *et al.*, 2022; Orhorhoro *et al.*, 2023a). Plastic materials have the advantages of being lighter, more ergonomically moldable to meet individual demands, and more affordable to produce than metal products used in medicine (Pan *et al.*, 2020). Additionally, a significant amount of the waste stream in many nations nowadays is made up of garbage from the careless dumping of used plastics. Marine plastic litters are even more concerning because they have been shown to break down into microplastics and nanoplastics, which aquatic animals then eat (Meys *et al.*, 2020; Lomonaco *et al.*, 2020; Li *et al.*, 2023; Orhorhoro *et al.*, 2025a; Orhorhoro 2025b). According to research, this has a major detrimental effect on zooplankton mortality and population, which is a crucial source of energy for the marine environment (Kedzierski *et al.*, 2020; Orhorhoro *et al.*, 2025a). PW now endanger the world's economy, people,

animals, and environment, particularly in emerging and underdeveloped nations with inadequate recycling infrastructure and lax laws governing the manufacture, use, and regulation of plastics (Orhorhoro *et al.*, 2023b; Orhorhoro *et al.*, 2023c). Plastic may contain some or all of the following additives, depending on its kind, use, and service condition: plasticizers, fire retardants, antioxidants, light stabilizers, lubricants, pigments, antistatic agents, and thermal stabilizers (Shen *et al.*, 2020; Erhinyodavwe *et al.*, 2025). Numerous additives have been shown to infiltrate human and animal systems and are categorized as endocrine disrupting chemicals (EDCs) due to their capacity to imitate, block, or interact with hormones in the body's endocrine system (Shi *et al.*, 2019). Even though plastics have shown great qualities and applications in the advancement of modern technology, improper use, waste disposal, and lax regulations regarding the addition of additives in plastics intended for food packaging can lead to the release of harmful substances, which are exacerbated by the open burning of household and commercial plastics (Orhorhoro *et al.*, 2016; Teymourian *et al.*, 2021; Torres-Agullo *et al.*, 2021). In an effort to avoid the pollution caused by wasted plastics, authorities worldwide have turned to non-scientific methods, such as waste plastic buybacks and partial or whole prohibitions of specific types of plastic products (Conlon, 2021).

However, due to both negative economic, legislative, political, technical, and operational limits, these initiatives have not produced a significant positive impact (Vogt *et al.*, 2021). It will need more than mechanical recycling methods, such as downcycling or upcycling wasted plastics to a more comprehensive close-loop approach, to stay up with the technological advancements brought about by the use of plastics and its sustainable economic growth. Only the time it takes for old plastics to reach landfills and the marine environment is slowed down by mechanical recycling. Despite some parts of PW issue have been lessened by contemporary waste management techniques, they are by no means comprehensive or long term. Investigating alternate techniques, including pyrolysis, becomes crucial as the world community struggles with the pressing need to develop workable answers. As a revolutionary and sustainable method, pyrolysis has the ability to overcome the drawbacks of existing procedures and open the door to a more effective and ecologically responsible PW management system. A comprehensive, closed-loop method for turning PW into energy in the form of solid, liquid, and gaseous fuels is pyrolysis (Hough *et al.*, 2018; Fivga & Dimitriou, 2018; Eze *et al.*, 2020; Wang *et al.*, 2020; Chen *et al.*, 2021; Seo *et al.*, 2022; Emifoniye *et al.*, 2025a; Emifoniye *et al.*, 2025b). As long as an effective technique for lowering toxic compounds is used, pyrolysis appears to be a viable alternative to mechanical recycling for recovering materials and energy from waste plastic without selecting specific types of plastic (thermoplastic or thermosetting), separating components, or sorting into different types of plastic (Orhorhoro *et al.*, 2026a). Unfortunately, material recycling struggles to diversify reuse and mostly concentrates on the manufacture of solid refused fuel (SRF). An additional strategy for recycling

diversification is energy recovery using thermo-chemical conversion methods. Pyrolysis is one of the thermo-chemical conversion methods that can be used to swiftly and inexpensively produce significant amounts of liquid oil by thermally breaking down and depolymerizing long-chain polymer molecules in an oxygen-free environment (Istadi *et al.*, 2011; Mighani *et al.*, 2017; Foong *et al.*, 2021). Accordingly, pyrolysis may be a viable choice for recovering energy from PW and converting it into chemicals and liquid fuel (Olivera *et al.*, 2020; Fu *et al.*, 2022; Husin *et al.*, 2023). However, without the need for expensive, time-consuming tests, Artificial Neural Networks (ANN) modeling of pyrolysis for PW is utilized to accurately anticipate complicated, non-linear process outcomes (product yield, composition). ANN models, which frequently achieve >99% accuracy, increase efficiency, improve fuel quality, and make it easier to scale up the recycling of industrial PW by optimizing factors like temperature and heating rates. In the subject of pyrolysis, ANN have become a potent tool for assessing and forecasting several elements of the process. The structure and operation of the human brain served as the inspiration for the ANN, a computational model made up of interconnected nodes known as neurons. Based on the links discovered from the input-output data, these networks are able to learn from data, spot intricate patterns, and generate predictions (Boes *et al.*, 2016). ANNs typically arrange data, "learn" to identify patterns, and then forecast the results for a fresh batch of comparable data. The central processing unit of an ANN is made up of neuron layers with less than two hidden layers. According to Zhang (Zhang, 2018), a deep neural network is one that has more than two hidden layers. As seen in Figure 1, an ANN is made up of three layers: (i) an input layer that receives input data; (ii) an output layer that makes predictions; and (iii) a hidden layer that sits in between the input and output levels and handles the majority of the network's functions.

