Chapter

The Theoretical Overview of the Selected Optimization and Prediction Models Useful in the Design of Aluminum Alloys and Aluminum Matrix Composites

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Abstract

The growing attention regarding aluminum alloy matrix composites within the aerospace, automotive, defense, and transportation industries make the development of new engineering materials with the improved mechanical properties. Currently, materials are selected because of their abilities to satisfy engineering demands high for strength-to-weight ratio, tensile strength, corrosion resistance, and workability. These properties make aluminum alloys and aluminum matrix composites (AMCs) an excellent option for various industrial applications. Soft computing methods such as the artificial neural network (ANN), adaptive-neuro fuzzy inference systems (ANFIS), and Taguchi with ANOVA are the most important approaches to solve the details of the mechanism and structure of materials. The optimal selection of variables has important effects on the final properties of the alloys and composites. The chapter presents original research papers from our works and taken from literature studies dealing with the theory of ANN, ANFIS, and Taguchi, and their applications in engineering design and manufacturing of aluminum alloys and AMCs. Also, the chapter identifies the strengths and limitations of the techniques. The ANFIS and ANN approaches stand out with wide properties, optimization, and prediction, and to solving the complex problems while the Taguchi experimental design technique provides the optimum results with fewer experiments.

Keywords: aluminum matrix composites, hybrid, modeling, engineering approaches, optimization, ANN, Taguchi, ANOVA, genetic algorithms, ANFIS

1. Introduction

Since the early 1920s, iron-based materials, which have an indisputable advantage in the industry, have gradually begun to leave their places to materials with high specific strength like metal matrix composites. Metal matrix composites have interesting physical and mechanical properties. In metal matrix composites, the properties of the matrix material and the properties of reinforcing materials are

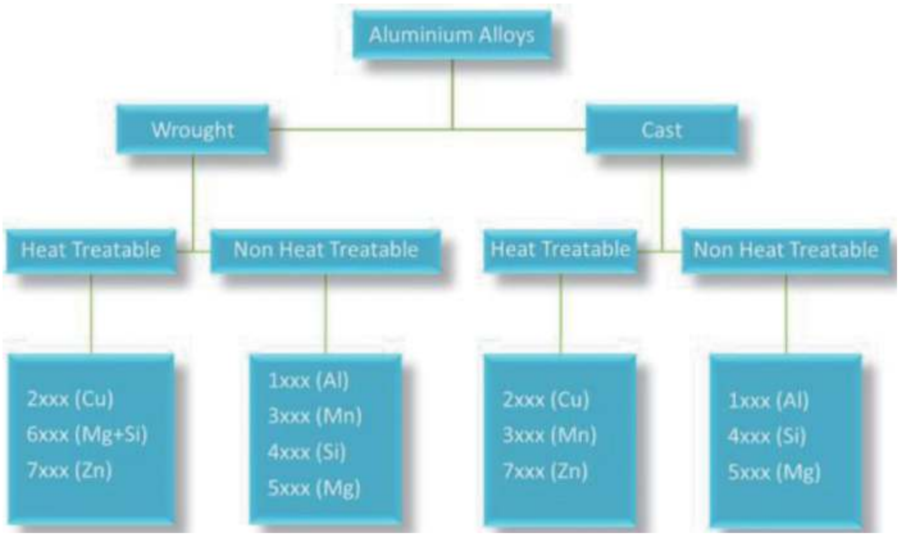

Figure 1.
Classification of aluminum alloys.

combined, resulting in higher mechanical and performance properties. Production costs are also an important factor, as well as the physical and mechanical properties of structural materials. Although high technology materials exhibit high physical and mechanical properties, high production costs restrict their use. Metal matrix composites are widely used in aerospace, automobile, military, and biomedical applications because of their high specific strength and considerably low density.

In the fabrication of MMCs, aluminum (Al) is one of the most popular matrix materials because of its low density, good corrosion resistance, and strengthening capability. Aluminum (Al) is a chemical element with the atomic number 13 and symbol Al. It is a non-magnetic and ductile metal that seems a color of silver in the boron group. Al is a metal with an atomic weight of 26.981 g/mol, melting temperature of 660°C and a density of 2.7 g/cm^3. The development of new materials will be of greater importance in future technological advances. Aluminum alloys and aluminum matrix composites can combine the beneficial properties of aluminum and other metals, ceramics and production techniques.

