**Significance of Artificial Neural Network Analytical Models in Materials Performance Prediction**

In materials science, performance prediction of materials plays an important role in improving the quality of materials as well as preventing serious damage to environment and threat to public safety. Traditional regression analysis models in materials science are still not perfect, limited to capture nonlinearities of data and time-consuming for prediction, and have a poor ability to handle large amount of data. It makes a strong demand on data analyses of materials data with the help of novel computer science methods. In recent years, artificial neural network (ANN) is increasingly performing as a strong tool to establish the relationships among data and being successfully applied in materials science. In this paper, some typical ANN applications for predicting various properties (corrosion, structural, tribological, etc.) of different materials servicing under multiple environments (atmosphere, stress, nuclear, weld, etc.) are reviewed. It highlights the significance of ANN in materials related problems and the trend of ANN in the context of materials science with some limitations.

**Keywords:** artificial neural network, materials performance prediction, materials design, multilayer perceptron

### **1. INtroduction**

Since material service safety is important to be maintained, many researchers devote their time to experimental testing and data analyzing to discover the different factors influencing on materials performance. Traditional mathematical analysis models used in materials science are still not perfect, limited to capture nonlinearities of data and time-consuming for prediction, and have poor ability to handle a large amount of data. In recent years, an emerging area of materials performance evaluation and prediction by artificial neural network (ANN) was evolved as an efficient way. ANN analysis can produce satisfactory prediction results of materials properties, compared to traditional data analysis ([Liu, Y Li et al. 2013](#_ENREF_48), [Huang, Jia et al. 2018](#_ENREF_24)).

One hot research target in materials science is to determine the unknown relations among materials properties. ANN can predict the output by exploring arbitrary interactions among the variables and enabling quantitative expression and understanding of very complicated problems ([Bhadeshia, Dimitriu et al. 2009](#_ENREF_7)). Because of its parallel structure and fast learning capacity, it can be used for linear and non-linear data analyses in applications such as pattern recognition, prediction, system identification and control. The main benefit of neural network is its generalization ability, noise tolerance, fault tolerance and prediction ability of unseen test data with savings in cost and time ([Vera and Ossandón 2014](#_ENREF_72)).

This paper aims to give a hand to materials and computer researchers with a comprehensive view of ANN models implemented in various prediction applications in material science researches. This review will highlight the significance of ANN in materials related areas and the facts that arouse continuous ANN implementation in future materials related problems.

The rest of the contents are arranged as follows. The basic introduction to ANN is firstly described in Section 2. Section 3 gives the significance of ANN in materials related researches, ranging from simple ANN models alone to more complicated ANN models along with other computing methods, as well as their advantages and shortcomings. The future trend of ANN application in materials science is pointed out in Section 4.

### **2. INTRODUCTION TO ARTIFICIAL NEURAL NETWORK**

**2.1 The Principal Idea of Neural Network**

ANN is one kind of network model established in mathematical way that is based upon the working principle of biological neurons connected to each other in biological neural network. In ANN, a neuron is an element that receives multiple inputs and generates a single output, and is characterized by its weights, bias and activation functions. Those neurons are firstly grouped into layers, and then those layers are connected to each other, thus forming a network model. The information from the input layer is moved as the input to the hidden layer that will do linear/non-linear processing to produce the final output to output layer. That kind of movement from the input layer to the output layer is known as feed forward propagation. When there is an error between an actual output and an expected output at the output layer, the weights and biases of neurons will be updated to reduce the error in a backpropagation process. Learning process, called as training, can learn from previous data and iteratively adjust the weight values to reduce the error between the actual output and the desired output. When the actual output is achieved at a satisfactory level, training is stopped and the weighted links between processing units are saved. The final weights and biases after training are used as analytical tools for prediction of unseen input data. Details of the neural network method itself can be found in ([Fausett 1994](#_ENREF_17), [Rojas 1996](#_ENREF_62), [Graupe 2013](#_ENREF_21)) and ([Demuth, Beale et al. 2014](#_ENREF_12)).

**2.2 The Simplest ANN**

Single layer neural network, generally known as perceptron, is the first and simplest neural network model ([Graupe 2013](#_ENREF_21)). It consists of only one layer which is composed of neurons. Figure 1 demonstrates a single layer perceptron neural network, in which m and n represent the number of inputs and the number of neurons, respectively, and xi connected to all neurons in only one layer and yi are not neurons, just input and output.



Figure 1. The Structure of Perceptron (Single Layer) Neural Network

As all neurons in a single layer perceptron network produce their corresponding output, the number of output is the same as the number of neuron (n). The input signals (x1, x2, …, xm) are connected to the neurons of the single layer via their corresponding weights (w11, w12, …, wnm) so that every neuron has the corresponding weight value for each input signal respectively. The input signal X can be expressed in vector form as the following formula.

(1)

The weight data can be expressed as the following matrix. Here n is the number of neuron and m is the number of inputs. Any connection between neurons and input of the network can be calculated based on the number of n and m. For example, Figure 1 shows the connection path between the first input (x1) and the second neuron (n2) can be easily seen as w21.

(2)

The working principle of an artificial neuron is shown in Figure 2. Since an artificial neuron is mainly constituted with two components: sum and activation function, it can be said that an artificial neuron works in two steps. In the first step, all input data in a neuron are multiplied with their respective weight data and those multiplications are summed to pass through the activation function. The second step accepts the sum as the input to the activation function that will produce the output. The netinput to the activation function in first step can be calculated in vector form as follows:

***netinput= WX =******w1\*x1 + w2\*x2 + w3\*x3+……+ wn\*xm*** (3)



Figure 2. The Working Principle of a Neuron

The weighted data (weight data \* input data) are summed and passed as the input to the activation function of the neuron in the second step. The activation function accepts the input and processes it to produce the output. The output of the entire network can also be calculated by passing the sum of multiplication of the input vector and weight vector to the activation function as follows:

***y= (Netout = F(netinput) =F (WX))*** (4)

To improve the performance of neural network, some neurons include weight data as well as bias data. By adding bias values b, the performance of the neurons is improved by shifting decision boundary of classifiers to left or right. The value of the bias is generally set to 1 and the mathematical model of the neuron with bias value can be expressed as

***Output*n=**  (5)

***y=Net out = ƒ(netinput) = ƒ(WX+b)*** (6)

**2.3 Activation (Transfer) Function**

Since every neuron uses an activation function to generate output from the weighted data and the accuracy of the output is dependent on activation function, it is important to choose the correct activation function for neurons. The widely used activation functions in neural network architecture are summarized in Table 1.

Among them, the three most widely used activation functions are linear, sigmoid and hard-limit function. Linear function operates no changes in incoming input signals to generate the original output values. Sigmoid non-linear function, also known as logistic function, can be defined as . It can generate the output between 0 and 1 for input value range of -∞ and ∞. Hard-limit function gives the output of neuron as 0 if the input is less than 0; otherwise, it gives the output as 1.

Table 1. Activation Functions Mostly Used in ANN

|  |  |  |
| --- | --- | --- |
| **Name** | **Formula** | **Range** |
| **Linear** |  |  |
| **Semi-linear** |  |  |
| **Logistic (sigmoidal)** |  |  |
| **Hyperbolic tangent (sigmoidal)** |  |  |
| **Exponential** |  |  |
| **Sinusoidal (sine)** |  |  |
| **Rational** |  |  |
| **Step** |  |  |
| **Hard limit (threshold)** |  |  |
| **Modular** |  |  |
| **Signed (signature)** |  |  |
| **ReLu** |  |  |
| **Leaky ReLu** |  |  |
| **Gaussian** |  |  |
| **Softmax** | for i=1,…, J |  |

**2.4 Classification of Neural Network**

Different neural network models can basically be classified due to the architecture of neural networks: type of connection, the number of layers, activation function and propagation direction.

**2.4.1 From Type of Connection**

The classification of neural network defined by network connection type includes fully connected and non-fully connected. Fully connected network means that every neuron of each layer is connected to all the neurons of the neighbor layer. In such kind of network, neurons of one layer transmit their output signal as input to the neurons of next layer. One of well-known fully connected neural network is Hopfield network ([J. Taylor 2006](#_ENREF_25)). In non-fully connected neural network, neurons of one layer do not connect to all neurons of neighbor layer, just connecting to some of corresponding neurons from the adjacent layer.

**2.4.2 From the Number of Layers**

The simplest neural network has only one layer. The input and output are connected directly with the neurons in a single layer. Neural networks composed of more than two layers (including input layer, one or more hidden layer and output layer) are known as multilayer perceptron (MLP) neural networks. In multi-layer neural networks, more neurons and layers are included to give better performance. The number of neurons of each layer can be same or different. Layers are connected to each other from left to right order. Network architecture can be described as (number of input layer neurons-number of hidden layer neurons-number of output layer neurons); for example, (5-8-1) structure means 5 neurons in input layer, 8 hidden neurons in hidden layer (hereby (5-8-8-1) means two hidden layers with 8 hidden neurons respectively) and 1 neuron in output layer.

**2.4.3 From Activation Function Type**

Activation function is important for the performance of ANN. From Table 1, we can see that there are many different kinds of activation function. ANN can be classified by the types of neurons of the network that use activation function: homogeneous network in which activation functions of the neurons in the network are same and heterogeneous network in which the neurons in the network use different activation functions. [Weingaertner, Tatai et al. (2002)](#_ENREF_74) presented a framework to develop the automatic design of heterogeneous neural networks by using different activation functions in hidden layer neurons of feed forward neural networks. [Lee, Lam et al. (2018)](#_ENREF_43) compared their proposed heterogeneous neural network with homogeneous neural network composed of the conventional neuron model, achieving improvement in error rate, training speed, and memory capacity.

**2.4.4 From Propagation Direction**

ANN can also be classified if it is feed forward (static) or feedback (dynamic) network according to its feeding direction between layers. ANN layers are usually connected in one direction from left to right order, known as feed forward. Layers of neural networks known as static networks are connected in one direction from one layer to another in feed forward way to calculate the output. But some networks are both feed forward and feedback connected. Feedback networks introduce signal loops (extensive feedback) between the neurons of a layer, and/or between the layers of the network in both directions, which are powerful and have more complicated structure. One of popular network models with feedback connection are known as recurrent networks (dynamic networks) ([Sinha, Gupta et al. 2000](#_ENREF_67)). Table 2 generally illustrates a classification of existing neural network models based on two classes of feed forward and feedback neural network in ([Jain, Mao et al. 1996](#_ENREF_27)) and types of ANN in ([Mehta 2019](#_ENREF_53)).

