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Artificial Neural Network in Mechanical Engineering: A Review

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Abstract: Artificial intelligence (AI) is a new technology that enables computers to sense, act, and react like humans. Artificial Neural Network (ANN) is one of the AI algorithms inspired by observable processes in the brain's biological neuron networks. ANN can recognize and learn patterns between inputs and related outputs. Once properly trained, ANN can predict the outcome of test input data. In this article, we review the existing ANN models and their applications in mechanical engineering. This review may help mechanical engineers in design, fluid, thermal, and manufacturing domains in understanding these intelligent programs.

***Keywords* —Artificial Intelligence, Artificial Neural Network, Mechanical Engineering, Training Algorithm.**

I. INTRODUCTION

Artificial intelligence (AI) is one of the techniques that enable machines to mimic human activity. It can modernize conventional technologies with human-like intelligence. The algorithms that provide intelligence to the computer system are called machine learning (ML).

Artificial neural network (ANN) is a popular machine learning algorithm. It is a computer structure inspired by observable characteristics of biological neuron networks. It consists of closely connected neurons which act as small computing units. One can train the ANN model by providing the training data. It can then recognize and learn the hidden patterns and relations between inputs and respective target values. This ML algorithm is especially helpful when the relationship between the underlying data sets is unclear. Once trained, ANN is capable to predict the results for fresh, independent input data points. Notably, ANN can deal with complicated and nonlinear data.

ANN has drawn a lot of interest due to its broad variety of applications and the ease with which it can overcome challenging problems [1]. One of the applications is conventional mechanical engineering. The use of a high degree of automation makes mechanical systems more simple and efficient to make complex decisions. ANN is widely used in the discipline of mechanical engineering [2].

This paper reviews the available artificial neural networks and their applications in the mechanical engineering field. We focus on the development of ANN and the architecture of ANN in Section 2. It is followed by, in section 3, a brief review of the application of ANN in the mechanical fields such as design, fluid and thermal, and manufacturing domains.

II. ARTIFICIAL NEURAL NETWORK

The architecture of ANN is based on a biological neural network in the human brain shown in Figure 1. The four pillars of ANN are neurons, layers, activation function, and training algorithm.

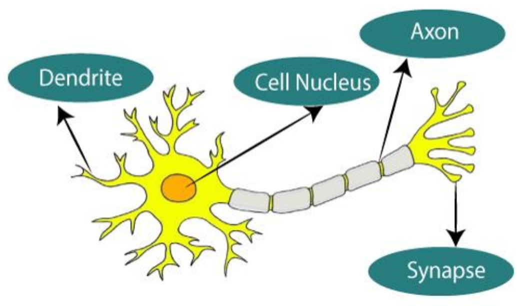

Figure 1 Biological Neural Network

A. Neuron

A natural neuron contains a cell body, dendrite, and axon. In the cell body, dendrites receive signals from another neuron in the electrochemical form. The cell body also known as a soma contains a nucleus. Nucleus in which actual processing happens. The signal from the neuron to other neurons is sent down the axon. Synapses are the points where the dendrites of two neurons interact. Dendrites allow the neuron to take in impulses from other neurons. Only the neuron emits its signal to the following neuron through the axon via synapse if the signal exceeds a specific threshold.

Neurons are the processing units that make up an artificial neural network. The goal of a synthetic neuron is to replicate the appearance and functionality of a biological neuron. A neuron consists of inputs (dendrites), nodes (cell nucleus), weights (synapse), and outputs (axon). An artificial neuron calculates and stores information. A single

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neuron gets a large number of inputs. After certain calculations, the output is predicted. The output is used as the input for the subsequent neurons. In a neural network, each link between two neurons is represented by a weight. Weight measures the strength of the connection. Finally, to construct a neural network, neurons are stacked together. To predict output Y_i following **Equation 1** is used.

$$Y_i = \sigma\left(\sum_{i=1}^{n} X_i W_i\right)$$

Equation 1

Where X_i indicates input given to the model, σ indicates the activation function, and W_i indicates Weight provides for that input.

B. Layers

An input layer, output layer, and hidden layer are the three layers of a neural network. The input layer receives signals and data from the outside world, while the output layer creates the outcomes of the system's processing. The hidden layer sits between the input and output layers and is completely concealed from the outer world. The most basic type of ANN architecture is the Perceptron (single-layer architecture of ANN as shown in Figure 2). For complex problems, multilayer perceptron (MLP) is used. MLP includes one input layer, one output layer, and more than one hidden layer as shown in Figure 3.