The mechanical, physical and chemical properties of aluminum alloys vary depending on the alloy elements and microstructure. Aluminum alloys are divided into two groups as wrought (forged) and cast alloys (**Figure 1**). This classification is as follows:

Given the composite materials, it can be said that one of the most important is the method of production. Production methods are classified according to the temperature of the metallic matrix during production. Aluminum matrix composites can be produced by many techniques such, as stir casting, compo casting, powder metallurgy, additive manufacturing, cold spray, friction stir processing, and infiltration, etc. All these methods have different advantages and disadvantages in terms of cost, appropriateness, labor, training, efficiency, time, temperature, and simplicity, etc. Therefore, the production methods of metal matrix composite materials can be divided into four groups;

1. Liquid phase production methods

    - Vortex addition technique

    - Compo-casting

- Pressure-less infiltration process
- Ultrasonic infiltration

2. Solid phase production methods
    - Powder metallurgical methods
    - Mechanical alloying
    - Diffusion bonding
    - Spark plasma sintering (SPS)
3. Gaseous state fabrication
    - Chemical vapor deposition (CVD)
    - Physical vapor deposition (PVD)
4. In-situ production method
    - Internal oxidation process
    - Unidirectional solidification process

Aluminum matrix composites can be produced with different kinds of reinforcement like MgO, SiC, Al_2O_3, B_4C, CNT and fibers are used to fabricate composites. **Figure 2** shows the reinforcement types for aluminum matrix composites. The type and ratio of matrix material and reinforcement and process parameters are some of the most variables in composite fabrication.

The most popular reinforcements for fabrication of aluminum matrix composites are carbon nanotubes (CNTs) and silicon carbide (SiC). For individual MWCNTs, they can achieve an elastic module approaching 1 TPa and tensile strength of 100 GPa. Especially, CNT are used to advance to strength of aluminum alloys. SiC is a material with low thermal conductivity; low thermal expansion coefficient, high thermal shock resistance, hard, semiconductor and greater

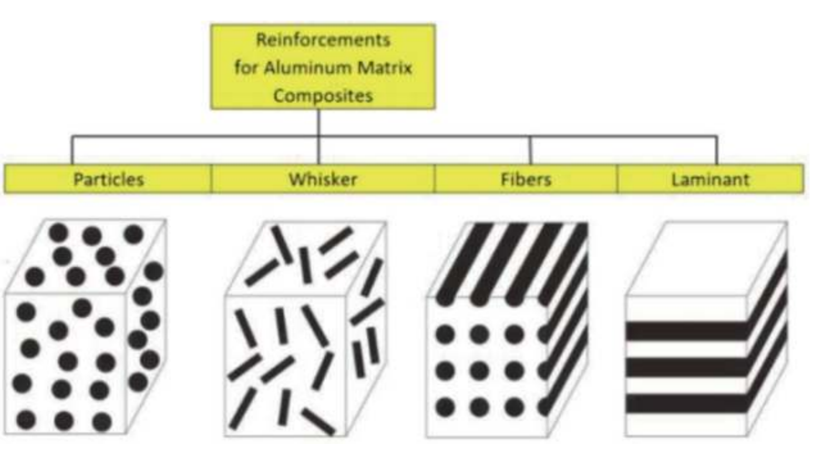

Figure 2.
Reinforcement types.

refractive index value than diamond and is one of the most suitable reinforcement materials to make highly wear-resistant composites. The role of the reinforcement in a composite material is fundamentally one of increasing the mechanical properties. The final properties of the composites reinforcement depend on the individual properties of the reinforcement selected and the matrix.

Aluminum matrix composites are utilized in a wide range of components for advanced manufacturing. Mechanical behavior of aluminum matrix composites can be examined in detail. Increased mechanical properties compared to non-reinforced aluminum enables the applications of these materials in different engineering fields to increase. The low costs of particle reinforced aluminum matrix composites in some applications compared to other composites make them very attractive materials. The fact that these materials exhibit good mechanical behavior in high-temperature applications is another important point for their commercial success.