Table 2. Typical Classification of Most Common ANN Types

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Propagation Direction** | **Name of Neural Networks** | **Connection Type** | **Number of Layers (Network Architecture)** | **Mostly Used Activation Function** | **Network Model  Topology Representation** |
| Feed Forward | Backpropa-gation neural network (BPNN) | fully | one input layer, one or more hidden layer and one output layer | logistic, hyperbolic tangent, linear, gaussian |  |
| Multilayer perceptron neural network (MLP) | fully | more than 2 layers (one input layer, one or more hidden layer and one output layer) | logistic, hyperbolic tangent, linear |  |
| Deep convolution-al neural network (CNN) | non-fully | convolutional layer, subsampling layer, fully connected layer | logistic, hyperbolic tangent, ReLU, Leaky ReLU, softmax |  |
| Deep feed forward neural network (DFF) | fully | one input layer, one or more hidden layer and one output layer | logistic, hyperbolic tangent, ReLU, Leaky ReLU, softmax |  |
| Deep belief network (DBN) | fully | multiple layers of Restricted Boltzmann Machine including a visible layer and a hidden layer | logistic, hyperbolic tangent, ReLU and Leaky ReLU, softmax |  |
| Radial basis function neural network (RBFNN) | fully | 3 layers (one input layer, one hidden layer and one output layer) | gaussian |  |
| Feedback | Recurrent neural network (RNN) | fully | one input layer, one or more hidden layer and one output layer | hyperbolic tangent, ReLU |  |
| Hopfield neural network | fully | a single layer with one or more fully connected recurrent neurons | logistic, hyperbolic tangent |  |
| Long/short term memory neural network (LSTM) | fully | a sequence input layer, a LSTM layer, a fully connected layer, a softmax layer, and a classification output layer (for classification)  a sequence input layer, a LSTM layer, a fully connected layer and a regression output layer (for regression) | logistic, hyperbolic tangent |  |

Besides neural network classifications mentioned above, two or more different types of neural networks can be combined for special purpose, known as hybrid neural network. Such kind of neural networks can be multilayer neural networks composed of multiple layers with different separate topologies and a special learning algorithm is needed for hybrid neural networks.

### **3. Significance of Neural Network Applications in Materials Researches**

Due to its powerful performance, ANN has been widely applied in many fields for materials performance, covering mechanical ([Ashtiani and Shahsavari 2016](#_ENREF_3)), metallurgy ([Yang, Zhu et al. 2012](#_ENREF_79)), hydrological ([Maier and Dandy 2000](#_ENREF_52)), atmospheric corrosion ([Pintos, Queipo et al. 2000](#_ENREF_59), [Zhang, Yu et al. 2011](#_ENREF_83)), civil engineering ([Sadowski 2013](#_ENREF_63)), etc. The critical equipment easy to failure attracts most attention, mainly including pressurized water reactors ([Shi, Wang et al. 2015](#_ENREF_66)), distribution and transmission electric energy lines ([Kenny, Paredes et al. 2009](#_ENREF_34)), nuclear waste disposal ([Kamrunnahar and Urquidi-Macdonald 2011](#_ENREF_32)), aerospace and aviation sectors ([Zhang, Bao et al. 2016](#_ENREF_84)), steel production lines ([Ghaisari, Jannesari et al. 2012](#_ENREF_20)), etc. ANN was established for forecasting materials performance as failure modes of fatigue ([Haque 2001](#_ENREF_23)), crack ([Shi, Wang et al. 2015](#_ENREF_66)), pitting ([Jiménez-Come, Turias et al. 2015](#_ENREF_30)), creep ([Evans 1999](#_ENREF_14)), flow stress ([Montakhab and Behjati 2010](#_ENREF_54)), wear ([Xu, Xing et al. 2007](#_ENREF_77)), elasticity ([Asteris, Roussis et al. 2017](#_ENREF_4)), toughness and hardness ([Faizabadi, Khalaj et al. 2014](#_ENREF_15)), hot deformation behavior ([Liu, Y Li et al. 2013](#_ENREF_48), [Yao, Wang et al. 2013](#_ENREF_80)), yield strength ([Birbilis, Cavanaugh et al. 2011](#_ENREF_8)), ultimate strength ([Sasikumar, Rajendraboopathy et al. 2008](#_ENREF_64)), elongation to fracture ([Kappatos, Chamos et al. 2010](#_ENREF_33)), etc. Exclusively for the prediction of the corrosion, corrosive environments in which the applications based on ANN were adopted can be specifically classified as atmosphere ([Osgerby and Fry 2007](#_ENREF_57), [Kenny, Paredes et al. 2009](#_ENREF_34), [Seidl, Jančíková et al. 2012](#_ENREF_65)), soil ([Jiang, Keller et al. 2016](#_ENREF_29)), and so on.

In this review, the significance of ANN in materials related researches was highlighted with several performance-predictive applications arranged by level of simplicity, ranging from simple ANN models alone to more complicated ANN models along with hybrid use of other computing and input ranking methods. Materials in researches were varied due to the intention materials researchers focused on. Several of them were steel ([Parthiban, Ravi et al. 2005](#_ENREF_58), [Lajevardi, Shahrabi et al. 2009](#_ENREF_42)), zinc ([Cai, Cottis et al. 1999](#_ENREF_9)), aluminum ([Forouzan and Akbarzadeh 2007](#_ENREF_18)), copper ([Kenny, Paredes et al. 2009](#_ENREF_34)), iron and titanium ([Kamrunnahar and Urquidi-Macdonald 2010](#_ENREF_31)), magnesium ([Xia, Nie et al. 2016](#_ENREF_75)), other metal alloys ([Li, Liu et al. 1998](#_ENREF_46), [Li, Qi et al. 2007](#_ENREF_47), [Montakhab and Behjati 2010](#_ENREF_54), [Kamrunnahar and Urquidi-Macdonald 2011](#_ENREF_32), [Yang, Zhu et al. 2012](#_ENREF_79), [Shi, Wang et al. 2015](#_ENREF_66), [Zhang, Bao et al. 2016](#_ENREF_84)), and so on. The majority of materials related applications were focused on implementing feed forward BPNN and MLP. Recent works on other powerful, complicated and efficient neural networks models, such as radial basis function neural network (RBFNN) ([Kappatos, Chamos et al. 2010](#_ENREF_33)), convolutional neural network (CNN) ([Xie and Grossman 2018](#_ENREF_76)) and generalized regression neural network (GRNN) ([Yilmaz and Ertunc 2007](#_ENREF_81)) could also give satisfactory prediction. The dataset for all those ANN modellings were obtained from experiments as well as from some reliable references. In materials science researches, it is important to know the role of variables affecting on material properties and determine which input variable is the most influencing factor on desired output variable. Therefore, some input ranking methods, such as change of MSE (COM), fuzzy curves and sensitivity analysis, have been applied to extract knowledge from trained ANN ([Sung 1998](#_ENREF_69)). Previous recent works have shown that integration of neural networks with other computing paradigms such as Bayesian framework ([Vasudevan, Bhaduri et al. 2005](#_ENREF_71)), genetic algorithm ([Aliofkhazraei and Rouhaghdam 2008](#_ENREF_1), [Fu, Mo et al. 2010](#_ENREF_19), [Huang, Jia et al. 2018](#_ENREF_24)), sensitivity analysis ([Cai, Cottis et al. 1999](#_ENREF_9), [Lajevardi, Shahrabi et al. 2009](#_ENREF_42), [Weckman, Young et al. 2010](#_ENREF_73)) and fuzzy logic ([Xia, Nie et al. 2016](#_ENREF_75)) can effectively be used to make the performance of neural network models more efficient. The development of more than one ANN types (such as linear model (LM) (simplest form of ANN), MLP, radial basis function (RBF) and so on) and hybrid use of different ANN models were also discussed in some researches ([Fathi and Aghakouchak 2007](#_ENREF_16), [Khadom 2013](#_ENREF_36), [Li, Lv et al. 2017](#_ENREF_44)) with their comparison with experimental reports.

[Bhadeshia (2008)](#_ENREF_6" \o "Bhadeshia, 2008 #495) reviewed on some weaknesses of traditional linear regression analysis and why neural network architecture came up to replace linear regression analysis with specific neural network applications in the context of materials science. We summarize the majority of neural network prediction models exploited in materials related problems for predicting different properties of different materials in general, shown in Table 3. Most of those ANN prediction results were agreed with experimental results. The summary of some nomenclatures and descriptions defined by researchers can be found in Appendix A and Appendix B.