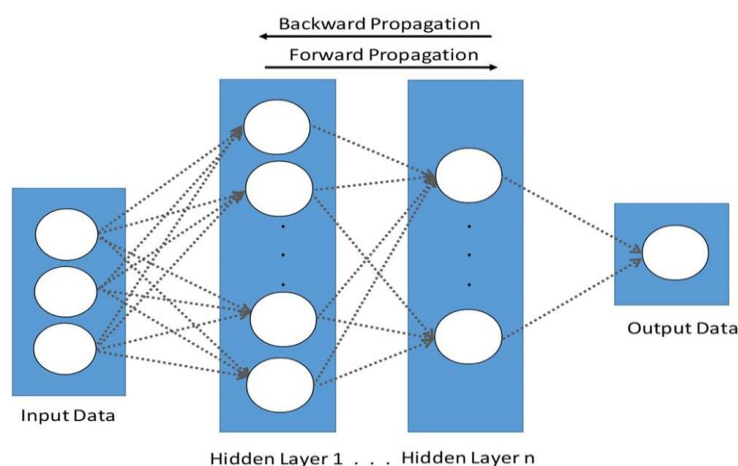


Figure 1. Schematic representation of a typical artificial neural network (ANN)

Past research work contains in-depth reviews of the underlying algorithms, architecture, and "forward" and "backward" propagation strategies used to train the networks

(Goldsmith *et al.*, 2018; Haghighatlari & Hachmann, 2019). According to Khan *et al.* (2023), the use of machine learning (ML) and its representative subset in engineering and other subfields has grown steadily over the past ten years. Drugs, materials design, and "in silico" catalyst production are some of the key areas with noteworthy advancements in this discipline (Peng *et al.*, 2022). The number of new applications to comprehend the connection between catalyst characteristics and reaction performance is growing quickly. Additionally, the ability to screen various reaction paths with non-linear correlations and get past conventional bottlenecks has improved with the present advancement of machine learning. A novel and more computationally viable method for predicting reaction yields, processes, and kinetic parameters is represented by the recent use of machine learning in plastic pyrolysis. The aforementioned elements are essential to scaling-up procedures, particularly those that conventional kinetic models are unable to monitor.

Conesa *et al.* (2004) have proven the use of machine learning in plastic pyrolysis. One of the earliest attempts to train an artificial neural network (ANN) to examine the kinetic parameters of the heat degradation of PE and other natural polymers is this study. In order to accurately predict the kinetic parameters (activation energy E_a , reaction order n , and the pre-exponential factor k_0) within the range reported in previous works by model free or model fitting approaches, the authors used 20 points from each of the experimental TGA curves at different heating rates as input data, along with 20 neurons in the input, 10 neurons in the hidden layer, and 3 neurons in the output layer (ANN:20:10:3). Similarly, Fazilat *et al.* (2012) were able to determine the kinetic parameters for the thermal degradation of Nylon 6 (also known as polycaprolactam) with a high degree of accuracy. This was accomplished by combining ANN with fuzzy interference-based adaptive networks to uncover the nature of the relationships the ANN formed. Their work marks a significant advancement in the use of ANN for plastic pyrolysis, even though the number of neuron layers is unknown. Their findings indicate that it may be possible to incorporate decision-making tools and predictive models into the plastic pyrolysis process.

The composition yield for the pyrolysis of PW, including HDPE, LDPE, PP, and PS, in a fixed bed reactor was estimated by (Abnisa *et al.*, 2019) using ANN. In addition, the authors trained the ANN using a combination of pyrolysis products and PW as output and input data. With a very low mean square error ($MSE < 2.6 \times 10^{-4}$) and a high coefficient of determination ($R^2 > 0.9$), the authors were able to accurately and successfully predict the experimental and reported data using an ANN architecture consisting of four neurons for the input layer, ten in the hidden layer, and the remaining three for the output layer (ANN:4:10:3). Nonetheless, Abnisa's *et al.* (2019) work was founded on architecture that was comparable to Conesa *et al.* (2004) version. The scientists employed data from a batch reactor, which is a more accurate scale than that used in earlier thermogravimetric analysis investigations. Al-Yaari and Dubdub (2020) developed a highly effective kinetic model for LDPE pyrolysis by comparing the effects of various neural network architectures and

transfer functions. Based on two distinct designs (ANN 2-10-10-1 or ANN 3-10-10-1), the results validate the adaptability of the ANN and the ability of the two transfer functions (Tan-sig-Logsig or Logsig-Logsig) to mimic the catalytic pyrolysis reaction of HDPE and LDPE, respectively. The ANN 3-10-10-1 and Logsig-Logsig are the best architecture and transfer functions, respectively, according to the MSE and R^2 achieved, even if the authors did not draw a conclusion favoring a particular strategy. The findings further support the effectiveness of ML applications in terms of MSE and R^2 . Complex chemical reactions and mechanisms that defy straightforward linear connections are involved in the pyrolysis of PW. Non-linear interactions occur between variables including temperature, heating rate, retention duration, and feedstock composition.

Conventional modeling techniques, such as kinetic modeling, frequently fall short of adequately capturing these interactions under a variety of real-world operating situations. Although ANNs are an effective tool for simulating the extremely non-linear process of PW pyrolysis, there are substantial research gaps that prevent these models from being widely used for POY prediction. Data on typical contaminants in real-world PW, like food residues, glue, or paper, which affect pyrolysis behavior and output quality, are rarely included in existing models. Also, past research analysis indicates that one or two hidden layers with ten neurons in each hidden layer are the optimal topologies for plastic pyrolysis. However, it takes some trial and error to figure out how many neurons or hidden layers to use for data modeling. Although Stathakis promotes the employment of a genetic algorithm, this is merely a broad concept, and as Al-Yaari & Dubdub, (2020) show, neuron layers must be shaped according to certain parameters. Furthermore, experts have suggested that using waste to energy (WTE) technologies like pyrolysis to turn solid PW into energy is a workable solution to PW. Numerous researches have demonstrated the potential for POY from PW. Additionally, studies have demonstrated that employing ANN to model the pyrolysis of PW offers a precise, data driven method of forecasting complicated, non-linear thermal degradation behaviors and product yields. The use of an ANN model to forecast the POY from a known mixed masses of PW has not, however, been further documented. Therefore, an effective, precise, and broadly applicable predictive model is desperately needed to maximize the output of POY from mixed PW. In addition to improving predictive accuracy, optimizing process parameters, and offering a sustainable substitute for experimental optimization, this study will concentrate on applying ANN modeling to forecast POY from PW. Additionally, to develop and evaluate an ANN model that can accurately forecast the POY from various types and combinations of PW, usually utilizing the Levenberg-Marquardt algorithm.

