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Review on Artificial Neural Network and its Application in the Field of Engineering

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Abstract - The engineers have been utilising artificial neural networks (ANNs), one of the most effective and adaptable tools offered by artificial intelligence, for many years in a variety of applications. A simple mathematical model of brain functions is provided by ANNs, which are computational tools. They can be used for tasks like modelling, categorisation, and prediction when combined with raw data and a learning system. They have recently experienced a sharp increase in popularity and are currently among the most important study topics in the disciplines of artificial intelligence and machine learning. Large groups of basic classifiers known as neurons make up an ANN. Chemical engineers use them to automate process controls, model complex linkages, and forecast reactor performance. Large data sets can benefit from ANNs' capacity for learning, but these systems can also overfit or become stuck in local minima and are challenging to reverse engineer. The function of artificial neural networks (ANNs) in chemical engineering is explored in this article. For creating chemical engineering processes, the ANN is quite helpful. The process is very quick and trustworthy. We also gathered several journal publications and current research articles, summarising the use of ANN in various chemical engineering fields and its processes.

Keywords - **ANN, mathematical modelling, process systems engineering, surface methodology, statistical theory.**

INTRODUCTION

A mathematical model or computer model that is inspired by the structure and/or functional characteristics of biological neural networks is known as an artificial neural network (ANN), sometimes known as a neural network (NN) [1]. A neural network uses a connectionist method of computation to process information and is made up of a network of artificial neurons that are connected to one another. In the majority of cases, an ANN is an adaptive system that modifies its structure in response to input coming from the outside or inside the network during the learning period. Tools for non-linear statistical data modelling include modern neural networks. They are typically applied to identify patterns in data or to model intricate relationships between inputs and outputs.

The study of central nervous systems and their neurons, axons, dendrites, and synapses—which make up the processing components of biological neural networks under investigation by neuroscience—provided the initial inspiration for the term Artificial Neural Network. The term "artificial neural network" refers to a network of nodes that mimics the biological neural networks. Simple artificial nodes, also known as "neurons", "neurodes", "processing elements" (PEs), or "units," are connected together to create an artificial neural network. The biological network and this share some similarities. Currently, neural network models used in statistics, cognitive psychology, and artificial intelligence are most often referred to as artificial neural networks (ANNs). Theoretical and computational neuroscience are concerned with neural network models created with simulation of the central nervous system (CNS) in mind.

There has been a good amount of literature produced on neural networks since the development of parallel distributed processing [2]. It is particularly challenging to comprehend the abundance of available information because neural networks are applied to such a diverse range of topics. To understand where the evolution of neural networks began, a concise history of neural networks has been provided. To prove the necessity of the suggested work in this study, papers on numerous themes relevant to it are described in depth.

In order to deal with the nonlinear, uncertain, complicated, and multivariate nature of biodiesel/bio-lubricant systems, data-driven machine learning (ML) technology provides a possible alternative to standard modelling methodologies [3]. Artificial neural network (ANN) technology is the most popular ML methodology currently being employed in biodiesel/bio-lubricant research [3–7]. A strong modelling method, ANN can model without making assumptions about the nature of phenomenological mechanisms, understand the mathematical underpinnings of the process, and learn both linear and nonlinear correlations between variables directly from a series of examples [8]. As a result, the next section provides a quick overview and description of the ANN technique.