Table 3. Neural Network Predictive Models Used in Materials Related Problems

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Material | Applied Area of Material | Experimental Condition that Produces Data for ANN or Data Sources for ANN | Input | Activation Function | Output | Predicted/ Relevant Property | ANN Model |
| steel and zinc ([Cai, Cottis et al. 1999](#_ENREF_9)) | industrial | data collection from reliable resources | T, TOW, TOE, SO2 and Cl- | sigmoidal (logistic) | corrosion depth | corrosion | MLP |
| 304 Stainless Steel ([Lajevardi, Shahrabi et al. 2009](#_ENREF_42)) | industrial | data collection from reliable resources (references, projects or other resources) | T, Cl- and applied stress | sigmoidal | time of failure of SCC | mechanical (structural) | MLP |
| Al, low carbon steel, copper ([Kenny, Paredes et al. 2009](#_ENREF_34)) | electrical | atmospheric exposure | TOE, T, RH, precipitation, TOW, WV, solar radiation, Cl-, sulfur, compounds, and dustfall | linear, sigmoidal (hyperbolic tangent and logistic) | laboratory evaluated atmospheric corrosion rates | corrosion | MLP |
| iron alloy, carbon and alloy steel, grade-2 titanium ([Kamrunnahar and Urquidi-Macdonald 2010](#_ENREF_31)) | industrial | data collection from reliable resources | Model 1: Mo at %, Ni at %, HCl, H2SO4, E, dE (general corrosion DC data on iron-alloy) | sigmoidal (hyperbolic tangent) | Model 1: log(i), Ecorr, icorr, and Rp (general corrosion DC data on iron-alloy) | corrosion | MLP |
| Model 2: compositions (B, C, Cr, Cu, Fe, Mn, Mo, Ni, P, S, Si, Ti, and V), TOE, log (TOE) (general corrosion DC data on carbon and alloy steel) | Model 2: corrosion rate and log (corrosion rate) (general corrosion DC data on carbon and alloy steel) |
| Model 3: incubation period and the duration of experiments (localized corrosion crevice corrosion on Ti-alloy) | Model 3: Dmax, W, Q, ratio Q/W, O2 consumed, log (Dmax), log (W), log (Q), log (Q/W), and log (O2consumed) (localized corrosion crevice corrosion on Ti-alloy) |
| nickel-based alloy 22 ([Kamrunnahar and Urquidi-Macdonald 2011](#_ENREF_32)) | industrial | data collection from reliable resources | Model 1: T, sample treatment types: welded or annealed, and exposure time (general corrosion) | sigmoidal (hyperbolic tangent) | Model 1: corrosion weight loss (general corrosion) | corrosion | MLP |
| Model 2: sample treatments: welded or annealed, T, pH, Cl-, aging time, types of corrosion: general or localized (localized (service) corrosion) | Model 2: repassivation potential (localized corrosion) |
| Model 3: w and log(w) (localized corrosion) | Model 3: Zr, Zi, abs(Z), and Phase (localized corrosion) |
| A357 alloy ([Yang, Zhu et al. 2012](#_ENREF_79)) | aeronautic | isothermal compression and quenching | deformation temperature, SR and strain | sigmoidal (hyperbolic tangent and logistic), linear | flow stress | mechanical (structural) | BPNN |
| alloy 600 ([Shi, Wang et al. 2015](#_ENREF_66)) | industrial | data collection from reliable resources | T, KI, pH, conductivity, ECP, YS, B(OH)3, LiOH | sigmoidal (hyperbolic tangent), linear | CGR | mechanical (structural) | BPNN |
| Sn-Ag alloy ([Li, Qi et al. 2007](#_ENREF_47)) | industrial | data collection from reference | compositions (In. Bi, Sb, Re, Sn, Ag, Cu) | sigmoidal, linear | tensile strength, shear strength and solidification temperature | mechanical (structural) | BPNN |
| Ti-5Al-2Sn-2Zr-4Cr-4Mo alloy ([Li, Liu et al. 1998](#_ENREF_46)) | industrial | homogeneous compression | deformation temperature, equivalent SR, and equivalent strain | sigmoidal (logistic), linear | flow stress | mechanical  (structural) | BPNN |
| steel ([Parthiban, Ravi et al. 2005](#_ENREF_58)) | constructional | open atmosphere | time intervals | sigmoidal (logistic) | E | corrosion | BPNN |
| dual-phase (DP) steels ([Haque 2001](#_ENREF_23)) | machinery | data collection from reliable resource | SIF (ΔK), and volume % of martensite content (%M) | gaussian | da/dN | corrosion | BPNN |
| Al7075-T6, Al2024-T315, D16 aluminum alloy,  350 WT steel ([Zhang, Bao et al. 2016](#_ENREF_84)) | aeronautic | data collection from reliable resource | equivalent SIF, SIF, and stress ratio | gaussian | CGR | mechanical  (structural) | RBFNN |
| polyph-enylene sulfide (PPS) matrix composites ([Gyurova and Friedrich 2011](#_ENREF_22)) | machinery | injection molding | material compositions (PPS matrix, short carbon fiber, TiO2, PTFE, graphite), and testing conditions (sliding speed, applied pressure) | sigmoidal (hyperbolic tangent), linear | tribological characteristic (coefficient of friction, specific wear rate) | mechanical (tribological) | MLP |
| micro-alloyed pipeline steels ([Narimani, Zarei et al. 2015](#_ENREF_55)) | petrochemical | electrochemi-cal and potentiodyna-mic testing | chemical compositions (C, Mn, Nb, Ti, N, Mo, Ni, Al, Cu, Cr, V and CEIIW), microstruc-ture consist of diffusion (ferrite/pear-lite and shear (bainite/ martensite) transforma-tions, and corrosion cell characteris-tics (reference electrode, scan rate, T, PO2, PCO2, NaCl, bicarbonate concentration) | sigmoidal (hyperbolic tangent), linear | icorr and Ecorr | corrosion | MLP |
| micro-alloyed API X70 line pipe steels ([Faizabadi, Khalaj et al. 2014](#_ENREF_15)) | petrochemical | chemical composition and thermo-mechanical control process | chemical compositions (CEIIW, CEPcm, VTiNb, NbV, CrMoNiCu) and tensile properties (YS, UTS, El) | sigmoidal (hyperbolic tangent), linear | toughness and hardness | mechanical (structural) | MLP |
| Ni–SiC composite coatings ([Xu, Zhu et al. 2014](#_ENREF_78)) | industrial | ultrasonic electrodepo-sition | Up, Csic, and Cd | not clearly defined | weight loss | corrosion | MLP |
| prestressed posttension-ed concrete (PC) ([Lu and Liu 2009](#_ENREF_50)) | constructional | accelerated carbonation | SL, W/C, C/FA, C/CA and TA | not clearly defined for BPNN, gaussian for RBFNN | DC | mechanical  (structural) | BPNN and RBFNN |
| steel reinforced concrete ([Sadowski 2013](#_ENREF_63)) | constructional | resistivity four-probe method, Galvanostatic resistivity measurement and the LPR method | T, ρAC,bar , ρAC,conc, and ρDC | not clearly defined | icorr | corrosion | MLP |
| mild steel ([Sonar, Dixit et al. 2005](#_ENREF_68)) | constructional | data collection from reliable resource | *f, v, d* and *a* | gaussian | Ra | mechanical (tribological) | RBFNN |
| aluminum alloys ([Li, Qiu et al. 2013](#_ENREF_45)) | aeronautic and domestic | atmospheric exposure | altitude, annual average temperature, average humidity, annual average sunshine and annual rainfall | not clearly defined | atmospheric corrosion rate | corrosion | BPNN |
| structural carbon steel ([Jančíková, Zimný et al. 2013](#_ENREF_28)) | industrial | atmospheric exposure | T, RH, amount of precipitation, pH, SO2 and TOE | not clearly defined | atmospheric corrosion weight loss | corrosion | MLP |
| AA3004 aluminum alloy ([Forouzan and Akbarzadeh 2007](#_ENREF_18)) | machinery | hot rolling, cold rolling and annealing processes | the ratio of initial to final thicknesses, reduction, preheating time and temperature, finish rolling temperature and the final annealing temperature | sigmoidal (logistic) | YS, El, UTS, , | mechanical  (structural) | MLP |
| steel strip ([Kermanpur, Ebnonnasir et al. 2007](#_ENREF_35)) | machinery | HP hydraulic descaling operation | spray pressure, water flowrate, spray angle and vertical spray height | linear, sigmoidal (hyperbolic tangent) | spray impact | mechanical (structural) | MLP |
| aluminium-based, particulate-reinforced metal matrix composites (MMCs) ([Altinkok and Koker 2006](#_ENREF_2)) | machinery | stirr casting process | different SiC (µm) particle size ranges | sigmoidal (logistic) | density and tensile strengths | mechanical(structural) | MLP |
| IN625 alloy ([Montakhab and Behjati 2010](#_ENREF_54)) | machinery | data collection from reliable resource | T, SR and strain | sigmoidal (hyperbolic tangent and logistic) | flow stress | mechanical (structural) | MLP |
| mild steel ([Khaled and Al-Mobarak 2012](#_ENREF_37)) | chemical and industrial | electrochemical testing | Hammett constants, dipole moment, HOMO energy, LUMO energy, energy gap, molecular area and volume | sigmoidal | corrosion inhibitor efficiency | corrosion | MLP |
| sandcrete materials ([Asteris, Roussis et al. 2017](#_ENREF_4)) | constructional | uniaxial compression | W/B, MK, B, SP and UV | sigmoidal (logistic and hyperbolic tangent) | compressive strength, modulus of elasticity | mechanical (structural) | BPNN |
| structural carbon steel ([Seidl, Jančíková et al. 2012](#_ENREF_65)) | industrial | atmospheric exposure | T, RH, precipitation, pH, SO2 and TOE | not clearly defined | corrosion weight loss | corrosion | MLP |
| Ti–6Al–4V alloy ([Upadhyay, Jain et al. 2013](#_ENREF_70)) | machinery | turning process | s, t, v | sigmoidal (hyperbolic tangent), linear | Ra | mechanical (tribological) | MLP |
| carbon steel manganese ([Komijani, Rezaeihassanabadi et al. 2016](#_ENREF_41)) | petrochemical | EIS | time, T and inhibitor concentration | gaussian | Zr and Zi | corrosion | RBFNN |

**3.1 ANN for Typical Materials Performance Prediction**

To predict materials properties is a challenge in materials related fields because it relies on a large number of variables that are in complex nonlinear relation with each other. ANN are models that can elucidate unknown correlation in physical models and solve complex problems in materials ([Zhang, Wang et al. 2007](#_ENREF_82)). Therefore, ANN was given an attention by materials researchers for predicting properties related with mechanical ([Rajendraboopathy, Sasikumar et al. 2008](#_ENREF_60), [Sasikumar, Rajendraboopathy et al. 2008](#_ENREF_64), [Ghaisari, Jannesari et al. 2012](#_ENREF_20), [Yang, Zhu et al. 2012](#_ENREF_79)) and tribological ([LiuJie, Davim et al. 2007](#_ENREF_49), [Ramesh and Gnanamoorthy 2007](#_ENREF_61)). There were also many published satisfactory ANN predictions dealing with chemical property in corrosion related problems ([Díaz and López 2007](#_ENREF_13), [Bassam, Ortega-Toledo et al. 2008](#_ENREF_5), [Colorado-Garrido, Ortega-Toledo et al. 2008](#_ENREF_10), [Kenny, Paredes et al. 2009](#_ENREF_34), [Kamrunnahar and Urquidi-Macdonald 2010](#_ENREF_31), [Kamrunnahar and Urquidi-Macdonald 2011](#_ENREF_32), [Khaled and Sherik 2013](#_ENREF_38)). Some experimental techniques, such as corrosion test, tensile test, theoretical deterministic methods, metallographic corrosion characterization, mechanical testing, electrochemical impedance spectroscopy, etc., were used to acquire the data for ANN training and result verifying.

Regarding to space limitation, it is not possible to describe all ANN applications in details so that some of them will be grouped and reviewed into three different properties.