Materials and Methods

Experimental Setup

A fixed bed pyrolysis pilot plant shown in Figure 2 was used as the reactor. It is a batch-operated thermal system designed to convert solid feedstocks such as biomass, and Pw into

pyrolysis oil, char, and gaseous products in the absence of oxygen. It is characterized by a stationary bed of feedstock inside a heated reactor. The PW used was a mixture of PET, HDPE, PVC, LDPE, PP, and PS collected from households in Okada town. The gathered PW is weighed, dried, then shredded. The reactor is sealed airtight after the feedstock is placed inside. To remove all oxygen from the system, nitrogen gas is run through the reactor for 15 to 30 minutes at room temperature. After igniting the heating chamber, the temperature is gradually increased until it reaches the target operating temperature of 400–600°C. Volatiles move to the condenser as the feed breaks down, cool, and are recovered as pyrolysis oil. The heating chamber is shut off after a specified retention period. The reactor is left to cool to room temperature. By creating connections between process operating conditions (inputs) and product yields (outputs), ANN models are trained using the experimental data from pyrolysis processes. By learning from this data, the ANN can forecast results for novel, unproven pyrolysis settings, which eliminates the need for intensive experimental work. The operation/process parameters of the fixed bed pyrolysis pilot plant are shown Table 1.



Figure 2. Experimental setup (Orhorhoro *et al.*, 2026b)

Table 1. Operational/process parameters

Parameters	Unit	Basis
Temperature	°C	Temperature range of 400°C-600°C will be required
Heating rate	°C/min	20
Residence time	min	50
Particle sizes	mm	0.5 to 0.8
Feedstock	N/A	PET, HDPE, PVC, LDPE, PP, PS
Pressure	Bar	5-10 bars

Artificial Neural Networks (ANNs) Approach

In this study, a pyrolysis pilot plant was used to model the generation of pyrolysis oil from PW using ANN. MATLAB R2022b's ANN toolbox was used to create the ANN model. A built-in utility in MATLAB, the ANN toolbox offers functions and applications for modeling complicated and robust nonlinear problems that are difficult for traditional methods to handle. The approach adopted for ANNs modeling in this study is depicted in Figure 3.

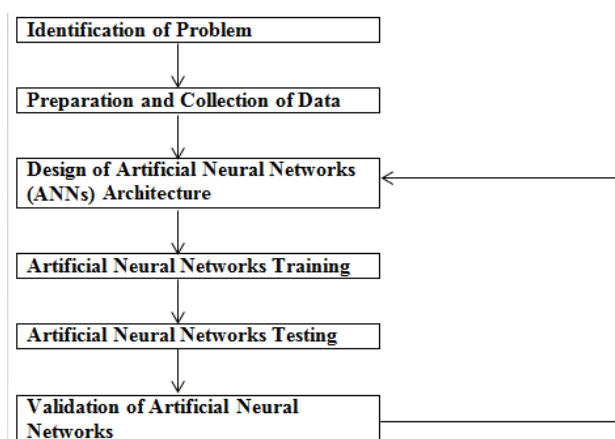


Figure 3. Artificial Neural Networks (ANNs) Approach

Preparation and Collection of Data

Performance test results of pyrolyzed mixed PW of weight (0.5 to 5 kg) were used to obtain the input and target data, which were then generated in a Microsoft Excel Spreadsheet. Temperature (T), pressure (P), particle sizes (PS), flow rate (FR), residence time (RT), heating rate (HR), and plastic waste feedstock (PW) were the input sets that were utilized.

Design of the Architecture of the Artificial Neural Network (ANN) Model

The design of the ANN's architecture, including its operational components, is the focus of this stage. It was determined how many layers there were and how many neurons were in each layer. The ANN model was designed using the multilayered feed forward architecture. It has a minimum of three node layers. With the exception of the input node, every node is a neuron that employs a nonlinear activation function. Three levels seven input layers, ten hidden layers, and one output layer were intended to be present in the networks. In order to determine the architecture of the ANN model, ten distinct numbers of hidden neurons (ranging from one to 10 neurons) were used in the hidden layer for three distinct data separation trials (training set percentage, validation set percentage, and testing set percentage), including 60%:20%:20%.

Artificial Neural Network (ANN) Training

In order to generate the outputs (pyrolysis oil yield-POY) using the provided inputs (T, P, PW, PS, FR, RT, HR), this phase entails controlling the data of the connection weights and biases. Training ANN is crucial since it dictates how broadly the model can be applied. In this study, the ANN was trained using the MATLAB R2022b ANN Toolbox and the Levenberg-Marquardt back propagation training technique (trainlm).

Back Propagation Network (BPN)

The most widely used training algorithm for multilayer feedforward neural networks is the back propagation network (BPN). An input layer with nodes representing the problem's input variables, an output layer with nodes representing the dependent variables under model, and hidden layers with nodes to help capture the nonlinearity in the data make up this structure. Supervised learning was used in this study. By employing examples, the networks can learn how to map one data space to another. The process by which the error calculated at the output side moves backward from the output layer to the hidden layer and then back to the input layer is known as back propagation. By doing this, there are no neuron-to-neuron connections within the same layer and all interconnections become unidirectional. As a result, the network receives the data without any feedback. Back propagation ANN, on the other hand, can have fully or partially linked neurons. The training diagram and the design of the artificial neural network that produced the best results are displayed in Figure 4.