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An artificial neural network (ANN) is a computational model made up of thousands of single units that are inspired by biological neurons and coupled by coefficients (weights) to construct the neural network [9]. Because of how they process information, these neurons are sometimes referred to as processing elements (PE). To calculate the neuron's level of activity, the weights of the inputs are added and the threshold removed [10]. The ability of neural networks to learn the link between input and output through training is another crucial feature [9]. When compared to statistical methods, ANN analysis is more flexible in terms of the quantity and nature of the training (experimental) data, allowing for the use of less formal experimental designs [10]. Before the construction of a network, a neural network does not require any modelling or screening. Neural networks can be used on data that has been designed or on data that hasn't been statistically designed. To create a neural network, sufficient data with all potential input variable operational circumstances are required. Next, a network model is built using the system's behaviour [11]. Within the given operating circumstances, the created model may be applied to predictions and other tasks. Less significant components are excluded from the model since the regression analysis depends on specified statistically significant levels. The model is more accurate since ANN makes use of all the data. Tasks that linear programming is unable to complete can be carried out using a neural network. Due to its parallel architecture, the neural network can still complete the task even if one of its components fails, necessitating no reprogramming [5]. The primary drawback of ANN is that it needs training to operate. Because a neural network's architecture differs from that of a microprocessor, where a large network requires a lot of processing time, a neural network must be imitated [12]. The use of various architectures in ANN may also necessitate the use of various algorithms [6]. The non-linear structure of the connections in the biochemical network makes it particularly difficult to create realistic models for biological reactions on chemical and physical basis. The use of advanced non-linear data analysis techniques such as ANN has been applied in various areas such as food science [13], biotechnology [14], chemical processes [8], equipment development [10], and biochemical engineering [15]. Comparative studies of ANN and RSM for fermentation processes employing wild strains have been reported [16]. Quite an increasing number of researchers around the globe have started to employ RSM and ANN as tools to predict and optimise biodiesel as well as bio-lubricant synthesis processes, as found in the following examples of work: bio-lubricant production using Novozym 435 and castor oil substrate [6], performance and exhaust emissions of a SI two-stroke engine with bio-lubricants [7], biodiesel production from castor oil [17], microwave mediated production of FAME from waste cooking oil [18], sustainable green lubricants by advance transesterification process [19], and optimisation of sustainable production of cotton bio-lubricant [5]. The data and outcomes from the use of RSM and ANN are better in terms of their sensitivity analysis. Figure 1 depicts a schematic representation of the comparison between a biological neuron and an artificial neuron [3,20].

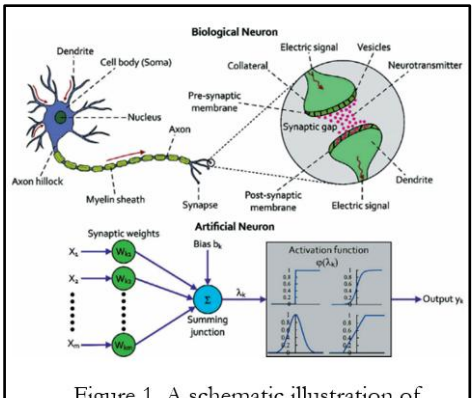

Figure 1. A schematic illustration of the analogy between a biological neuron and an artificial neuron.

HISTORY OF NEURAL NETWORKS

The effort to model the neuron can be linked to the development of neural networks. Physiologists McCulloch and Pitts created the first model of a neuron in 1943 [21]. They produced a model with two inputs and one output. McCulloch and Pitts observed that if only one of the inputs was active, a neuron would not activate. Each input had equal weights, and the output was binary. The output would be zero up until the sum of the inputs reached a predetermined level. Modern terminology refers to the McCulloch and Pitts' neuron as a logic circuit.

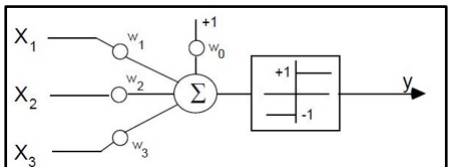

Figure 2. The Perceptron; x is the input vector of the node, w is the vector of weights of the node, y is the output of the node.

Figure 2 illustrates the perceptron, which was created as the following model of the neuron by Rosenblatt (1958) [22]. In order to create "learning", physiologist Rosenblatt randomly connected the perceptrons and changed the weights through trial and error. Ironically, the perceptron is a considerably worse model than the McCulloch and Pitts' neuron for the electrochemical activity that takes place inside the neron.

A neuron's electrochemical mechanism functions similarly to a voltage-to-frequency converter [23]. The inputs to the neuron trigger a chemical reaction, and the neuron discharges when the chemical reaction reaches a specific threshold. The magnitude of the neuron's output remains constant even if the neuron fires more frequently in response to increased input levels (Figure 3). The perceptron is a relatively straightforward mathematical model of the neuron.