**3.1.1 Corrosion Property**

Corrosion is a kind of gradual destruction of materials by chemical and/or electrochemical reaction with their environment, such as atmosphere and specific solution. The atmosphere can cause a big deal in corrosion degradation process of materials. Statistical regression analysis models mostly used for prediction cannot give superb performance because the complexity and non-linearity of meterological variables on atmospheric corrosion is apparently high. To observe local atmospheric corrositivity, in the region of São Luis, five Atmospheric Corrosion Stations (ACS) were installed to monitor the local atmospheric corrosivity and three representative metallic specimens of low-carbon steel, copper, and aluminum were exposed to the atmosphere for almost two years. According to corrosivity degree measurement of ACS test sites, the corrosion rates and thickness losses of low-carbon steel, copper and aluminum were respectively categorized into three corrosion metrics: generalized corrosion, alveolar corrosion, and localized corrosion. A mathematical model based MLP was established by [Kenny, Paredes et al. (2009)](#_ENREF_34), with linear and sigmoidal tangent transfer function at the first hidden layer, logarithmic transfer functions at the second intermediate layer and Levenberg–Marquardt backpropagation training algorithm to analyze corrosion rates of three different matereials. Meterological data, including TOE (time of exposure), T (temperature), RH (relative humidity), precipitation, TOW (time of wetness), WV (wind velocity), SR (solar radiation), Cl- (chloride ions), sulfur compounds, and dustfall, were collected as the input to train ANN and laboratory evaluated corrosion rates of specimens were used as the output to analyze the atmospheric corrosion rates. The good correlations between input and output parameters demonstrate ANN performed greatly in estimating the corrosion rate. It supports one major benefit of ANN that ANN performs well in estimating high complexity and nonlinear correlation between input and output parameters. For long-term corrosion prediction, Pourbaix equation ([M. Pourbaix 1990](#_ENREF_51)) evaluated with parameters derived from ANN analysis also showed agreement with experimental results of two year period.

To deal with different corrosion metrics of different materials, [Kamrunnahar and Urquidi-Macdonald (2010)](#_ENREF_31) developed multiple MLP models to predict different kinds of corrosion behavior. Three ANNs were modeled for two general corrosion data on carbon and alloy steel, and one localized corrosion data on Ti-alloy. The ANN model developed for grade-2 titanium showed an excellent agreement with the experimental data and then was used for predictions of future maximum pit depth and other variables under similar operating conditions, giving very good agreements with experiments. In 2010, In an extended work ([Kamrunnahar and Urquidi-Macdonald 2011](#_ENREF_32)) of their previous work ([Kamrunnahar and Urquidi-Macdonald 2010](#_ENREF_31)), the authors emphasized on different corrosion metrics of one material, and established three different neural networks for localized and general corrosion of alloy 22, with the best network structures of 8-5-5-1 for localized cervice corrosion, of 2-100-100-10-4 for localized corrosion (AC impedance data), and of 4-5-5-1 for general corrosion study. The aim of both works was to predict corrosion behavior of metal alloys, such as metallic glasses, carbon steel, and grade-2 titanium as well as alloy 22. Data from two different sources (publicly available publications, etc. and personal communication) were together brought into ANN models. Both works had shown that ANN prediction results were good agreements with experimental data.

Concerned with electrochemical reaction, [Bassam, Ortega-Toledo et al. (2008)](#_ENREF_5) and [Colorado-Garrido, Ortega-Toledo et al. (2008)](#_ENREF_10) had also implemented the prediction ability of MLP in the application of electrochemical impedance techniques. [Bassam, Ortega-Toledo et al. (2008)](#_ENREF_5) trained a MLP model with 4-5-1 network architecture, Levenberg–Marquardt learning algorithm, hyperbolic tangent sigmoid, and linear transfer functions for the determination of different types of corrosion by using electrochemical impedance spectroscopy curves from different inhibitor concentrations. Correlation coefficient of R > 0.9905 described a good agreement between predicted and experimetal data. It was expected that the model may also enable the implementation of smart sensors for online quality determination (corrosion type) in pipeline steel. [Colorado-Garrido, Ortega-Toledo et al. (2008)](#_ENREF_10) described the application of MLP neural network to electrochemical testing by predicting impedance spectroscopy values, with the same network parameters used in the work of [Bassam, Ortega-Toledo et al. (2008)](#_ENREF_5). The best network architecture was obtained with 2-5-1 for 5 ppm of inhibitor and 2-2-1 for 25 ppm of inhibitor, and correlation coefficients R value of 0.984 for 5 ppm and 0.994 for 25 ppm showed good agreement between simulations and theoretical data. In this case, the model’s aim was to predict the imaginary impedance based on the real part of the impedance as a function of time to determine the corrosion resistance of the tested material in the solution. By using the same network parameters, the performance results of those two works gave good agreements between the actual and the predicted data.

As a note came up from the above materials corrosion predictive researches, more than one ANN models can differently and separately be developed depending on the different aspects of any underlying problem. No matter what the number of ANN models are, the critical point to take account is that more data points would be needed to establish a more robust and reliable ANN model with higher confidence and more representative results. Also, it can be concluded that a good ANN model can progressively be used for future prediction in the context of the problem with same nature, from the works of [Bassam, Ortega-Toledo et al. (2008)](#_ENREF_5) and [Colorado-Garrido, Ortega-Toledo et al. (2008)](#_ENREF_10).

**3.1.2 Mechanical (Structural) Property**

Multivariate nonlinear regression method has been used to represent the complicated interactions of flow stress with strain, strain rate and temperature. But the complicated correlation of flow stress with their affecting factors (microstructure and processing parameters) is difficult to be evaluated by any simple constitutive model. To overcome the repeated calculation of regression parameters for new experimental data in simple constitutive model, [Yang, Zhu et al. (2012)](#_ENREF_79) developed an accurate thermal stress model with strain rate and strain to solve the problems of quench distortion of parts by ANN with back propagation learning algorithm. In this model, the author used batch training from two network training types: sequential training and batch training. Batch training of BPNN with the best network structure (3-6-8-1) including two hidden layers provided about 3% error rate between the predicted output and the actual output. According to a strong positive linear correlation relationship between the predicted data and the experimental data by correlation coefficient calculation, the model was chosen to achieve good network performance to predict thermal stress of quenched A357 alloy with a higher precision. In this work, the authors were concerned with training types of ANN so that stability was found in performance of network.

[Sasikumar, Rajendraboopathy et al. (2008)](#_ENREF_64) presented a BPNN that had the best training result with 66-45-1 network architecture, and AE (Acoustic Emission) amplitude frequency data collected up to 50% of failure loads were used as input to BPNN for failure load (ultimate strength of unidirectional T-300/914 tensile specimens) prediction. Levenberg-Marquardt algorithm and the linear transfer function were used for establishing the ANN. In this work, it can be found that the network could not predict the ultimate loads outside the training range. At this point, it made incapability of the network because it is necessary to subsequently add the AE data of specimens with extreme error rate that lies beyond the training range into the training set, thereby decreasing the acceptable maximum error rate from 8.37% to 1.22%. Other key parameters such as duration, energy, events and counts were also used along with BPNN for material characterization and structural integrity evaluation for further analysis. From the analysis above, it was found that amplitude frequency is the most affecting factor in predicting failure load of composite hardware.

The authors have done another similar work in ([Rajendraboopathy, Sasikumar et al. 2008](#_ENREF_60)) in which three different BPNNs were built for predicting the failure strength of composite tensile coupons using acoustic emission technique. But up to 30%, 40% and 50% of failure loads were used as input to three neural networks, respectively. Three optimal network structures were 66-37-1 constructed with 30% of AE data, 66-22-1 constructed with 40% of AE data and 66-45-1 constructed with 50% of AE data, respectively. All of them were applied with the same network parameters, like learning rate of 0.01, momentum of 0.9, hyperbolic tangent transfer function, and backpropagation training algorithm. However, the comparison of three networks showed that the network trained with more data could provide better performance.

By ANN analytical models in ([Sasikumar, Rajendraboopathy et al. 2008](#_ENREF_64)) and ([Rajendraboopathy, Sasikumar et al. 2008](#_ENREF_60)), the prediction results of tensile strength indicated that proof test can be done on more sophisticated composites at lower loads so that the actual failure load of composite hardware was predicted. But there was the same finding from both works that inadequate training data did not produce the optimal prediction.

**3.1.3 Mechanical (Tribological) Property**

Predicting tribological properties of polymer composites friction materials to determine performance potential is a challenge in materials science because the available experimental dataset is relatively small, noisy, complex and highly non-linear, and the process of developing and testing a new composite material on trail-error based experimental method is time-consuming and laborious as well as complex and costly. ANN can make the problem-independent solution to prediction of tribological properties due to its advantage of nonlinearity, adaptive learning, and generalization. [Gyurova and Friedrich (2011)](#_ENREF_22) established two MLP neural networks for predicting tribological properties (coefficient of friction and specific wear rates) of polyphenylene sulfide (PPS) matrix composites. A new measurement series was performed with thermoplastic matrix composites and preexisting five experimental training datasets collected or expanded throughout a period of three years were used for training and testing the developed network models. Material compositions and testing conditions were used as input parameters to predict the tribological properties. The tansig function and purelin function were used as transfer functions for the hidden layer and the output layer respectively. The best network structures achieved with coefficient of friction and specific wear rate were 7-[3-1]2-1 and 7-[9-3]2-1, respectively. A user-friendly graphical interface was developed for performing network training and prediction, and it could easily predict even for unseen input. The network performance was evaluated by a comparison of the MRE (mean relative error) generated after training of the ANN with the different training datasets, thereby improving significantly with the enlarged datasets. The satisfactory ANN predicted results had good correlation with the measured values. The optimized ANN models was also used to analyze the impact of SCF (short carbon fiber), sub-micro TiO2, on the sliding friction and wear properties of PPS composites. It gave the excellent generalization of ANN without performing exhaustive experimental work. When those ANN models were also applied for studying the effect of internal lubricants (Gr and PTFE) in hybrid polymer systems, a good correlation existed between the actual and the predicted output.

[LiuJie, Davim et al. (2007)](#_ENREF_49) predicted friction coefficient and wear weight loss of carbon-fibre-reinforced polyetheretherketone composite (PEEK-CF30) as a function of *pv* factor and contact temperature by two BPNN models of which generalization capability was improved by implementing Bayesian regularization in combination with Levenberg–Marquardt learning algorithm. The best network was obtained with (2-7-1) and (2-8-1) architectures and sigmoid and pureline transfer function were used for hidden and output layers. In this work, the authors were dealed with data normalization and unnormalization methods so that the importance of each parameter was balanced and the networks were trained smoothly about 33 and 56 cycles. Those well-trained ANNs gave optimized generalization capability such that friction coefficient and wear weight loss were predicted with high accuracy of relative error lower than 10%. From the analysis, it was found that friction coefficient was strongly effected by the value of *pv* factor whereas compact temperature is the strongly influencing factor for wear weight loss.