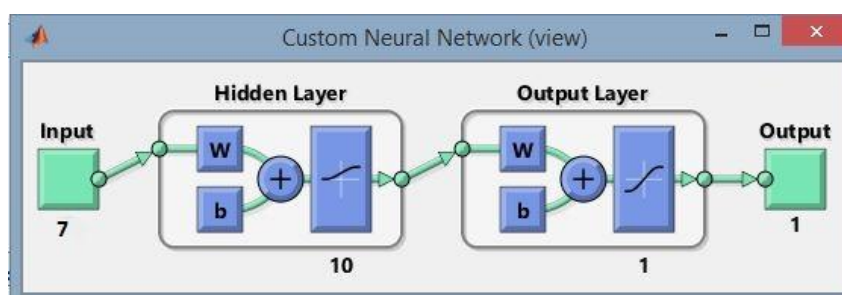


Figure 4. Artificial Neural Network Training Diagram

Validation of Artificial Neural Network (ANN) Model

The ability of the ANN model to assess and resolve the issues found is determined by its validation. The built ANN was validated in this study using the performance evaluation findings of the pyrolysis of various masses of PW. Data on several statistically significant measures, such as the model's performance, gradient, MSE, regression plots, coefficient of determination (R^2), plot error histogram, and plot regression, are available in the neural network toolbox in MATLAB R2022b. The R^2 can be found using equation (1).

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = \frac{\sum_{i=1}^m (P_i - M_i)^2}{(M_i - \bar{M})^2} \quad (1)$$

Where the sum of squares of residuals is denoted by SS_{res} and the sum of squares of deviations by SS_{tot} . P_i stands for the expected value of point i in the model, M_i for the measured value of point i , $\bar{M}$ for the mean of the measured value, and m for the number of measurements. The RMSE calculation results are shown in equation (2).

$$RMSE = \sqrt{MSE} = \sqrt{\sum_{i=1}^m \frac{(P_i - M_i)^2}{m}} \quad (2)$$

Where m is the number of measurements, M_i is the measured value of point i , P_i is the model predicted value of point i , and MSE is the Mean Square Error. The percentage prediction error, a frequently used metric to evaluate prediction accuracy, can be obtained using equation (3). A smaller prediction error value indicates higher accuracy. Point i 's measured value is denoted by M_i , while its anticipated value is represented by P_i .

$$Prediction\ error\ (\%) = \frac{M_i - P_i}{M_i} \times 100\% \quad (3)$$

Results and Discussion

Results

The regression model for the training, testing, validating, and overall phases of the ANN is displayed in Figure 5. The datasets are tested and evaluated to provide the output parameters (POY). The pyrolysis oil production was predicted using the MATLAB R2022b toolbox. The dataset was loaded into the MATLAB toolbox. To achieve a useful or almost optimal result, 20% of each dataset has been sectioned for testing and validation, while 60% of the dataset has been sectioned for training. The Levenberg-Marquardt algorithm is used to forecast the output parameters. The network consists of an output layer (pyrolysis oil yield) and a hidden layer with ten (10) hidden neurons apiece. The linear function "purelin" serves as the activation function, and the sigmoid "tansig" transfer function is employed in the hidden layer. Temperature (T), pressure (P), particle sizes (PS), flow rate (FR), residence time (RT), heating rate (HR), and plastic waste feedstock (PW) were the input sets that were utilized.

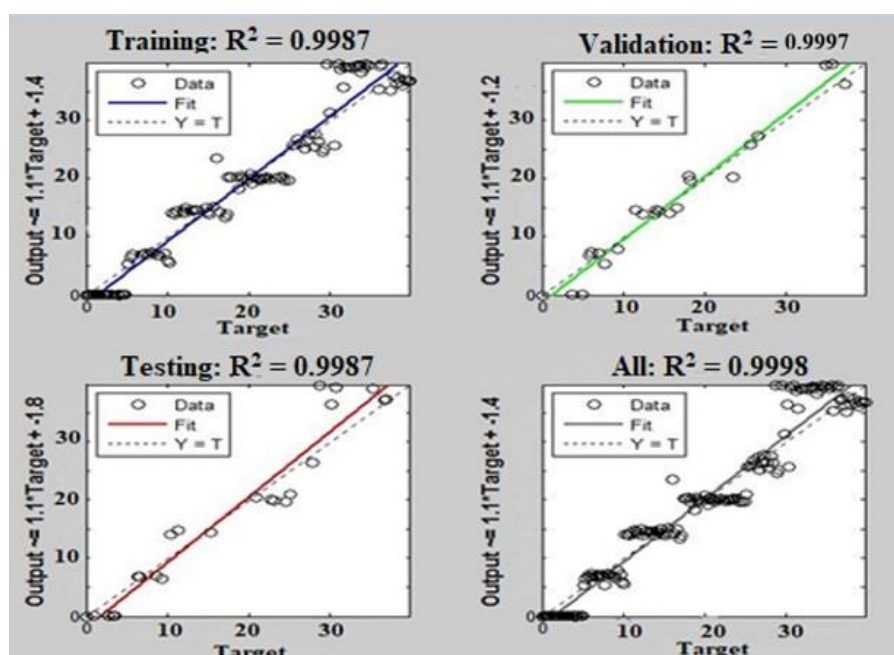


Figure 5. Regression plot of ANN for training, testing and validation

Figure 6 displays the MSE for the training, testing, and validation of the ANN model with respect to the epoch.

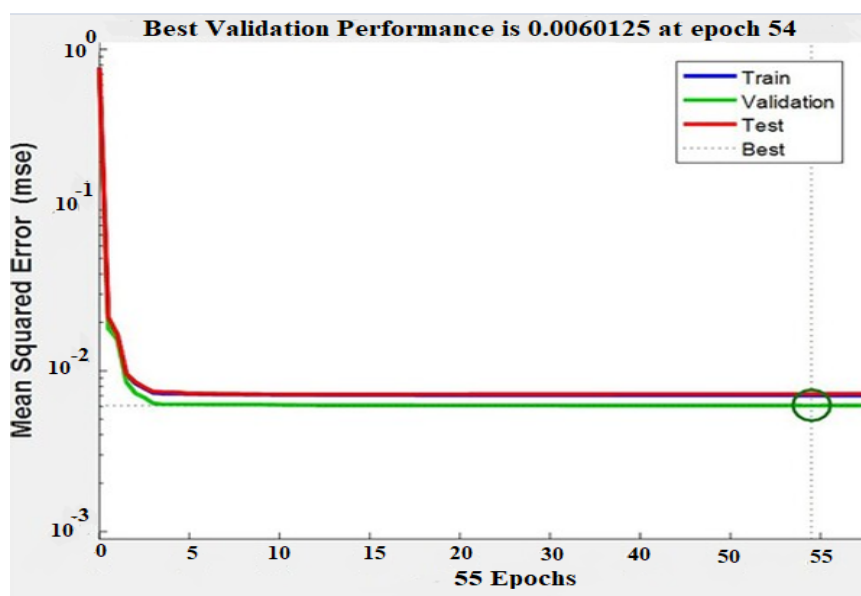


Figure 6. MSE ANN performance validation plot

Figure 7 and Table 2 illustrate the relationship between the data utilized for validation and the estimated pyrolysis oil yield estimates.