Thus, it is important to select the optimal levels of the parameters and variables. Therefore, experimental parameter relationships can be accurately predicted and the need for materials and time can be eliminated using these approaches, ANFIS and Taguchi, are widely used on the complicated and nonlinear systems of the different engineering applications. These approaches are widely used in advanced engineering applications as they are a combination of various calculation methods. They also include process design, numerical modeling, estimation and optimization, and the control process. Modeling, estimation and optimization of features are useful and the most important part of engineering to solve complex problem. Important advantages of the calculation techniques are determined during the design and optimization of the process variables to be used during the production phase. These methods are useful for selecting the desired parameters optimally, placing them in systems, analyzing results, digitizing production, minimizing power consumption, and solving real-life problems in the process.

2. Production methods and data collection

The prediction or optimization methods require large experimental data sets that are expensive to produce. Here we describe methods to discover material parameters in the absence of experimental data. In effect, this algorithm strategy starts with the ability to "learn" and from its experience to accelerate the evolutionary process. This algorithm is tested against several problems and demonstrates that it matches and typically exceeds the efficiency and reproducibility of standard. The success of these methods in a range of problems is to accelerate materials design in the absence of a lack of experimental data.

In addition to experimental effort, modeling with artificial intelligence (AI) is one of the most important approaches to solve the details of the system and make life easier. The purpose of artificial intelligence is to obtain results with high efficiency using knowledge and make it a reality. The most commonly used artificial intelligence techniques to solve complex problems are the adaptive network-based fuzzy inference systems (ANFIS), Taguchi and artificial neural networks (ANN), and these systems are also called soft computing methods. The use of soft computing techniques is powerful modeling techniques related to the statistical approach for predicting parameters.

Over the last decades, the interest of the modeling techniques in different fields of materials science has been increased [1–7]. It is aimed to find the optimum solution with better performance by using human intuition, thinking and decision-making ability, eliminating uncertainties with simple and low-cost solutions and in solving complex and difficult to solve problems. In our previous works, new

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formulations are developed for the ultimate tension strength (UTS), wettability, critical angle, wear properties of aluminum alloys and composites and welding properties of produced metals using ANN, Taguchi, ANOVA and ANFIS, respectively.

3. Optimization methods

3.1 The artificial neural networks (ANNs)

Artificial intelligence is defined in the world of science as the ability of a computer or a computer-assisted machine to perform tasks related to higher logic processes such as human qualities, finding solutions, and understanding, making sense, generalizing and learning from past experiences. Learning ability underlies the logic of artificial intelligence. The greatest contribution of artificial intelligence will be to implement the most correct way they have learned very quickly. Artificial intelligence technologies consist of expert systems, fuzzy logic artificial, neural networks and machine learning and genetic algorithms [8].

ANNs are computer software where basic functions such as generating new data from the data collected by the brain by learning, remembering, and generalizing by imitating the learning path of the human brain. ANN is synthetic structure that mimics biological neural networks. ANNs; inspired by the human brain, it has emerged as a result of the mathematical modeling of the learning process.

3.1.1 ANNs structure

Since artificial neural networks are modeling of biological neural networks, first of all, it is necessary to look at the structure of the biological nervous system. The structure of neurons, the basic building block of the biological nervous system, consists of four main parts; dendrite, axon, nucleus and connections (**Figure 3a**). It has a tree-rooted structure located at the end of the dendrites nerve cell. The task of dendrites is to transmit signals from other neurons or sense organs to which it is attached to the nucleus. The nucleus collects the signals coming from the dendrite and transmits them to the axon. These collected signals are processed by the axon and sent to the connections at the other end of the neuron. Connections transmit newly produced signals to other neurons.

Biological nerve cell and artificial neural network simulations are given in **Figure 3a** and **b**. As shown in **Figure 3b**, n data is entered into a cell. The entered data is multiplied by weights and all data are collected and then bias is added, resulting in clear judgment. The net input is passed through the activation function and data output is obtained.

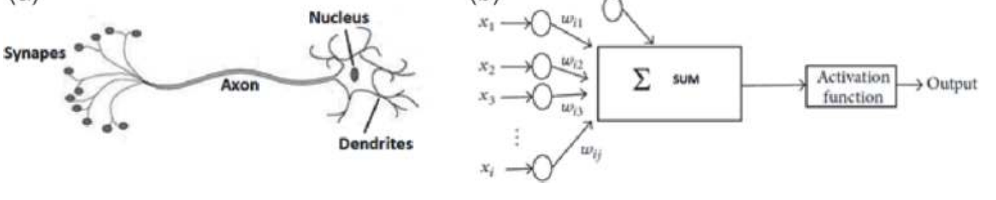

Figure 3.
(a) Biological nerve cell and (b) artificial neural network.