It was shown that the advantage of ANN, its generalization ability, makes existing ANN models to be used for other problems with similar nature and produces highly accurate prediction results. It can be seen that predicting triobological properties of materials by ANN models reduces excessive experimental work by yielding satisfactory and acceptable results compared to experimental results, and ANN performance can also be optimized with other computing technologies, such as bayesian regularisation framework.

**3.2 ANN for Materials Design**

The relation among composition, process and properties of new materials design is influenced by many complicated factors. In the context of materials science, ANN performs a great job for prediction and function approximation with respect to materials’ performance, but there are not many ANN applications enough for forecasting materials properties for materials design. [Li, Qi et al. (2007)](#_ENREF_47) studied a new route for the designing of lead-free solder that can find out the influence of adding input variables (the contents of In. Bi, Sb, RE, Sn, Ag, Cu) to tensile strength, shear strength and solidification temperature of Sn-Ag alloy by using a multilayer neural network. The best network structure 7-40-40-40-1 with three hidden layers was chosen. Data from one reference came into the ANN for training and testing. The analysis result showed that the error rates between the expected output and the predicted output was within 5%, but only one of them gave 7% error rate because of less amount of training data, unexact measurement of shear strength and poor-proportionally distributed data. This work also indicated that more accurate prediction results can be obtained with big amount of training data. However, ANN still gave a good agreement with the given experimental conditions, and it was verified for making the feasible estimates of the property of the lead-free solder.

More recently, [Xie and Grossman (2018)](#_ENREF_76) developed a highly accurate prediction model of density functional theory (DFT) calculated properties from Materials Project ([Jain, Ong et al. 2013](#_ENREF_26)), with a database of a diverse set of inorganic crystals ranging from simple metals to complex minerals (including 46744 materials covering 87 elements, 7 lattice systems, and 216 space groups). A crystal graph convolutional neural networks (CGCNN) framework, an innovated universal and interpretable representation of crystalline materials, could directly learn material properties from the connection of atoms in the crystal and discover empirical rules of materials design, that were consistent with the common knowledge for discovering more stable materials. Thus, the search space for high-throughput screening could be significantly reduced by additional information provided by CGCNN for material design. Traditional methods used to represent the arbitrary size of crystal systems as a fixed length vector was well replaced by CGCNN by grabbing the benefit of deep learning. The authors also designed a new convolution function to make learning deeper networks easier, that improved generalization ability of CGCNN as well as prediction performance of different materials properties. Compared to previous statistical learning (SL) framework presented by [De Jong, Chen et al. (2016)](#_ENREF_11) that implemented multivariate local regression to predict elastic properties on the same dataset, CGCNN provided similar results, but it had the advantage of predicting properties by extracting features only from the crystal structure. And when CGCNN model was used for 1585 new crystals that were recently added into Materials Project database, it could also provide a good generalization to materials from potentially different crystal groups. It was a kind of evidence that ANN had good generalization ability. CGCNN could also predict discrete properties as well as the classifications of metal and semiconductor with the same framework, using a SoftMax activation function for the output layer and a cross entropy cost function.

Most current materials applications based on ANN highlighted the advantage of backpropagation feed forward neural networks, and their performance results were pointed out as being similar in making comparison with experimental results. The authors in ([Xie and Grossman 2018](#_ENREF_76)) just brought a great contribution into materials science by implementing the concept of deep learning to mine valuable knowledge from a large dataset to accelerate the design of crystalline materials.

**3.3 ANN with Other Computing Paradigms**

Integration of neural networks with other computing paradigms, such as Bayesian framework, fuzzy logic, sensitivity analysis, and genetic algorithm, can also enhance the performance of ANN. [Cai, Cottis et al. (1999)](#_ENREF_9) used multilayer perceptron ANN analysis integrated with sensitivity analysis to analyze the phenomena of atmospheric corrosion behavior of steel and zinc. This work investigated a system with environmental variables including temperature (T), time of wetness, exposure time (TOE), and concentrations of Sulphur dioxide (SO2) and Cl-, and found out the complex interactions between those variables and atmospheric corrosion. The database was big enough to be used for this work, including information from corrosion tests, climatological tables and rainfall data from thirty-three countries around the world. But those data were measured by different methods in different sources so that corrosion data might have inherently scattered. According to sensitivity analysis, almost linear relationship between input (TOW and SO2), that are the most affecting input variables on atmospheric corrosion in industrial environment, and output (atmospheric corrosion of steel and zinc) were found at a specified condition. The network structure (5-8-1) with one hidden layer and sigmoid transfer function showed that the ANN results accounted for approximately 70% of the variance seen in the real data sets. Although this work did not consider about other possibly more important parameters on atmospheric corrosion (such as effect of microclimate) for prediction model, it can be seen that ANN could still give more satisfactory results by its fault-tolerance ability than previous linear regression analysis.

To find out the solution to the challenge of predicting the time to failure of 304 stainless steel as a result of stress corrosion cracking (SCC) in aqueous chloride solution, [Lajevardi, Shahrabi et al. (2009)](#_ENREF_42) had implemented a similar approach adopted by [Cai, Cottis et al. (1999)](#_ENREF_9), in which a MLP with backpropagation algorithm was constructed and evaluated using the collection of experimental data associated with the SCC of AISI 304. The data used to train the network was extracted from 24 references. The best network structure was (3-4-4-1) with sigmoid transfer function. In this work, Monte Carlo optimization has been used to evaluate the initial set of weight values to reduce the local optima phenomenon. Both of those works have conducted sensitivity analysis to improve the network efficiency by demonstrating the effects of the important variables and showed the effects of the other affecting variables. Sensitivity analysis showed that among three input parameters (applied stress, temperature and Cl-), applied stress was regarded as the most influencing parameter on time to failure. Those ANN models can account for about 70% and 74% of the variance of the experimental data, but these two works have some limitations in unseen possible affecting variables, unexplained variances in prediction and data accuracy.

Later, another effective input ranking method called fuzzy curve was adopted by [Xia, Nie et al. (2016)](#_ENREF_75) to rank the importance of input parameters that might have a great impact on the output. The authors built two BP neural networks for investigating non-linear correlation and predicting hardness and corrosion rate of magnesium alloy as a function of compositions. ANN prediction results demonstrated that there was an excellent correlation for hardness and although correlation for corrosion rates was lower than hardness, it was still considerably good result because of the inherently chemical activity of Mg and complex interactions between alloy additions. Fuzzy curve analysis was also used in integration with ANN to analyze the impact of each alloying element on the performance of alloy. The sequence of the alloying elements in terms of their ability to improve the performance of Mg alloys was ranked with relatively low alloying level for high hardness as Ca ≥ Zr  Sr Zn Gd whereas fuzzy curves gave complex results for corrosion rate, but the impact of each alloy element on corrosion rate were respectively described. It can be seen that non-linear correlations have been existing between hardness and corrosion rate. However, fuzzy curve analysis could improve the performance of ANN with satisfactory accuracy, and the model can be used for corrosion prediction of other existing and future Mg alloys.

ANN is a technology that can learn by examples and then make prediction for new situations. ANN model needs sufficient amount of extensive and representative data to constitute a good training set to solve the problem. Many unnecessary input parameters that do not have a strong interaction with the desired output in training data makes an exhausted training and degrades the network performance. In materials science researches, it is critical to know the importance of each input variables affecting on material properties and identify which input variable is the most influencing factor on materials’ properties. By using input ranking methods, like sensitivity analysis and fuzzy curve, unimportant input parameters will be easily found out and eliminated from the problem, and then model will be made simpler and easier to define future possible mechanisms, and the solution will be more fruitful and exact. And modeling ability of ANN can be improved by considering all other possible variables that have the strong impact on the output at a given condition and constructing a more enriched dataset.

The benefit of other computing technologies, such as genetic algorithm and Bayesian framework, can fix the defects of ANN model, like overfitting occurred while training the network and uncertainty and instability of ANN, and then the performance of network is significantly improved. That fact was supported by the work of ([Huang, Jia et al. 2018](#_ENREF_24)) in which the authors made a comparison of three different approaches to predict flow behavior and find out the optimum hot working processing parameters of 5754 aluminum alloy as a function of deformation parameters. Three forecasting models: strain-compensation Arrhenius (SA), back propagation (BP) ANN, and an optimized BP-ANN model based on genetic algorithm (ANN-GA) were constructed. Their comparison showed that four-layered BP-ANN model provided more accurate prediction than SA model. But it was found that BP-ANN model was weak to optimize globally so that local optimum occurred in learning algorithm. This weakness made the instability in network performance. BP-ANN was optimized by genetic algorithm (GA) to form a new model with network structure (3-10-8-1) that produced higher accuracy and stability (Correlation Coefficient R=0.9999 and Average Absolute Relative Error ARRE=0.0232–1.0485) within the whole deformation range by calculating the fitness values of each individual in GA by the predictive error norm of the neural network. Therefore, ANN-GA model was found as the most efficient and accurate model among three models because genetic algorithm (GA) can remove the uncertainty of ANN, and improve its stability and accuracy by searching for the optimal weight and threshold for ANN at the same time.

Steel strip data set from the hot strip mills of Mobarakeh Steel Complex was employed by [Kermanpur, Ebnonnasir et al. (2007)](#_ENREF_35) to construct a novel analytical predictive framework, named analytical–artificial neural network (AANN) model to estimate the spray impact from spray angle, spray pressure, vertical spray height and water flowrate. The predictive model was coupled with Bayesian regularization that can reduce the overfitting problem of Levenberg–Marquardt ANN learning algorithm and improve the network prediction ability for unseen data. The combined network could be used as a proper tool to evaluate the efficiency of a high pressure (HP) hydraulic descaling operation using flat spray nozzles in terms of achieving the highest spray impact under any process condition. With an optimal network structure of one input layer with four input variables, two hidden layers and one output layer with one output variable, a maximum amount of output (spray impact) was obtained. The prediction result showed a good agreement for correlation coefficient R2 of 0.992. In this work, sensitivity analysis was also carried out, in which input parameter spray angle resulted in the highest influence on spray impact was followed by the spray height. The authors were also progressively using their current AANN model to predict the effect of all input parameters on the spray overlap.

In recent works, we can see that there are many successful ANN applications in materials related problems. Herein, the hybrid system, the joint implementation with other computing methodologies in which ANN plays a major role, can make more satisfactory improvement in ANN performance compared to simple ANN model alone.