The weight space concept was introduced to the perceptron by Selfridge in 1959 [24]. Rosenblatt experimented with several

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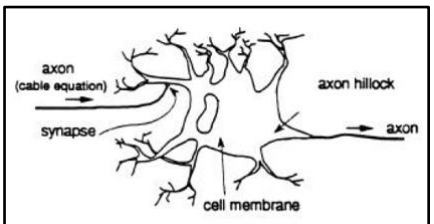

Figure 3. The Neuron.

weight adjustments [22]. Selfridge changed the weights by selecting a direction vector at random. The weights were reset to their initial levels and a new random direction vector was selected if the performance did not improve. This procedure was referred to as "climbing the 7 mountain" by Selfridge.

The weights can be adjusted using a mathematical technique created by Widrow and Hoff in 1960 [25]. A gradient search strategy was used, which was predicated on minimising the error squared, assuming that the desired response existed. LMS, or least mean squares, is the name given to this method in the future. LMS and its variants have been widely employed in a range of applications, particularly in recent years. This gradient search strategy gave mathematicians a way to find an answer with the least amount of error. There was no trial-and-error component to the learning process. Selfridge's work reduced the computational time, but the LMS method further cut the computational time, making the usage of perceptrons possible.

The research was abruptly stopped by one book, Perceptrons (Minsky and Papert, 1969) [26]. The book makes the claim that perceptrons could only resolve problems with linear separability. One node represents a perceptron. According to perceptrons, n-1 nodes are required to solve an n-separable issue. Only 2-separable or linearly separable problems could thus be solved by a perceptron. After the publication of Perceptrons, funding for neural network research stopped, and it would continue to do so until a solution to n-separable problems was found. The back propagation algorithm was created for the first time by Werbos in 1974 [27]. Then, concurrently, Parker (1985) and Rumelhart and McClelland (1986) independently rediscovered it [28,29].

An outstanding source of the work completed before to 1986 is A foundation of Research (Anderson and Rosenfeld, 1987) [23]. It is a compilation of publications that provides a fascinating summary of what happened in the field of neural networks prior to 1986. Despite the fact that the golden age of neural network research came to an end 25 years ago, the discovery of back propagation has revived this field of study.

PROPERTIES OF ANNS

- Learning from examples: labelled or unlabelled
- Adaptively: changing the connection strengths to learn things
- Non-linearity: the non-linear activation functions are essential
- Fault tolerance: if one of the neurons or connections is damaged, the whole network still works quite well

They might be better alternatives than classical solutions for problems characterised by:

- Nonlinearities
- High dimensionality
- Noisy, complex, imprecise, imperfect and/or error prone sensor data
- A lack of a clearly stated mathematical solution or algorithm

RESEARCH AND APPLICATION OF ANN IN THE FIELD OF CHEMICAL ENGINEERING

Main applications of ANN in the field of chemical engineering are

- fault detection
- prediction of quality
- data rectification
- modelling and control

For the application of ANN in the field of chemical engineering, various studies have been conducted. These are listed below: Without incorporating any explicit representations of the rules, artificial neural network models, according to Himmelblau et al. in 1988, demonstrate the rule-following behaviour of knowledge-based expert systems [30]. The neural network model relies on a number of extremely basic neuron-like processing components that interact locally through a series of unidirectional weighted connections in place of explicit rules. Internally, knowledge is represented by the weights' values and the connections' topologies. The connection weights are modified as a result of learning. Complex engineering systems, which are challenging to model using either conventional model-based engineering or knowledge-based expert systems, can be represented by networks that can learn from and adapt to inputs from the actual processes. The properties of neural networks deemed suitable for knowledge representation in chemical engineering processes are described in this paper. It offers a neural network design and simulation environment that may be used for experimentation and discusses the properties of neural networks with a focus on the nodes, the connections, and their capacity for learning. They use a straightforward chemical engineering procedure to show how an artificial neural network may successfully learn and differentiate between errors in order to teach the

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principles. The outcomes of a hybrid neural model (HNM) technique applied to modelling supercritical fluid extraction (SCFE) curves derived from two Brazilian vegetable matrices (pepper and Brazilian rosemary oil) are presented by Fonseca et al. in 1999 [31]. A neural network is used by the serial HNM in use to estimate phenomenological model parameters. For each vegetable, they produced a tiny set of SCFE data. Then they cross-checked the results with other widely used results. The HNM displays strong agreement with the experimental data, and it is demonstrated that the predictions made using this method may have promise for SCFE applications.