Table 2. Results of actual performance test results versus predicted pyrolysis oil yields by ANN

Weight of PWs (kg)	Actual POY	ANN Predicted POYs
0.00	0.00	0.00
0.50	0.49	0.50
0.50	0.49	0.51
0.55	0.49	0.58
0.80	0.79	0.80
0.80	0.79	0.81
0.80	0.79	0.80
1.20	1.20	1.25
1.20	1.20	1.24
1.20	1.20	1.25
1.21	1.21	1.26
1.21	1.21	1.26
1.40	1.39	1.40
1.40	1.39	1.40
1.40	1.38	1.40
1.41	1.40	1.41
1.41	1.39	1.41
1.70	1.69	1.70
1.70	1.69	1.70
1.71	1.71	1.71
1.71	1.71	1.71
1.90	1.89	1.99
1.90	1.89	1.90
1.91	1.99	1.90
1.91	1.99	1.91
2.10	2.07	2.13
2.10	2.06	2.12
2.10	2.06	2.13
2.11	2.07	2.13
2.11	2.06	2.14
2.30	2.28	2.31
2.30	2.28	2.31
2.31	2.29	2.30
2.31	2.30	2.31
2.31	2.29	2.31
2.40	2.38	2.41
2.40	2.38	2.40
2.41	2.39	2.41
2.41	2.40	2.42

Weight of PWs (kg)	Actual POY	ANN Predicted POYs
2.60	2.59	2.62
2.60	2.59	2.62
2.61	2.60	2.63
2.61	2.60	2.64
2.70	2.68	2.69
2.70	2.68	2.70
2.71	2.69	2.70
2.71	2.69	2.71
2.90	2.89	2.92
2.90	2.89	2.92
2.91	2.90	2.92
2.91	2.90	2.93
3.10	3.08	3.10
3.10	3.09	3.12
3.11	3.10	3.12
3.11	3.10	3.13
3.30	3.28	3.29
3.30	3.28	3.29
3.30	3.29	3.30
3.30	3.29	3.30
3.60	3.58	3.59
3.90	3.88	3.89
3.90	3.88	3.90
3.91	3.89	3.95
3.91	3.90	3.98
4.10	4.09	4.10
4.10	4.09	4.10
4.11	4.10	4.10
4.11	4.09	4.11
4.30	4.28	4.29
4.30	4.29	4.30
4.31	4.29	4.30
4.31	4.30	4.31
4.70	4.69	4.70
4.70	4.68	4.69
4.71	4.69	4.70
4.71	4.69	4.70
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5.00	4.98	5.00
5.00	4.98	5.10
5.00	4.99	5.10

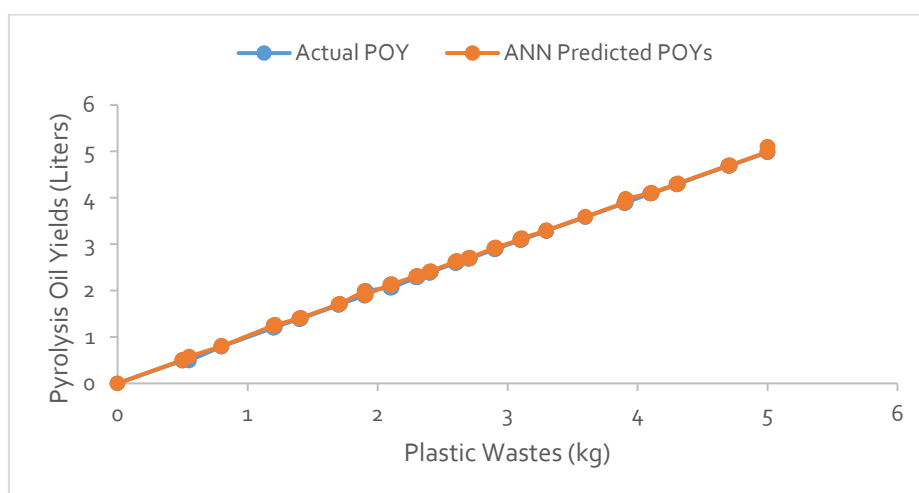


Figure 6. Evaluation of actual performance test results versus predicted pyrolysis oil yields by ANN

Discussion

Pyrolysis results are greatly influenced by operational factors like temperature, pressure, and residence duration. Longer residence times and lower temperatures promote the creation of oil, whereas higher temperatures promote the development of gas. Optimal parameter changes can boost pyrolysis efficiency and product yields while preserving environmental sustainability. The four plots in Figure 5 display excellent results, with an R^2 value that is nearly equal to 1. The R^2 values comprise training (0.9987), validation (0.9997), testing (0.9987), and the total (0.9998) value. The R^2 's proximity to 1 indicates a proper relation model between the expected values and the actual output. These findings are consistent with a study by Abnisa *et al.* (2019) that used artificial neural networks (ANN) to examine the composition yield for the pyrolysis of plastic wastes, such as HDPE, LDPE, PP, and PS, in a fixed bed reactor. As per Yel *et al.* (2018); Abnisa *et al.* (2019), the model can be considered accurate and successful if it has a coefficient of determination R^2 value near 1 and a very low mean square error. Thus, it may be concluded that the architecture of the neural network model produces a satisfactory linearity with the intended values. For generalization purposes, the total R^2 value was used to evaluate the system's performance before accounting for the MSE. As a result, the run with the highest overall R^2 value was chosen as the best model for predicting the oil output from pyrolysis. However, the preferred model was expressly chosen using the sum of the R^2 values from each experiment. The pyrolysis oil quality's best overall R^2 value is 0.9998, which may suggest about 99.98% model performance. The best-performing model with the lowest validation phase means square error (MSE) and the highest overall coefficient correlation (R^2) was produced after the algorithm's development simulation was run. The simulation of the ANN model as depicted in Figure 6 shows that the best validation performance was seen at epoch 54, with a value of 0.0060125, when it was trained using Levenberg-Marquardt methods. The