**3.4 Other Powerful ANN Models in Materials Applications**

The other powerful and efficient neural network models rather than multilayer BPNN have also brought successful prediction results in recent works to determine the tensile mechanical properties of materials. [Yilmaz and Ertunc (2007)](#_ENREF_81) introduced a neural network model, named generalized regression neural network (GRNN), to predict tensile strength of steel wires by using all the production parameters (the amount of carbon, ferrite and inclusions) and the diameter of steel wires. That approach was constructed with four layers: input layer, a layer of radial basis centers, a linear layer of regression unit and the output layer. A very good statistical performance with a 0.96 correlation coefficient between the target data and the predicted output demonstrated the result of the tensile strength of steel with high accuracy and reliability.

[Kappatos, Chamos et al. (2010)](#_ENREF_33) adopted a radial basis function (RBF) neural network, one of the mostly used feed forward network models after multilayer network, to assess the effect of existing corrosion damage on the tensile behaviour of the wrought magnesium alloy AZ31 by predicting the time dependency of the tensile mechanical properties degradation. The data used to train the network were derived from extensive experimental investigation. The authors used only two input parameters (pit depth and pitting density) that had stronger discriminant capability on output (elongation of fracture and ultimate tensile strength). Although there was no need to determine the number of hidden layers for RBF that includes a single hidden layer, extensive trials were carried out to determine the optimum number of hidden neurons to achieve the best prediction accuracy. Conventional linear modelling techniques fully optimized the simple linear transformation at the output layer of RBF network. Greater RBF networks with 40 and 20 hidden neurons gave higher prediction accuracy from 99.61% to 99.83% for elongation of fracture and from 99.27% to 99.68% for ultimate tensile strength, respectively. ANN results made a comparison between two input parameters to find their impact on the output such that more accurate output tensile strength was achieved with pitting density while the pit depth had stronger effect on the decrease of the mechanical properties than pitting density. RBF neural network prediction results were very good agreement with experimental results.

Most of successful materials-related ANN researches have been done with multilayer BPNN. Here, it can be found that other ANN types are as powerful and efficient as multilayer BPNN in prediction performance. Regarding to physical background of the problem, input parameters should be selected as important features that have a strong relation with output parameters so that computational cost and size of training data can be reduced to improve the prediction performance.

**3.5 ANN Models in Comparison and Hybrid ANN Models**

In some literatures, ANN prediction result was compared to not only experimental results but also other feed forward ANN models’ results. In turning process, to control the desired surface roughness by establishing a functional relationship between process parameters of turning process and surface roughness, MLP neural networks have been mostly implemented for a decade. But MLP needs to determine the number of hidden layers and hidden neurons in each layer with a costly trial-and-error approach. Unlike MLP, as radial basis function (RBF) neutral network has the advantage of having only one hidden layer and the number of hidden neurons can automatically be adjusted in learning algorithm, less computational time and simpler training can give faster and more accurate results. [Sonar, Dixit et al. (2005)](#_ENREF_68) used the advantage of RBF neural network to construct a predictive model for the surface roughness of mild steel with process parameters (feed rate ( *f* ), cutting speed (*v*), depth of cut (*d*) and acceleration of radial vibration (*a*)) in a turning process by HSS (high speed steel) and carbide tools, and its performance was compared with the reported performance of a MLP neural network by [Kohli and Dixit (2004)](#_ENREF_39) as well as experimental results. The RBF neural network has been implemented for predicting the most likely estimate as well as the upper and lower estimate, calculated by fuzzy linear interval regression model, of surface roughness. The results showed that experimental values exist between the range of the lower and upper estimate and the most likely estimate in most cases is close to experimental values. Also, compared to MLP, the root mean squares errors of RBF are nearly the same as MLP. But RBF made slightly inferior performance against MLP with less computational time, and the errors were more than 20% with a few testing data, but still reasonable results were given. The authors discussed about increasing the number of training and testing data to increase the network accuracy.

Another similar comparison of different ANN models was found in ([Lu and Liu 2009](#_ENREF_50)) in which the carbonation depth of prestressed concrete under different stress states was analyzed by adopting two feed forward ANNs, BPNN and RBFNN with concrete mixture parameters, together with comparison in their performance and comparison with experimental results as well. Training data and test data for two ANNs were produced by an accelerated carbonation practical experiment of prestressed concrete. The 5-10-1 structure of BPNN is the optimal network structure for prediction. RBFNN was also established with the same number of input and output parameters. RBFNN results have the largest absolute percentage error of 8.46% whereas the largest absolute percentage error of BPNN is 10.88%. In this work, although RBFNN gave better precision than BPNN, the precision level of BPNN can be improved by adding the number of hidden layers appropriately that will lead to a costly trial-and-error approach. Since the error rates of both models were acceptable and their estimation results were good agreement with experimental results, ANN has a high generalization ability to analyze and predict carbonation depth in concrete. The authors suggested that RBFNN is a better model for predicting carbonation depth in concrete and solving other civil engineering related problems as well. However, they reported that enough training and testing data was still needed to construct a perfect ANN for providing a new practical approach to concrete carbonation analysis.

From previous works, it is inevitable that different ANN analytical models based on artificial intelligence can yield somewhat reasonable, acceptable and satisfactory results. Besides, not only single ANN alone but also hybrid ANN (that combines two or more different ANNs) can give reasonable and acceptable results for prediction. That fact was supported by [Li, Lv et al. (2017)](#_ENREF_44) who established a hybrid ANN (HNN) composed of one BP and one RBF by combining their advantages to construct an optimal ANN prediction model. The tribological properties of solid lubricants reinforced nano-TiO2/polyamide6 composites (friction coefficient and ware rate) were analyzed as a function of material composition, testing loads, and velocities. In this work, adaptive genetic algorithm (AGA), that computes the optimal number of hidden neurons and mixed coefficients of BP and RBF, was also coupled with HNN to improve network prediction performance by covering the disadvantages of genetic algorithm (GA) of being prone to premature and slow to converge. The HNN could estimate the tribological properties with high accuracy of under 5% small relative errors and over 0.99 high correlation index and establish the relationship of tribological properties and process parameters so that exhausted experimental work can be dramatically reduced for future prediction.

However, there is no defined universal ANN model that always outperforms on other ANN models. The right choice of ANN model should be made in accordance with the problem to be solved at hand. The network performance relies on the level of complexity and nonlinearity of input-output mapping as well as the amount of training and testing data and network topology (such as learning rate, learning algorithm, number of hidden layers, activation function and number of hidden neurons). Moreover, to make a result comparison with experimental results for optimal result, ANN models must be trained and tested with the same data set as experimental model.

**3.6 Summary**

Materials data are becoming so abundant that their relationship is quite complicated to handle well. Traditional linear regression analysis is mostly not able to handle a large number of variables and nonlinear relationship among them. The main benefit of ANN over conventional regression analysis is that ANN can model problems in which there is no clear relationships between inputs and outputs and construct the solutions that can not be easily formulated within short time without specifying the form of interactions between variables. From previous works, it can be said that ANN is a good estimator for materials related problems against statistical linear regression analysis due to its advantages of fault-tolerance, noise-tolerance and generalization ability. It can solve both nonlinear and linear problems with high accuracy. As a disadvantage, although ANN has benefit of parallel structure, it sometimes spends long training and operating time and occurs instability when applied to larger problems. Important features that have a strong relation with output parameters should carefully be selected as input into ANN training such that unnecessary computational overhead and increased size of training data can be reduced to attain high classification performance.

But it is critical to be noted that misuse of over-complicated networks cannot give the optimal results. ANN should be correctly implemented according to types of problems to be solved to avoid the misuse of ANN benefit. If the number of hidden neurons, compared to the number of data pairs in evaluating the fitting parameters, are not enough as in ([Altinkok and Koker 2006](#_ENREF_2), [Koker, Altinkok et al. 2007](#_ENREF_40)) or more redundant as in ([Forouzan and Akbarzadeh 2007](#_ENREF_18)), it will lead to the misuse of ANN. Moreover, it does not mean the more complicated the networks, the better the results. The number of neurons in hidden layers of neural networks should also be increased within a limit depending on the problem, otherwise; mathematically undefined situation, known as overfitting, in which determining more fitting parameters than the available data points is difficult, will make poor network generalization ability on unseen data. No matter what the number of ANN models are, the critical point to take account is that more data points would be needed to establish a more robust and reliable ANN model with higher confidence and more representative results. Also, it can be concluded that a good ANN model can progressively be used for future prediction in the context of the problem with same nature. The joint implementation of ANN and other computing paradigms should further be considered due to their good cooperation results.

### **4. Trends of the ANN Applications in Materials Area**

At present, researchers are trying to implement ANN models to predict the performance, and the predictions of stability and structure of materials are also great challenges in materials science. According to National Institute for Materials Science [NIMS (Policy Paper 2007)](#_ENREF_56), in 2020, materials industries that supply steel, petrochemical products, cement, etc., will be the key technology of automotive industry to develop new structural materials. ANN can accelerate the design of new materials by predicting material properties with high accuracy. To combine materials science with computer science by ANN prediction for materials properties is a great solution for researchers not only at present but also in the future.

Previous works described their network parameters: network structures, training algorithms, transfer functions, and data used to train and test ANN, in related researches so that those works can be expanded and enhanced by new researchers. Since their prediction results gave satisfactory and acceptable outcomes against experimental results, ANN prediction models can significantly reduce quantitative experimental works. But most of recent works showed that a large amount of data were still needed to train ANN. ANN performance can be extended when there is data big enough for constructing an optimized neural network model, and then the prediction results will be more exact for future use. Since ANN has the abilities of noise-tolerence and fault-tolerence, it can deal well with real-world data that are somewhat noisy, uncertain, complex and incomplete, and is an appropriate solution to complicated problems to give the satisfactory result.

Most neural network models in the context of materials science are feed forward types, and other popular, powerful and efficient feedback neural networks (Recurrent Neural Network, Long/Short Term Memory Neural Network, etc.), that are currently widely implemented in image and video recognition, time series prediction, handwriting recognition, speech recognition, automated robotics and machine translation applications in computer science researches, and hybrid use of different network types would be future research trends in materials science too. It is still necessary to conduct more researches related with those networks in materials related fields to give strongly recommended results to new researchers. And also, by using input ranking methods that made a great contribution to ANN performance, unnecessary input parameters will easily be removed from ANN model to become simpler model that can give more fruitful results. Hence, the implementation of ANN in the prediction of material properties may achieve higher score and find more application prospects in the long-term horizon.

The purpose of this paper is to reveal the significance of ANN in many aspects of materials related problems, and it can be seen that ANN prediction accuracy has been apparently improved in recent researches compared to traditional statistical regression equations. It is expected that this paper can assist materials researchers by providing a comprehensive review of the applications of neural network in the context of materials science.