The diagnosis of chemical kinetics in chemical plants can be seen as a process of classification, according to Iordache et al. (1993) [32]. Recorded data can be connected to several kinetic model types, and the kinetic model type can be identified through comparison with previously recorded data. It is suggested that a new neural network (NN) frame be used to perform the categorisation. This study looks into the possibility of this adaptive, hierarchised frame set up as a "polystochastic" model. This method is based on comparing the separations between two observed kinetic data pathways. A set of potential kinetic models yields a matrix of distances, and algorithms for categorising models are created using this matrix. Between two distance matrices, a different kind of distance—an informational type—is proposed in order to compare one classification to another or to a reference classification. It is suggested and put to the test how to train the internet using informational criteria. The limited number of resulting weights are modified through a quick adaptive process to take reference cases into account. The kinetic modelling of a fermentation process serves as an example of the net's usefulness. Another conventional net is also compared with this one.

Chemical engineering neural network modellers often concentrate on selecting and applying a single, presumably ideal, neural network model [32]. Using a single optimal model implicitly presupposes that all the information in a given data set can be extracted by a single neural network model and that the other potential models are redundant. In general, there is no guarantee that any one model has taken all of the pertinent data out of the data set. Wolpert (1992) recently advanced the concept of stacking generalisation to bring together various models [33]. By fusing many neural networks into a structure known as stacked neural networks, Sridhar et al. (1999) created the stacking generalisation for neural network models (SNNs) [34]. SNNs, which combine candidate neural networks, have been demonstrated to provide better chemical process modelling. But in Sridhar's research, SNNs could only combine linear artificial neural networks.

According to Stich et al. (2000) [35], heat was used throughout the induction hardening procedure [35]. In order to surface-harden the metal, heat was produced by directing high frequency induced electrical currents across the chosen area. This study has demonstrated the potential for enhancing product quality and strengthening process control during induction hardening. The tools utilised in a closed-looped system for automated control of the process were a prediction neural network and a feedback neural network. 32 sets of the original process data were used to evaluate the prediction neural network. Each data set included two inputs: the motor speed (RPM) and the part temperature (°F). The prediction neural network then returned the output hardness value for each data set. The procedure was significantly improved by utilising the technique proposed in this study. In validations 1 and 2, the capability index of the process centre (CPK) more than doubled and improved by more than 80%.

In this study, a chaotic system with quantifiable state variables was found by Hwi et al. (2001) [36]. The state variable has fewer degrees of freedom than the tile. They coupled dynamic training with the Artificial Neural Network (ANN) approach. Embedded trajectories are used to validate the discovered models rather than the more traditional Sum of Square Errors method (SSE). When there is no exogenous input, they compared the maximum Lyapunov exponent and the correlation dimension, and when there is, they compared the bifurcation diagram. The largest Lyapunov exponent and correlation dimension for the original system were 0.004 and 1.53, respectively, and 0.019 and 1.07 for the ANN system with h=5. By using bifurcation analysis, they forecast the qualitative shifts in the original system's nonlinear behaviour when the control input is changed (exogenous input). No isothermal, irreversible, first-order series reaction in a CSTR is demonstrated using this technique.

The development of artificial neural network (ANN) models for three steady state chemical engineering systems—a crude oil distillation column for real-time optimisation, the physical characteristics of palm oil constituents, and pore size determination for membrane characterisation—is presented in this paper [36]. Diverse ANN applications to represent steady state systems have been on the rise.