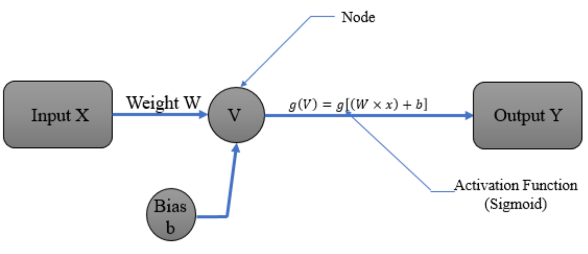

Figure 2 Single Layer Architecture of ANN

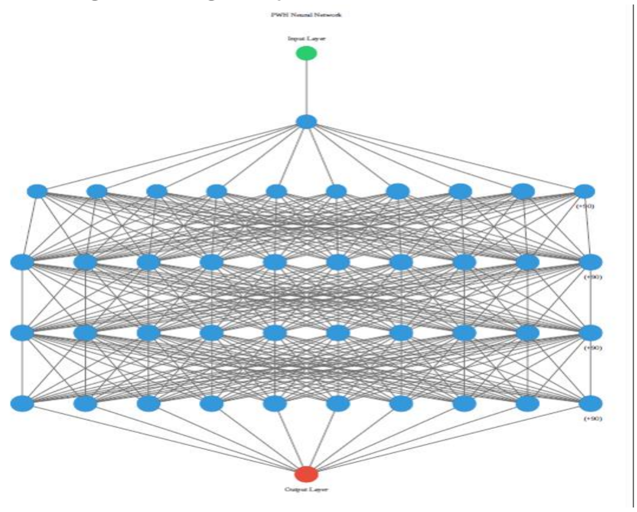

Figure 3 Multilayer Architecture of ANN

C. Activation Function

The purpose of the activation function is to choose whether or not to stimulate a neuron. And yet another is to make a neuron's output non-linear. Bias and weighted sum (the product of weight and input) make up the activation function. Numerous activation options are available. The sigmoid function is the most used activation function. Step, linear, hyperbolic tangent, log sigmoid, and other activation functions are also available. Every link between two neurons is given weight. The value of weight might be positive, negative, or zero. A negative weight indicates a weaker signal, while a zero indicates no connection between any two neurons. To get the desired output the weights are adjusted. The process of adjusting weights is known as learning or training.

D. Training Algorithm

The objective of the training is to minimize error (difference between target output and predicted output). The error is useful for measuring the performance of neural network model. The method most frequently employed to reduce error is back propagation. In this method, the weights are changed after propagating the predicted output back to the layers. For a certain input, this predicted output is compared against the desired outcomes. Based on this difference, the error is calculated and flows back from the output layer to hidden layer and from hidden layer to input layer. This propagated error changes the weights between the neurons. This cycle of input to output and again output to input is known as epoch or iterations. Numerous such epochs are performed on the network until the error is within a predetermined limit. This overall process is known as training. To adjust the weights various algorithms are used. There are various training algorithms in the neural network. The most commonly used training algorithms are Gradient descent, conjugate gradient, newton method, quasi-newton, and levenberg-marquardt method.

1) Gradient Descent

This method is a simple training algorithm. In this method, network weights and biases are updated in the direction in which the performance function decreases more rapidly. The updated weight W_k is given as follows:

$$W_{k+1} = W_k - \eta \frac{\partial E}{\partial w}$$

2) Conjugate Gradient

In the conjugate gradient method at each iteration different search directions are used. It first starts with the steepest descent algorithm and then at each iteration step size is adjusted. So that it converges faster than gradient descent.

$$W_{k+1} = W_k - \eta(\nabla E_k + \beta_k p_{k-1})$$

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3) Quasi-Newton Method

This process is frequently used. Compared to the gradient and conjugate gradient methods, it is quicker. Hessian matrix and its inverse evaluated in the quasi-newton. Hessian matrix is composed of the partial derivatives of the error function. Q_k = Inverse of Hessian matrix.