**Conflict of Interests**

The authors declare that they have no conflict of interests.

**APPENDIX A- Nomenclature**

The following were alphabetically ordered.

ρAC,bar AC resistivity over the steel bar

ρAC,conc AC resistivity remote from the steel bar

ρDC DC resistivity over the steel bar

*a*  acceleration of radial vibration

Ag silver

Al aluminum

B binder

B(OH)3 boron content

Bi bismuth

BPNN backpropagation neural network

C carbon

Cd current density

Csic SiC particle concentration

C/CA cement-coarse aggregate ratio

C/FA cement-fine aggregate ratio

CEIIW carbon equivalent

CEPcm carbon equivalent based on the Ito-Bessyo equation

CGR crack growth rate

Cl- chloride ions concentration

Cr chromium

CrMoNiCu the sum of chromium, molybdenum, nickel and copper concentrations

Cu copper

*d* (or) t depth of cut

d*a*/d*N* corrosion–fatigue crack growth

DC depth of carbonation

Dmax maximum pit depth

E potential

Ecorr corrosion potential

ECP principal environmental factor

EIS electrochemical impedance spectroscopy

El elongation

*f* (or) s feed rate

Fe iron

H2SO4  sulfuric acid

HCl hydrochloric acid

HP high pressure

icorr corrosion current density

In indium

KI  principal mechanical factor

LiOH lithium content

LPR linear polarization resistance

MK metakaolin addition

MLP multiplayer perceptron

Mn magnesium

Mo molybdenum

N nitrogen

NaCl chloride ion

Nb niobium

NbV the sum of niobium and vanadium concentrations

Ni nickel

P phosphorus

PCO2 pressure of purged CO2

PO2 relative pressure of oxygen

PTFE polytetrafluoroethylene

Q charge amount

planar anisotropy

Ra surface roughness

Rp polarization resistance

RBFNN radial basis function neural network

Re rhenium

RH relative humidity

S sulfur

Sb antimony

SCC stress corrosion cracking

Si silicon

SIF stress intensity factor

SL stress level of concrete

Sn tin

SO2 sulphur dioxide

SP superplasticizer

SR strain rate

T temperature

TA testing age

Ti titanium

TiO2 titanium dioxide

TOE time of exposure

TOW time of wetness

Up ultrasonic power

UTS ultimate tensile strength

UV ultrasonic velocity

*v* cutting speed

V vanadium

VTiNb the sum of niobium, vanadium and titanium concentrations

w frequency

W sample weight change

W/B water-to-binder ratio

W/C water-cement ratio

WV wind velocity

YS yield strength

Zr and Zi real and imaginary impedances

**APPENDIX B- description**

BPNN: BPNN is an ANN that uses backpropagation learning/training algorithm, and has one input layer, one hidden layer (enough for large majority of problems) or at least two hidden layers (for complex problems) and one output layer.

MLP: An ANN consists of at least three layers of nodes: an input layer, one or more hidden layers and an output layer.

RBFNN: A multi-layer feed forward neural network consists of three layers: one input layer, one hidden layer in which hidden neurons use radial basis function (RBF) and one output layer.

**REFERENCES**

Aliofkhazraei, M. and A. S. Rouhaghdam (2008). "Neural networks prediction of different frequencies effects on corrosion resistance obtained from pulsed nanocrystalline plasma electrolytic carburizing." Materials Letters **62**(14): 2192-2195.

Altinkok, N. and R. Koker (2006). "Modelling of the prediction of tensile and density properties in particle reinforced metal matrix composites by using neural networks." Materials & Design **27**(8): 625-631.

Ashtiani, H. R. R. and P. Shahsavari (2016). "A comparative study on the phenomenological and artificial neural network models to predict hot deformation behavior of AlCuMgPb alloy." Journal of Alloys and Compounds **687**: 263-273.

Asteris, P. G., P. C. Roussis and M. G. Douvika (2017). "Feed-Forward Neural Network Prediction of the Mechanical Properties of Sandcrete Materials." Sensors (Basel) **17**(6).

Bassam, A., D. Ortega-Toledo, J. A. Hernandez, J. G. Gonzalez-Rodriguez and J. Uruchurtu (2008). "Artificial neural network for the evaluation of CO2 corrosion in a pipeline steel." Journal of Solid State Electrochemistry **13**(5): 773-780.

Bhadeshia, H. K. D. H. (2008). Neural Networks in Materials Science. Encyclopedia of Materials: Science and Technology, Elsevier**:** 1-5.

Bhadeshia, H. K. D. H., R. C. Dimitriu, S. Forsik, J. H. Pak and J. H. Ryu (2009). "Performance of neural networks in materials science." Materials Science and Technology **25**(4): 504-510.

Birbilis, N., M. K. Cavanaugh, A. D. Sudholz, S. M. Zhu, M. A. Easton and M. A. Gibson (2011). "A combined neural network and mechanistic approach for the prediction of corrosion rate and yield strength of magnesium-rare earth alloys." Corrosion Science **53**(1): 168-176.

Cai, J., R. A. Cottis and S. B. Lyon (1999). "Phenomenological modelling of atmospheric corrosion using an artificial neural network." Corrosion Science **41**(10): 2001-2030.

Colorado-Garrido, D., D. M. Ortega-Toledo, J. A. Hernández, J. G. González-Rodríguez and J. Uruchurtu (2008). "Neural networks for Nyquist plots prediction during corrosion inhibition of a pipeline steel." Journal of Solid State Electrochemistry **13**(11): 1715-1722.

De Jong, M., W. Chen, R. Notestine, K. Persson, G. Ceder, A. Jain, M. Asta and A. Gamst (2016). "A Statistical Learning Framework for Materials Science: Application to Elastic Moduli of k-nary Inorganic Polycrystalline Compounds."

Demuth, H. B., M. H. Beale, O. D. Jess and M. T. Hagan (2014). Neural Network Design, Martin Hagan.

Díaz, V. and C. López (2007). "Discovering key meteorological variables in atmospheric corrosion through an artificial neural network model." Corrosion Science **49**(3): 949-962.

Evans, M. (1999). "Method for improving parametric creep rupture life of 2·25Cr–1Mo steel using artificial neural networks." Materials Science and Technology **15**(6): 647-658.

Faizabadi, M. J., G. Khalaj, H. Pouraliakbar and M. R. Jandaghi (2014). "Predictions of toughness and hardness by using chemical composition and tensile properties in microalloyed line pipe steels." Neural Computing and Applications **25**(7-8): 1993-1999.

Fathi, A. and A. Aghakouchak (2007). "Prediction of fatigue crack growth rate in welded tubular joints using neural network." International Journal of Fatigue **29**(2): 261-275.

Fausett, L. V. (1994). Fundamentals of neural networks: architectures, algorithms, and applications, Prentice-Hall Englewood Cliffs.

Forouzan, S. and A. Akbarzadeh (2007). "Prediction of effect of thermo-mechanical parameters on mechanical properties and anisotropy of aluminum alloy AA3004 using artificial neural network." Materials & Design **28**(5): 1678-1684.

Fu, Z., J. Mo, L. Chen and W. Chen (2010). "Using genetic algorithm-back propagation neural network prediction and finite-element model simulation to optimize the process of multiple-step incremental air-bending forming of sheet metal." Materials & Design **31**(1): 267-277.

Ghaisari, J., H. Jannesari and M. Vatani (2012). "Artificial neural network predictors for mechanical properties of cold rolling products." Advances in Engineering Software **45**(1): 91-99.

Graupe, D. (2013). Principles of Artificial Neural Networks, WORLD SCIENTIFIC.

Gyurova, L. A. and K. Friedrich (2011). "Artificial neural networks for predicting sliding friction and wear properties of polyphenylene sulfide composites." Tribology International **44**(5): 603-609.

Haque, M. (2001). "Prediction of corrosion–fatigue behavior of DP steel through artificial neural network." International Journal of Fatigue **23**(1): 1-4.

Huang, C., X. Jia and Z. Zhang (2018). "A Modified Back Propagation Artificial Neural Network Model Based on Genetic Algorithm to Predict the Flow Behavior of 5754 Aluminum Alloy." Materials (Basel) **11**(5).

J. Taylor, B. (2006). Methods and Procedures for the Verification and Validation of Artificial Neural Networks.

Jain, A., S. P. Ong, G. Hautier, W. Chen, W. D. Richards, S. Dacek, S. Cholia, D. Gunter, D. Skinner, G. Ceder and K. A. Persson (2013). "Commentary: The Materials Project: A materials genome approach to accelerating materials innovation." APL Materials **1**(1): 011002.

Jain, A. K., J. Mao and K. M. Mohiuddin (1996). "Artificial Neural Networks: A Tutorial." IEEE Computer **29**(3): 31-44.

Jančíková, Z., O. Zimný and P. Koštial (2013). Prediction of metal corrosion by neural networks.

Jiang, G., J. Keller, P. L. Bond and Z. Yuan (2016). "Predicting concrete corrosion of sewers using artificial neural network." Water Res **92**: 52-60.

Jiménez-Come, M. J., I. J. Turias, J. J. Ruiz-Aguilar and F. J. Trujillo (2015). "Characterization of pitting corrosion of stainless steel using artificial neural networks." Materials and Corrosion **66**(10): 1084-1091.

Kamrunnahar, M. and M. Urquidi-Macdonald (2010). "Prediction of corrosion behavior using neural network as a data mining tool." Corrosion Science **52**(3): 669-677.

Kamrunnahar, M. and M. Urquidi-Macdonald (2011). "Prediction of corrosion behaviour of Alloy 22 using neural network as a data mining tool." Corrosion Science **53**(3): 961-967.

Kappatos, V., A. N. Chamos and S. G. Pantelakis (2010). "Assessment of the effect of existing corrosion on the tensile behaviour of magnesium alloy AZ31 using neural networks." Materials & Design **31**(1): 336-342.

Kenny, E. D., R. S. C. Paredes, L. A. de Lacerda, Y. C. Sica, G. P. de Souza and J. Lázaris (2009). "Artificial neural network corrosion modeling for metals in an equatorial climate." Corrosion Science **51**(10): 2266-2278.

Kermanpur, A., A. Ebnonnasir and M. Hedayati (2007). "A novel analytical–artificial neural network model to improve efficiency of high pressure descaling nozzles in hot strip rolling of steels." Materials Science and Technology **23**(8): 951-957.

Khadom, A. A. (2013). "Modeling of corrosion reaction data in inhibited acid environment using regressions and artificial neural networks." Korean Journal of Chemical Engineering **30**(12): 2197-2204.