The breakdown of organic matter in starch wastewater treated in an inverse fluidised bed reactor was successfully predicted in this work using radial basis network function [37]. The suggested method, which makes use of the radial basis function, may predict the behaviour of the system with a small number of trial data. Without prior knowledge of the correlations of the process variables under consideration, a straightforward well-trained neural network can be used to solve the reactor modelling issues. To anticipate the performance of the Inverse Fluidized Bed Bioreactor (IFBBR), the starting substrate concentration (2250 mg COD/L, 4475 mg COD/L, 6730 mg COD/L, and 8910 mg COD/L) and hydraulic retention duration were varied

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continuously in different stages (40, 32, 24, 16 and 8 h). Several experimental runs were carried out to gather data on the behaviour of the process and to train the network. Absolute standard deviation (ABSD) was 25.56 for substrate concentration, 2250 mg COD/L, and HRT 40 h, while root mean square error (RMSE) was 5.32 %. Absolute standard deviation (ABSD) was 219 for substrate concentration, 8910 mg COD/L, and HRT 8 h, and root mean square error (RMSE) was 4.81 %.

The fundamental goal of this study, according to Chetouani (2007) [38], is to construct a trustworthy model for both the steady-state and unsteady-state regimes of a nonlinear process. The application of this model should mirror the process' actual behaviour under typical operating settings and enable the distinction between a normal mode and an abnormal mode. In this study, the neural black-box identification using a NARMAX model has been adopted to produce this trustworthy model for the process dynamics. The modelling research demonstrates the neural network's selection and functionality during the training and testing phases. Additionally, a study is done on how the hidden neurons, time delay, and input choices affect how the neural estimator behaves. A mixture to be separated (toluene-methylcyclohexane) with a mass composition of 23 % methylcyclohexane is present in the feed tank. The experimental findings are validated using three statistical criteria. A Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) is trained with input-output experimental data to implement the model.

LABVIEW is a graphical programming language with origins in automation control and data capture, according to Canete et al. (2008) [39]. In this study, they had made use of this platform to offer a potent toolkit for the process identification and management of nonlinear systems based on ANNs (ANN). The monitoring and management of a DELTALAB DC-SP laboratory-scale distillation column had been done using this technology. The suggested control strategy gives zero stationary error for dual composition control and high speed of response for set point adjustments.

In this study, Dabhade et al. (2008) [40] discuss the application of the actinomycete N. hydrocarbonoxydans (NCIM 2386) for the degradation of phenol. In order to ensure that microorganisms and the substrate came into contact effectively, N. hydrocarbonoxydans was immobilised on GAC and employed in a spouted bed contactor. By adjusting the contactor's flow rates, influent concentrations, and solids loading, the performance of the contactor was examined. An artificial neural network was used in a modelling research to examine the impact of these variables on phenol degradation (ANN). The model was developed using a feed forward neural network with back propagation. The face centred cube design (FCCD) was used to plan the trials, and the results from four further experimental runs were utilised to evaluate and validate the model. Based on the mean square error, the network's number of neurons was optimised. The effluent concentration for the specified operating parameters in the spouted bed contactor was found to be accurately predicted by the ANN model with three layers, three input neurons, eight neurons in hidden layers, and one output neuron. For this ANN model, the mean square error was found to be 9.318×10^{12}. Additionally, using multiple regression (MR) and experimental data, a second order nonlinear empirical model was developed. The results were compared to ANN using the correlation coefficient (R^2), average absolute error (AAE), and root mean square error (RMSE). Results indicate that the MR model's R^2, AAE, and RMSE values were 0.93, 2.08, and 2.33 % respectively, whereas the ANN model's values were 0.99, 0.59, and 1.26 %. This demonstrates that ANN model prediction is superior to that of multiple regression model.

Ghanta et. al (2008) [41] outline a reliable hybrid artificial neural network (ANN) methodology in this paper that can provide superior performance for significant process engineering challenges. For effective tuning of ANN Meta parameters, the method uses a hybrid artificial neural network and differential evolution technique (ANN-DE). For the purpose of predicting the pressure drop of a solid-liquid slurry flow, the algorithm has been used. They conducted a comparison with a few chosen relationships. It demonstrated that throughout a wide range of operating conditions, physical characteristics, and pipe diameters, the established ANN correlation significantly enhanced the prediction of pressure declines.