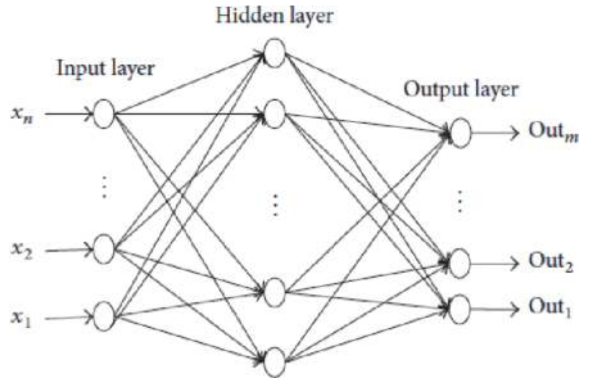

Figure 4.
Layers in ANN.

Artificial neural networks are structures formed by the binding of artificial nerve cells. Artificial neural networks are examined in three main layers; input layer, hidden layers and output layer (**Figures 3b** and **4**) [9].

Input layer: it is the layer where inputs from the outside world come to the artificial neural network. Although there are as many cells in this layer as the number of entries from the outside world, the inputs are usually transmitted to the lower layers without any processing.

Hidden layer(s): information from the input layer comes to this layer. The number of hidden layers can vary from network to network. The number of neurons in the intermediate layers is independent of the number of inputs and outputs. Although increasing the number of intermediate layers and the number of neurons in these layers increases the computational complexity and duration, the artificial neural network can also be used in the solution of more complex problems.

Output layer(s): it is the layer that produces the outputs of the network by processing the information from the intermediate layers. The outputs produced in this layer are sent to the outside world. New weight values of the network are calculated by using the output produced in this layer in feedback networks.

Artificial nerve cells are similar to biological nerve cells. Artificial neurons also form artificial neural networks by bonding between them. Just like biological neurons, artificial neurons have sections where they receive input signals, collect and process these signals, and transmit outputs. An artificial nerve cell consists of five parts;

i. **Inputs:** inputs are data coming to neurons.

ii. **Weights:** the information coming to the artificial nerve cell is transmitted to the nucleus by multiplying the weight of the connections they arrive before reaching the nucleus through the inputs. The values of these weights can be positive, negative or zero.

iii. **Transfer function (combining function):** transfer function is a function that calculates the net input of that cell by multiplying the incoming inputs by multiplying the weights of an artificial nerve cell. Some transfer functions are given in **Table 1**.

iv. **Activation function:** this function designates the response that the cell will produce in response to this input by processing the net input to the cell. The activation function is usually chosen as a nonlinear function which are a feature of ANNs, come from non-linear feature. Today, "Sigmoid function and Tangent Hyperbolic Function" are the most widely used as the activation functions in general. **Table 2** shows the activation functions.

v. **Outputs:** the value of the activation function is the output value of the cell.

$Net = \sum_{i=1}^{N} X_i * W_i$	The weight values are multiplied by the inputs and the net values are calculated by adding together the found values.
$Net = \prod_{i=1}^{N} X_i * W_i$	The weight values are multiplied by the inputs and then the net input is calculated by multiplying the values found by each other.
$Net = Max(X_i * W_i)$	After the weights of n inputs are multiplied by the inputs, the largest of them is considered as net input.
$Net = Min(X_i * W_i)$	After the weights of n inputs are multiplied by the inputs, the smallest of them is considered as net input.

Table 1.
Transfer function.

Sigmoid function	$F(Net) = \frac{1}{1+e^{-Net}}$	The sigmoid activation function is continuous and derivable function. It is the most commonly used function in ANN applications due to its non-linearity. The function produces a value between 0 and 1 for each of the input values.
Tangent hyperbolic function	$F(Net) = \frac{e^{Net}+e^{-Net}}{e^{Net}-e^{-Net}}$	Tangent hyperbolic function is a function similar to sigmoid function. In the sigmoid function, the outcome values range from 0 to 1, while the output values of the hyperbolic tangent function range from −1 to 1.