Khaled, K. and N. A. Al-Mobarak (2012). A Predictive Model for Corrosion Inhibition of Mild Steel by Thiophene and Its Derivatives Using Artificial Neural Network.

Khaled, K. and A. Sherik (2013). Using Neural Networks for Corrosion Inhibition Efficiency Prediction during Corrosion of Steel in Chloride Solutions.

Kohli, A. and U. S. Dixit (2004). "A neural-network-based methodology for the prediction of surface roughness in a turning process." The International Journal of Advanced Manufacturing Technology **25**(1-2): 118-129.

Koker, R., N. Altinkok and A. Demir (2007). "Neural network based prediction of mechanical properties of particulate reinforced metal matrix composites using various training algorithms." Materials & Design **28**(2): 616-627.

Komijani, H., S. Rezaeihassanabadi, M. R. Parsaei and S. Maleki (2016). "Radial Basis Function Neural Network for Electrochemical Impedance Prediction at Presence of Corrosion Inhibitor." Periodica Polytechnica Chemical Engineering.

Lajevardi, S. A., T. Shahrabi, V. Baigi and A. Shafiei M (2009). "Prediction of time to failure in stress corrosion cracking of 304 stainless steel in aqueous chloride solution by artificial neural network." Protection of Metals and Physical Chemistry of Surfaces **45**(5): 610-615.

Lee, A., B. Lam, W. Li, H. Lee, W.-H. Chen, M.-F. Chang and K. Wang (2018). Conditional Activation for Diverse Neurons in Heterogeneous Networks.

Li, D., R. Lv, G. Si and Y. You (2017). "Hybrid neural network-based prediction model for tribological properties of polyamide6-based friction materials." Polymer Composites **38**(8): 1705-1711.

Li, L., P. Qiu, S. B. Xing and X. Su (2013). "Research on Corrosion Rate Prediction of Aluminum Alloys in Typical Domestic Areas Based on BP Artificial Neural Network." Advanced Materials Research **652-654**: 1088-1091.

Li, M., X. Liu, S. Wu and X. Zhang (1998). "Approach to constitutive relationships of a Ti-5AI-2Sn-2Zr-4Cr-4Mo alloy by artificial neural networks." Materials Science and Technology **14**(2): 136-138.

Li, S., F. Qi, Z. Hou and Y. Xiao (2007). The Prediction of Sn-Ag Solder Properties Based on BP Algorithm of Artificial Neutral Network. 2007 8th International Conference on Electronic Packaging Technology, IEEE.

Liu, Y., H. Y Li, H. F Jiang and X. J Su (2013). Artificial neural network modelling to predict hot deformation behaviour of zinc–aluminium alloy.

LiuJie, X., J. P. Davim and R. Cardoso (2007). "Prediction on tribological behaviour of composite PEEK-CF30 using artificial neural networks." Journal of Materials Processing Technology **189**(1-3): 374-378.

Lu, C. and R. Liu (2009). "Predicting Carbonation Depth of Prestressed Concrete under Different Stress States Using Artificial Neural Network." Advances in Artificial Neural Systems **2009**: 1-8.

M. Pourbaix, s. (1990). "International cooperation in the prevention of corrosion of materials." IX International Congress of Metallic Corrosion, Florença, Itália, Anais.

Maier, H. R. and G. C. Dandy (2000). "Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications." Environmental Modelling & Software **15**(1): 101-124.

Mehta, A. (2019). "A Complete Guide to Types of Neural Networks." Available Online:. <https://www.digitalvidya.com/blog/types-of-neural-networks/>.

Montakhab, M. and P. Behjati (2010). "Modelling correlation between hot working parameters and flow stress of IN625 alloy using neural network." Materials Science and Technology **26**(5): 621-625.

Narimani, N., B. Zarei, H. Pouraliakbar and G. Khalaj (2015). "Predictions of corrosion current density and potential by using chemical composition and corrosion cell characteristics in microalloyed pipeline steels." Measurement **62**: 97-107.

NIMS (Policy Paper 2007). "A Vision of Materials Science in the Year 2020." Excerpts from the 2020 NIMS Policy Paper, Independent Administrative Institution National Institute for Materials Science.

Osgerby, S. and A. T. Fry (2007). "The use of neural networks in understanding and predicting oxidation and corrosion behaviour in advanced energy conversion systems." Materials at High Temperatures **24**(4): 259-263.

Parthiban, T., R. Ravi, G. T. Parthiban, S. Srinivasan, K. R. Ramakrishnan and M. Raghavan (2005). "Neural network analysis for corrosion of steel in concrete." Corrosion Science **47**(7): 1625-1642.

Pintos, S., N. V. Queipo, O. Troconis de Rincón, A. Rincón and M. Morcillo (2000). "Artificial neural network modeling of atmospheric corrosion in the MICAT project." Corrosion Science **42**(1): 35-52.

Rajendraboopathy, S., T. Sasikumar, K. M. Usha and E. S. Vasudev (2008). "Artificial neural network a tool for predicting failure strength of composite tensile coupons using acoustic emission technique." The International Journal of Advanced Manufacturing Technology **44**(3-4): 399-404.

Ramesh, R. and R. Gnanamoorthy (2007). "Artificial Neural Network Prediction of Fretting Wear Behavior of Structural Steel, En 24 Against Bearing Steel, En 31." Journal of Materials Engineering and Performance **16**(6): 703-709.

Rojas, R. (1996). Neural networks: a systematic introduction, Springer-Verlag.

Sadowski, L. (2013). "Non-destructive investigation of corrosion current density in steel reinforced concrete by artificial neural networks." Archives of Civil and Mechanical Engineering **13**(1): 104-111.

Sasikumar, T., S. Rajendraboopathy, K. M. Usha and E. S. Vasudev (2008). "Artificial Neural Network Prediction of Ultimate Strength of Unidirectional T-300/914 Tensile Specimens Using Acoustic Emission Response." Journal of Nondestructive Evaluation **27**(4): 127-133.

Seidl, D., Z. Jančíková, P. Koštial, I. Ružiak, I. Kopal and K. Kreislova (2012). "Exploitation of Artificial Intelligence Methods for Prediction of Atmospheric Corrosion." Defect and Diffusion Forum **326-328**: 65-68.

Shi, J., J. Wang and D. D. Macdonald (2015). "Prediction of primary water stress corrosion crack growth rates in Alloy 600 using artificial neural networks." Corrosion Science **92**: 217-227.

Sinha, N. K., M. M. Gupta and D. H. Rao (2000). Dynamic neural networks: an overview. Proceedings of IEEE International Conference on Industrial Technology 2000 (IEEE Cat. No.00TH8482).

Sonar, D. K., U. S. Dixit and D. K. Ojha (2005). "The application of a radial basis function neural network for predicting the surface roughness in a turning process." The International Journal of Advanced Manufacturing Technology **27**(7-8): 661-666.

Sung, A. H. (1998). "Ranking importance of input parameters of neural networks." Expert Systems with Applications **15**(3): 405-411.

Upadhyay, V., P. K. Jain and N. K. Mehta (2013). "In-process prediction of surface roughness in turning of Ti–6Al–4V alloy using cutting parameters and vibration signals." Measurement **46**(1): 154-160.

Vasudevan, M., A. K. Bhaduri, B. Raj and K. P. Rao (2005). "Modelling correlation between alloy composition and ferrite number in duplex stainless steel welds using artificial neural networks." Materials Science and Technology **21**(4): 387-392.

Vera, R. and S. Ossandón (2014). On the Prediction of Atmospheric Corrosion of Metals and Alloys in Chile Using Artificial Neural Networks.

Weckman, G. R., W. Young, S. Hernández, M. Rangwala and V. Ghai (2010). "EXTRACTING KNOWLEDGE FROM CARBON DIOXIDE CORROSION INHIBITION WITH ARTIFICIAL NEURAL NETWORKS." International Journal of Industrial Engineering: Theory, Applications and Practice; Vol 17, No 1 (2010).

Weingaertner, D., V. K. Tatai, R. R. Gudwin and F. J. V. Zuben (2002). Hierarchical evolution of heterogeneous neural networks. Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No.02TH8600).

Xia, X., J. F. Nie, C. H. J. Davies, W. N. Tang, S. W. Xu and N. Birbilis (2016). "An artificial neural network for predicting corrosion rate and hardness of magnesium alloys." Materials & Design **90**: 1034-1043.

Xie, T. and J. C. Grossman (2018). "Crystal Graph Convolutional Neural Networks for an Accurate and Interpretable Prediction of Material Properties." Phys Rev Lett **120**(14): 145301.

Xu, L. J., J. D. Xing, S. Z. Wei, Y. Z. Zhang and R. Long (2007). Artificial neural network prediction on wear properties of high vanadium high speed steel (HVHSS) rolls.

Xu, Y., Y. Zhu, G. Xiao and C. Ma (2014). "Application of artificial neural networks to predict corrosion behavior of Ni–SiC composite coatings deposited by ultrasonic electrodeposition." Ceramics International **40**(4): 5425-5430.

Yang, X. W., J. C. Zhu, Z. H. Lai, Y. R. Kong, R. D. Zhao and D. He (2012). "Application of artificial neural network to predict flow stress of as quenched A357 alloy." Materials Science and Technology **28**(2): 151-155.

Yao, C. G., B. Wang, D. Q. Yi, B. Wang and X. F. Ding (2013). "Artificial neural network modelling to predict hot deformation behaviour of as HIPed FGH4169 superalloy." Materials Science and Technology **30**(10): 1170-1176.

Yilmaz, M. and H. M. Ertunc (2007). "The prediction of mechanical behavior for steel wires and cord materials using neural networks." Materials & Design **28**(2): 599-608.

Zhang, H. J., X. J. Wang, Q. L. Jia and H. W. Sun (2007). "Artificial neural network analysis of preparation of nanoα-Al2O3powders by thermal decomposition of ammonium aluminium carbonate hydroxide." Materials Science and Technology **23**(9): 1021-1026.

Zhang, M., J. F. Yu, S. W. Yang and X. L. He (2011). "Analysis in Atmospheric Corrosion Behavior of Bainite Steel Exposed in Offshore Platform Based on the Artificial Neural Network." Advanced Materials Research **291-294**: 1212-1216.

Zhang, W., Z. Bao, S. Jiang and J. He (2016). "An Artificial Neural Network-Based Algorithm for Evaluation of Fatigue Crack Propagation Considering Nonlinear Damage Accumulation." Materials (Basel) **9**(6).