Due to their excellent efficiency and longevity, diesel engines are growing in popularity. Unfortunately, the diesel engine produces a lot of nitrogen oxides (NO_x) [42]. In order to meet ever-stricter emissions rules while achieving ever-increasing efficiency increases, close control of combustion in the engine will be necessary. In this study, artificial neural networks (ANNs) were trained on experimental data and utilised to forecast nitrogen oxide (NO_x) emissions under different operating conditions. The tests were conducted using a stationary, light-duty Nissan diesel engine test rig that was built and configured to enable testing of the engine in a lab setting. The operating parameters and exhaust emissions of the engine were measured using industry-standard laboratory techniques. Nitrogen oxide (NOx) emissions under different operating conditions were predicted using artificial neural networks (ANNs) trained on experimental data. In the sensitivity analysis, the fraction of variance (R^2) and mean absolute percentage error (ξ) were compared. The best outcomes were obtained using the 11-neuron Levenberg-Marquardt (LM) algorithm. The best averaged accuracy was achieved with a set of 0.05, 0.05, and 0.3 for learning rate, momentum, and weight, respectively, among the many architectures of back propagation (BP) designs that were investigated. Using the LM technique, ξ were determined to be between 0.68 and 3.34 % for pre-specified engine speeds and loads.

The experimental determination of the various features of diesel-biodiesel blends takes a long time [43]. Any technology that

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makes it possible to estimate these properties without conducting experiments is extremely useful. Other instruments for determining the characteristics of diesel-biodiesel mixtures were employed in this investigation. The density and viscosity of diesel and biodiesel mixtures were estimated using the usual statistical method of linear regression (principle of least squares). To select the best Artificial Neural Network (ANN) to predict the aforementioned attributes of diesel-biodiesel mixtures, a set of seven distinct neural network topologies, three training procedures, and 10 different combinations of weights and biases were studied. By employing methanol and a basic catalyst during the trans-esterification process with soybean oil, biodiesel was created. The effectiveness of both the conventional linear regression and the ANN approaches was then contrasted to determine whether they could accurately predict the characteristics of different blends of diesel and biodiesel. The blend of biodiesel (25%) and diesel (75%) produced the following results: viscosity (cSt) 7.29, flash point (°C) 56.5, fire point (°C) 66.3, and density (g/mL) 0.85.

By creating inverse and forward model-based neural networks, Biyanto et al. (2011) [44] studied A Neural Network Internal Model Control (NN-IMC) technique (NN). The simulations of the two different NN-based inverse models were correct (i.e. with and without disturbance input). They discover that neural networks have a good root mean square error and can quickly create forward and inverse models from a small set of input-output open loop data of a single distillation column (RMSE).

Artificial neural network (ANN) is used in this study by Wang et al. (2010) [45] to analyse the hydro desulfurisation (HDS) process using light-cycle oil as feedstock and $NiMo/Al_2O_3$ as the catalyst. ANN models usually function as a "black box," making the model imperceptible to users and necessitating a large amount of training data. This work suggests a brand-new ANN. Incorporating the Langmuir-Hinshelwood kinetic mechanism forces the suggested ANN model to adhere to the specified reaction processes. Both the benefits of ANN's capacity for self-learning and the knowledge base of HDS were taken into consideration. Minimising the lengthy training procedure On the sulphur removal rate, the effects of operating temperature, pressure, and LHSV are investigated. Investigations into nitrogen compound inhibition are also conducted. It has been demonstrated that nitrogen can greatly slow down the conversion of sulphur components, especially hard sulfurs like 4,6-DMDBT.

Applications of ANNs in the field of textile engineering have primarily gained popularity after 1990 [46]. Over time, it became clear that they are capable of solving challenging engineering issues. When faced with a multiparameter, non-linear problem that lacked an obvious or simple analytical solution, several researchers have resorted to ANNs. In an effort to cover this developing topic up to the most recent technological and research advancements, an extensive review of the application of artificial neural network approaches for the solution of textile problems is offered. It is evident that the research community is producing more and more corresponding publications on the subject.

Artificial neural networks were used in a fault detection system by Rahman (2010) [47]. This study uses a batch reactor to produce ethyl acetate from the reaction of acetic acid and ethanol (batch esterification process). The data gathered from the experiment is used to run the neural network with normal and defective events. The architecture of the training network captures the relationship between normal-faulty events.