performance function of MSE serves as an indicator for constructing the ideal ANN model, together with the coefficient of determination. The average difference of squared data between the computed and actual output values is measured statistically by the Mean Squared Error, or MSE. A lower MSE score indicates smaller errors when predicting the dataset's actual outcomes (Orhorhoro *et al.*, 2017; Lee *et al.*, 2021). The R^2 is the proportion of variance in the observable parameters that the independent variables predicted. In general, during the training phase, the MSE will be minimized by the coupling weight configurations of the ANN model. This neural network model function is used to provide the predictive model with good coefficient of determination values for the training, testing, and checking phases. Figure 6 demonstrates that ANN successfully predicted the PW yield from the pyrolysis process. This further confirmed the prediction power of ANN optimization.

As a risk function, the mean squared error (MSE) is a crucial estimator in mathematical optimization and decision theory. The ANN model yields a low MSE (0.006013) when estimating the output values of the answers, which leads to a decrease in error and variance. The fact that the ANNs were able to forecast and maximize pyrolysis oil yields suggests that they had a thorough understanding of the relationship between the reactor's input and the pyrolysis stream's output. Even if it is correct that ANN models are "black-box" in nature, which means they do not directly explain the underlying chemical processes (such bond formation or breaking). Large datasets are also necessary for them to avoid overfitting. Besides, in order to avoid overfitting, which occurs when a machine learning model learns the training data including its noise and outliers too well and performs badly on fresh, unknown data, large datasets are necessary. Large, varied datasets enable models to more effectively separate underlying patterns from random noise, improving generalization. More so, the model has learned underlying patterns rather than simply memorizing noise (overfitting) and this has been shown from the validation results. Thus, this study has demonstrated that using artificial neural networks (ANN) to model the pyrolysis of plastic waste is a highly successful, non-linear, "black-box" method that achieves high accuracy in forecasting product yields, and ideal operating parameters.

Conclusion

ANN was used to model and forecast the pyrolysis oil yield from collected PW. According to the results obtained, it can be deduced that the use of ANN to simulate the pyrolysis of PW are highly favorable, highlighting their accuracy, efficiency, and potential for waste to energy process optimization. The study also shows that ANN is a very powerful non-linear modeling method that can capture intricate, nuanced correlations between PW input parameters and POY. The model functions as a dependable instrument for real-time monitoring and early identification of possible quality deviations by precisely predicting POY from PW inputs. Besides, with correlation coefficients (R^2), the ANN model shows

outstanding ability in forecasting plastic pyrolysis results. The R^2 's proximity to 1 indicates a proper relation model between the expected values and the actual output. The POY best overall R^2 value is 0.9998, which may suggest about 99.98% model performance. Runs of the algorithm's development simulation yielded the best performing model with the lowest validation phase means square error (MSE) and the highest overall coefficient correlation (R^2). Even when the predictions marginally differ from the actual values, the model performs exceptionally well. Additionally, the ANN model yields a low MSE (0.006013) when estimating the output values of the responses, which translates to a decrease in error and variation. As a result, the ANN model was able to forecast and optimize POY, suggesting that the ANN had learned the relationship between reactor input and PW pyrolysis stream output. Therefore, ANN is an essential tool for enhancing the thermochemical valorization of PW into pyrolysis oil since it offers a highly accurate, efficient, and dependable alternative.

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References

- Abnisa, F., Anuar Sharuddin, S.D., Binzanil, M.F., Wan Daud, W.M.A., Indra Mahlia, T.M. (2019). The yield prediction of synthetic fuel production from pyrolysis of plastic waste by Levenberg–Marquardt approach in feedforward neural networks model. *Polymers (Basel)*, 11, 1853. <https://doi.org/10.3390/polym11111853>
- Al-Yaari, M., Dubdub, I. (2020). Application of artificial neural networks to predict the catalytic pyrolysis of HDPE using non-isothermal TGA data. *Polymers (Basel)*, 12, 1813. <https://doi.org/10.3390/polym12081813>
- Boes, J.R., Groenenboom, M.C., Keith, J.A., Kitchin, J.R. (2016). Neural network and ReaxFF comparison for Au properties. *Int J Quantum Chem.*, 116, 979–987. <https://doi.org/10.1002/qua.25115>
- Chen, W.H., Lin, B.J., Lin, Y.Y., Chu, Y.S., Ubando, A.T., Show, P.I., Ong, H.C., Chang, J.S., Ho, S.H., Culaba, A.B. (2021). Progress in biomass torrefaction: principles, applications and challenges. *Prog. Energy Combust. Sci.*, 82, 100887. <https://doi.org/10.1016/J.PECS.2020.100887>
- Conesa, J.A. Caballero, J.A. Reyes-Labarta, J.A. (2004). Artificial neural network for modelling thermal decompositions. *J. Anal Appl Pyrolysis*, 71, 343–352. [https://doi.org/10.1016/S0165-2370\(03\)00093-7](https://doi.org/10.1016/S0165-2370(03)00093-7)
- Conlon, K. (2021). A social systems approach to sustainable waste management: leverage points for plastic reduction in Colombo, Sri Lanka. *Int J Sustainable Dev. World Ecol.*, 1–19
- Erhinyodavwe, O., Orhorhoro, E.K., Amize, H. (2025). Categorization of Plastic Waste Generated for Conceptualization of Pyrolysis Plant Development in Agbor Town, Delta State, Nigeria. *J. Appl. Sci. Environ. Manage.* 29 (6), 1890–1897. <https://dx.doi.org/10.4314/jasem.v29i6.20>
- Emifoniye, E.U., Eramah, A.A., Orhorhoro, E.K. (2025a). Investigation of proximate and ultimate analysis of household generated plastic waste for feasible design of a pyrolysis pilot plant. *World Journal*