$$W_{k+1} = W_k - \eta Q_k \frac{\partial E}{\partial w}$$

4) Levenberg-Marquardt Method

The Levenberg-Marquardt technique was created to approximate second-order training speed without having to compute the Hessian matrix, much like quasi-Newton approaches. Considering that the error function is a kind of squared sum. Calculating the Jacobian matrix is less computationally intensive than computing the Hessian matrix [3].

$$W_{k+1} = W_k - [J^T J + \mu I]^{-1} J^T e$$

III. APPLICATION OF ANN IN MECHANICAL ENGINEERING

Design Engineering

In design engineering, the stress concentration factor is one of the important parameters. To predict the SCF, ANN is the most popular approach. The researchers have done extensive work in the ANN to predict the SCF for a plate with hole [4], crankshaft [5], and spring [6]. For this work author used two methods like the finite element method and artificial neural network. The authors took Peterson's handbook, created a finite element model in ANSYS, and tested the model against data. They also created an ANN model to forecast the stress concentration factor. Using data supplied by ANSYS, they trained and validated the ANN model. Similarly, a study has been done to predict SCF for crack structure [7]. Using FEM findings, they retrieved data regarding stress concentration from the route between the fracture's origin and the stress-released region. The nonlinear learning of the relationship between stress concentration factor and crack parameter leads to a stress concentration factor prediction model based on BP neural networks. They utilized five sets of data to validate the BP neural network-based prediction model's accuracy. Recently, with the developments in AI; researchers have a great deal of attraction to non-linear problems in the mechanical properties of alloys. Many of the researchers carried the work in the field of mechanical properties prediction by using ANN. Author made efforts to attempt to develop the best ANN to predict the stress-strain curve of titanium alloy [8]. Also, another attempt is made to obtain the optimized model for evaluating the flow stress in the hot rolling process using ANN [9].

Thermal Engineering

In recent decades, ANN has gained popularity in a variety of fields, including solar radiation, load forecasting, prediction, and refrigeration, as well as modeling and control of power production systems. Numerous scholars have recently conducted studies on the use of ANN in energy systems. Because of the rising energy demand in recent years, absorption systems that utilize this kind of thermal energy have gained a lot of popularity. Additionally, natural fluid pairs that don't harm ozone are employed as working fluids in the absorption systems. [10]. Author investigated artificial neural networks (ANNs) utilized to calculate the thermodynamic characteristics of LiBr- and LiCl-water fluid couples, both of which have no ozone depletion potential. ANN is employed in vapor absorption refrigeration to forecast the specific heat capacity of the working fluid LiBr-H2O [11]. In this work, author has compared the performance of three training functions. The comparison is shown based on percentage relative error, R-square, and root mean square error. Researchers investigated the feasibility of predicting the performance of a cascade refrigeration system using a multi-layer feed-forward network [12]. They mention that COP, input, and heating power results predicted with the help of ANN closer to the experimental results. In addition, the author looked at using a generalized radial basis function (GRBF) neural network to predict a vapor–compression liquid heat pump's steady-state performance. The chilled water outlet temperature from the evaporator, cooling water input temperature to the condenser, and evaporator capacity was used to compute the COP of a heat pump driven by R22, LPG, and R290.

Manufacturing Engineering

In manufacturing processes use of ANN increases day by day. In manufacturing, sheet metal is an important operation. ANN technique to the sheet metal involves the prediction of life of compound die punch [13], prediction of life of piercing punches using ANN and ANFIS method [14]. Researchers investigate the prediction of spring back in the sheet metal components [15]. In this work, author studied the influence of process variables such as type of hole, number of holes, etc. on predicting spring back in sheet metal components using FEA and ANN. And then compare it with the experimental method. In blanking operation clearance between die and punch is important to forecast. Author predicted the clearance between the die and the punch during the blanking process using the FEA and ANN [16].

IV. CONCLUSION

This research provides information on the evolution of artificial neural networks, their general structure, activation function, application areas, and classifications for artificial intelligence studies. Artificial neural networks

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have achieved a wide application area in tackling challenging and complicated problems faced in real life, according to the study. Furthermore, in mechanical fields like design, thermal, and production engineering, the use of many hidden layer topologies of artificial neural networks has shown highly positive outcomes. In general, AI systems have a wide range of applications, and they may be used in any system that requires the substitution of human skill to produce a beneficial answer. Using artificial intelligence, future research scope may be identified in numerous applications of mechanical engineering integrated with robotics and automation engineering.

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