In this study, Qiao et al. (2011) [48] model the water quality parameters (i.e. Chemical Oxygen Demand, Biological Oxygen Demand, Suspended Solid,Ammonia Nitrogen etc.). A recurrent high-order neural network is utilised for the wastewater treatment process, and the neural network is trained by a filtering algorithm, due to the multi-variable, nonlinear, substantial time delay, and strong coupling aspects of the wastewater treatment process. A wastewater treatment plant's operational data is used to demonstrate the effectiveness of the suggested modelling approach. To determine the modelling accuracy of the recurrent high-order neural network, the findings are also compared with feed-forward neural networks and conventional recurrent neural networks.

To estimate the mass transfer characteristics of papaya's osmotic dehydration, this study compared artificial neural networks (ANN) with response surface methodology (RSM) [49]. A three-level, three-factor Box-Behnken experimental design was used to examine the impact of process variables such as temperature, osmotic solution concentration, and agitation speed on water loss, weight loss, and solid gain during osmotic dehydration.

A back-propagation neural network model has been created in this study's research to forecast how various biolubricants will affect a 200 cc two-stroke engine's performance and exhaust emissions [7]. Engine speed, lambda, and lubricant type are the model's inputs.

As an alternative, using bioremediation methods that harness the power of microorganisms might be a successful way to remove Cr from the environment (VI) [50]. In this study, we reported a newly isolated bacterium from agricultural soil in Malaysia, named Acinetobacter radioresistens sp. NS-MIE. Utilising RSM and ANN approaches, the chromate reduction potential of strain NS-MIE was improved. In order to forecast the water absorption, compressive strength, flexural strength, split tensile strength, and slump for steel fibre reinforced concrete, the study compares Response Surface Methodology (RSM) with hybridised Genetic Algorithm of Artificial Neural Network (GA-ANN) [51]. Using the central composite design of response

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surface approach, the effects of process factors such as aspect ratio, water-cement ratio, and cement content were examined. This study was unique from others since the effectiveness of the various artificial neural network (ANN) models was assessed in order to determine the best ANN design for predicting the H_2 production rate [52]. The produced nanocatalyst had a large specific surface area (885 m^2/g) and evenly dispersed Ni-Co bimetallic alloys, which increased the electrochemically active surface area for hydrolysis of NaBH4. The results demonstrated the improved catalytic activity of Ni-Co@3DG toward $NaBH_4$ hydrolysis (starting concentration of 0.5 M), with a hydrogen production rate of 82.65 mmol/min at 25 °C, and catalyst loading of 0.05 g.

In physics, chemistry, and material science, artificial neural networks (ANNs) are a machine learning (ML) technique that is now widely employed [53]. With the use of data, ANN can recognise nonlinear trends and make precise forecasts. Although ML techniques, and ANNs in particular, have already shown useful in resolving a number of chemical engineering issues, pyrolysis, thermal analysis, and particularly thermokinetic research applications are still in the early stages of development. The current article provides a critical overview and summary of the literature that has been published on the use of ANNs in the fields of thermodynamic studies, thermal analysis, and pyrolysis.

CONCLUSION

Artificial neural networks are used as mathematical models in computer science, artificial intelligence, and neurology. They categorise data, develop models, and make forecasts. ANNs have been around since the middle of the 20th century, but they really took off in the 1980s when back propagation was introduced, and again in the 2000s when deep learning was developed. In recent years, the latter has dominated the field of machine learning and artificial intelligence. We may infer from the entire study that a very large amount of Artificial Neural Network (ANN) application is made in chemical process engineering. ANN calculates and generates process calculation data very correctly. In the future, we might strive to improve or develop an ANN model that can be used for calculations, control, or processes in chemical engineering.

ANNs are boundless in chemical engineering [54–56]; we use them in all fields, including polymerisation, oil production, battery heating, modelling, industrial plant control, and catalysis. The vast majority of this study uses for-profit software programmes like the MATLAB Deep Learning Toolbox. A third of the studies analysed synthetic data, which limits the ability of the learnt model to generalise and is present in many datasets with merely tens or hundreds of data points. It implies that hybrid models, which combine a mechanical understanding of processes with the data-driven models provided by ANNs, are especially promising.

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