- of *Advanced Engineering Technology and Sciences*, 15(01), 2107-2118. <https://doi.org/10.30574/wjaets.2025.15.1.0416>
- Emifoniye, E.U., Erameh, A.A., Orhororo, E.K. (2025b). A Machine Learning Approach for Pyrolysis of Plastic Waste: An Overview of Types, and Applications. *International Journal of Scientific Research and Engineering Development*, 8(3), 27-39
- Eze, W.U., Madufor, I.C., Onyeagoro, G.N. (2020). The effect of Kankara zeolite-Y-based catalyst on some physical properties of liquid fuel from mixed waste plastics (MWP) pyrolysis. *Polym. Bull*, 77, 1399–1415
- Fazilat, H., Akhlaghi, S., Shiri, M.E., Sharif, A. (2012). Predicting thermal degradation kinetics of nylon6/feather keratin blends using artificial intelligence techniques. *Polymer (Guildf)*, 53, 2255-2264. <https://doi.org/10.1016/j.polymer.2012.03.053>
- Fivga, A., Dimitriou, I. (2018). Pyrolysis of plastic waste for production of heavy fuel substitute: A techno-economic assessment. *Energy*, 149, 865–74
- Foong, S.Y., Chan, Y.H., Cheah, Y.W., Kamaludin, N.K., Tengku Ibrahim, T.N.B., Sonne, C. (2021). Progress in waste valorization using advanced pyrolysis techniques for hydrogen and gaseous fuel production. *Bioresour Technol*, 320, 124299
- Fu, L., Xiong, Q., Wang, Q., Cai, L., Chen, Z., Zhou, Y. (2022). Catalytic Pyrolysis of Waste Polyethylene Using Combined CaO and Ga/ZSM-5 Catalysts for High Value-Added Aromatics Production. *ACS Sustain Chem Eng.*, 10, 9612–23
- Goldsmith, B.R., Esterhuizen, J., Liu, J.X., Bartel, J.C., Sutton, C. (2018). Machine learning for heterogeneous catalyst design and discovery. *AIChE J.*, 64, 2311–2323 <https://doi.org/10.1002/aic.16198>
- Haghighatlari, M., Hachmann, J. (2019). Advances of machine learning in molecular modeling and simulation. *Curr Opin Chem Eng.*, 23, 51–57. <https://doi.org/10.1016/j.cocoe.2019.02.009>
- Hough, B.R., Beck, D.A.C., Schwartz, D.T., Pfaendtner, J. (2017). Application of machine learning to pyrolysis reaction networks: Reducing model solution time to enable process optimization. *Comput. Chem Eng.*, 104, 56–63. <https://doi.org/10.1016/j.compchemeng.2017.04.012>
- Husin, H., Mahidin, M., Marwan, M., Nasution, F., Erdiwaysyah, E., Ahmadi, A., Muchtar, S., Yani, F.T., Mamat, R. (2023). Conversion of polypropylene-derived crude pyrolytic oils using hydrothermal autoclave reactor and Ni/aceh natural zeolite as catalysts. *Heliyon*, 9. <https://doi.org/10.1016/j.heliyon.2023.e14880>
- Istadi, I., Buchori, L., Suherman, S. (2011). Plastic waste conversion to liquid fuels over modified residual catalytic cracking catalysts: modeling and optimization using hybrid artificial neural network genetic algorithm, *Reaktor*, 13, 131. <https://doi.org/10.14710/reaktor.13.3.131-139>
- Kedzierski, M., Lechat, B., Sire, O., Le Maguer, G., Le Tilly, V., Bruzard, S. (2020). Microplastic contamination of packaged meat: Occurrence and associated risks. *Food Packag. Shelf Life*, 24, 100489
- Khan, M., Raza Naqvi, S., Ullah, Z., Ali Ammar Taqvi, S., Nouman Aslam Khan, M., Farooq, W., Taqi Mehran, M., Juchelková, N., Stepanec, L. (2023). Applications of machine learning in thermochemical conversion of biomass-a review. *Fuel*, 332, 126055. <https://doi.org/10.1016/J.FUEL.2022.126055>
- Lee, S., Kim, J., Kang, H., Kang, D.Y., Park, J. (2021). Genetic algorithm based deep learning neural network structure and hyperparameter optimization. *Appl Sci.*, 11, 744. <https://doi.org/10.3390/app11020744>
- Li, Y., Tao, L., Wang, Q., Wang, F., Li, G., Song, M. (2023). Potential Health Impact of Microplastics: A Review of Environmental Distribution, Human Exposure, and Toxic Effects, *Environ. Health*, 1, 249–257. <https://doi.org/10.1021/envhealth.3c00052>

- Lomonaco, T., Manco, E., Corti, A. (2020). Release of harmful volatile organic compounds (VOCs) from photodegraded plastic debris: A neglected source of environmental pollution. *Journal of Hazardous Materials*, 394, 122596
- Meys, R., Frick, F., Westhues, S., Sternberg, A., Klankermayer, J., Bardow, A. (2020). Towards a circular economy for plastic packaging wastes – the environmental potential of chemical recycling, *Resour. Conserv. Recycl.*, 162, 105010
- Mighani, M., Shahi, A., Antonioni, G. (2017). Catalytic pyrolysis of plastic waste products: time series modeling using least square support vector machine and artificial neural network. In: 16th International Conference on Sustainable Energy Technologies, Bologna
- Olivera, M., Musso, M., De Leon, A., Volonterio, E., Amaya, A., Tancredi, N., Bussi, J. (2020). Catalytic assessment of solid materials for the pyrolytic conversion of low-density polyethylene into fuel. *Heliyon*. <https://doi.org/10.1016/j.heliyon.2020.e05080>
- Orhorhoro, E.K., Ikpe, A.E., Tamuno, R.I. (2016). Performance Analysis of Locally Design Plastic Crushing Machine for Domestic and Industrial Use in Nigeria. *Euro. J. Eng. Res. Sci.*, 1(2), 26-30. <https://ej-eng.org/index.php/ejeng/article/download/153/49>
- Orhorhoro, E.K., Ebunilo, P.O., Sadjere, E.G. (2017). Development of a Predictive Model for Biogas Yield Using Artificial Neural Networks (ANNs) Approach. *American Journal of Energy and Power Engineering*, 4(6), 71-77
- Orhorhoro, E.K., Emifoniye, E.U., Okuma, S.O. (2023a). Prediction of the Tensile Strength of an Experimental Design Reinforce Polyvinyl Chloride Composite using Response Surface Methodology. *Jordan J. Mech. Indust. Eng.*, 17(3), 403–412. <https://doi.org/10.59038/jjmie/170309>
- Orhorhoro, E.K., Emifoniye, E.U., Okuma, S.O. (2023b). Numerical Optimization of the Input Factors and Responses of an Experimental Design Reinforce PVC Composite. *J. Adv. Mech. Eng. Appl.*, 4(2), 38-48. <https://doi.org/10.30880/jamea.2023.04.02.006>
- Orhorhoro, E.K., Tamuno, R.I., Azuka, J.C. (2023c). Development of Variance Model for the Prediction of Water Absorption and Thickness Swelling for an Experimental Designed PVC Reinforced Composite Pipes. *Appl. Res. Smart Tech.*, 4(1), 16-24, <https://doi.org/10.23917/arstech.v4i1.1435>
- Orhorhoro, E.K., Oghoghorie, O., Igbagbon, J.E. (2025a). Microplastics Impact on Aquaculture Environment: An Overview of Generation, Removal Techniques, Policies, and Prospects, The 3rd International Conference of The National Institute of Professional Engineers and Scientists (NIPES) in collaboration with National Centre for Energy & Environment, Energy Commission of Nigeria (NCEE) 9th-11th April. 2025, University of Benin, Nigeria www.nipes.org
- Orhorhoro, E.K. (2025b). A review of plastic waste management for a sustainable environment: Composition and approaches. *European Journal of Sustainable Development Research*, 9(3), em0314. <https://doi.org/10.29333/ejosdr/16359>
- Orhorhoro, E.K., Erameh, A.A., Emifoniye, E.U. (2026a). Management of Plastic Waste using Pyrolysis Approach, Scholar Press, 120 High Road, East Finchley, London, N2 9ED, United Kingdom, ISBN-978-620-9-59810-4
- Orhorhoro, E.K., Erameh, A.A., Emifoniye, E.U. (2026b). Assessment of the Effectiveness of a Miniature Pyrolysis Pilot Plant Developed to Manage Plastic Waste Generated in Ovia North-East LGA, Nigeria. *Advanced Engineering Forum*, 58, 139-156. <https://doi.org/10.4028/p-3mInKG>
- Pal, S., Kumar, A., Sharma, A.K., Ghodke, P.K., Pandey, S., Patel, A. (2022). Recent Advances in Catalytic Pyrolysis of Municipal Plastic Waste for the Production of Hydrocarbon Fuels, *Processes*, 2022, 10, 1497
- Pan, D., Su, F., Liu, C., Guo, Z. (2020). Research progress for plastic waste management and manufacture of value-added products. *Adv. Compos. Hybrid Mater.*, 3, 443–461. <https://doi.org/10.1007/s42114-020-00190-0>.

- Peng, Y., Wang, Y., Ke, L. Dai, L., Wu, Q., Cobb, K. (2022). A review on catalytic pyrolysis of plastic wastes to high-value products. *Energ Conver Manage*, 254, 115243
- Shen, M., Huang, W., Chen, M., Song, B., Zeng, S., Zhang, Y. (2020). (Micro)plastic crisis: un-ignorable contribution to global greenhouse gas emissions and climate change. *J. Clean. Prod.*, 254, 2020, 120138.
- Seo, M.W., Lee, S.H., Nam, H., Lee, D., Tokmurzin, D., Wang, S., Park, Y.K. (2022). Recent advances of thermochemical conversion processes for biorefinery. *Bioresour. Technol.*, 343, 126109. <https://doi.org/10.1016/J.BIORTECH.2021.126109>
- Shi, M., Sun, Y., Wang, Z., He, G., Quan, H. He, H. (2019). Plastic film mulching increased the accumulation and human health risks of phthalate esters in wheat grains. *Environ. Pollut.*, 250, 1–7
- Teymourian, T. Teymoorian, T., Kowsari, E., Ramakrishna, R. (2021). Challenges, strategies, and recommendations for the huge surge in plastic and medical waste during the global COVID-19 pandemic with circular economy approach. *Mater. Circ. Econ.*, 3(1), 6.
- Torres-Agullo, A. Karanasiou, A., Moreno, T., Lacorte, S. (2021). Overview on the occurrence of microplastics in air and implications from the use of face masks during the COVID-19 pandemic. *Sci. Total Environ.*, 800, 149555. <https://doi.org/10.1016/j.scitotenv.2021.149555>
- Vogt, B.D., Stokes, K.K. Kumar, S.K. (2021). why is recycling of postconsumer plastics so challenging? *ACS Appl. Polym. Mater.*, 3 (9), 4325–4346
- Wang, G., Dai, Y., Yang, H., Xiong, Q., Wang, K., Zhou, J., Li, Y., Wang, S. (2020). A review of recent advances in biomass pyrolysis, *Energy Fuels*, 34, 15557–15578. <https://doi.org/10.1021/ACS.ENERGYFUELS.0C03107/ASSET/IMA>
- Wojnowska-Baryła, I., Kulikowska, D., Bernat, K. (2020). Effect of bio-based products on Waste Management. *Sustainability*, 12, 2088. <https://doi.org/10.3390/su12052088>
- Yel, E., Tezel, G., Uymaz, S.A. (2018). ANN modelling for predicting the water absorption of composites with waste plastic pyrolysis char fillers. *Data Sci Appl.*, 1, 45–51
- Zhang, S.U. (2018). Degradation classification of 3D printing thermoplastics using fourier transform infrared spectroscopy and artificial neural networks. *Appl Sci.*, 8, 1224. <https://doi.org/10.3390/app8081224>