Table 2.
Activation function.

3.1.2 Classification of ANNs

ANNs have the following key features such as, non-linearity, parallel operation, learning, generalization, error tolerance and flexibility, working with missing data, using multiple variables and parameters and adaptability. Artificial neural networks applications are mostly used in prediction, classification, data association, data interpretation and data filtering processes. In ANNs, according to their structure; artificial neural networks are divided into two as forward and feedback depending on the way the neurons they contain. There is only a link from one layer to the next layers. In contrast to feed-forward (FF) neural networks, feed-out of a cell is not only input to the layer of the cell that comes after it. It can also be linked as input to any cell in its previous layer or its layer. With this structure, feedback neural networks display a nonlinear dynamic behavior. ANNs are divided into three as consulting, advisor-less and reinforced learning according to learning algorithms. Artificial neural networks are divided into two as static and dynamic learning according to learning time. According to layers, single layer networks consist only of input and output. In multilayer sensors, the structure to which many neurons, which are structurally nonlinear activation functions, are connected with certain superiority, are called multilayer sensors.

3.1.3 Training and testing of ANNs

Although the structure of an ANN and the number of nerve cells vary, there are no accepted rules for the formation of an artificial neural network. While artificial neural networks with less than the required hidden layers are insufficient in solving complicated functions, artificial neural networks with too many hidden layers encounter undesirable instability. The problem encountered after determining the number of hidden layers is in deciding how many neurons will be present in each layer. There is no problem with the input layer; this number is equal to the number of inputs in the system. Likewise, the output layer can be determined by the desired output number. The main problem is to specify the neurons number in the hidden layers. The traditional matrix algorithm says that the matrix dimensions must be either equal to the inputs number or the number of outputs. Unfortunately, there is no mathematical test about how many neurons will be found in the hidden layer in the most efficiently. The decision should be made by applying the trial and error method [10].

In the learning process of artificial neural networks, inputs are received from the external environment; a reaction output is generated by passing through the activation function. This output is again compared to the output given by experience. Errors are found with various learning algorithms and the real output is tried to be approached. In general, 80% of the samples are given to the network and the network is trained. Then the remaining 20% is given and the behavior of the network is examined. Thus, the network is tested.

It is the step of finding examples that have already occurred for the event that the network wants to learn. As the samples are collected for training the network (training set), the samples (test set) must be collected to test the network. After learning the network event, the performance of the network is measured by showing the examples in the test set. His success against the examples he has never seen reveals whether the network has learned well.

3.2 Adaptive-neuro fuzzy inference systems (ANFIS)

ANFIS is a kind of artificial neural network that is based on Takagi-Sugeno fuzzy inference system. The technique is developed in the early 1990s [1]. Various methods have been developed to increase the effectiveness of fuzzy systems and to contribute to the adaptation technique. One of them is the ANFIS technique, in which the identification process is performed with a fuzzy model, the operation of which takes place within the adaptive network structure. Neural adaptive learning techniques allow developing a model that "learns" the system by using the data set for the fuzzy modeling procedure. The fuzzy model to be used in the identification of the system has acquired the ability to update itself by using the environmental information about the system and by utilizing the input and output data related to the system thanks to its adaptive network structure. Essentially, the ANFIS structure consists of the representation of Sugeno fuzzy systems as a network structure with neural learning capabilities. This network consists of a combination of nodes, each placed in layers, to perform a certain function. 52 fuzzy inference system selection of membership functions is arbitrary, it depends on the user. The form of membership functions also depends on the parameters. However, it cannot be easily noticed how some form of membership function should be based on the data in some models [2].

3.2.1 General architecture and operation

Neural adaptive learning techniques enable to develop a model that "learns" the system by using the data set for the fuzzy modeling procedure. In other words, ANFIS creates a fuzzy inference system (FIS) by editing the membership function parameters using the input/output data set back-propagation (BP) algorithm alone or in combination with the least-squares method. This arrangement allows the system to learn the related system with the help of data modeled by our fuzzy system. In other words, it adapts to the data it will model. It is therefore adaptable. Thanks to its adaptive network structure functioning, it has acquired the ability to update itself by using environmental information about the system as well as utilizing the input and output data related to the system. It also includes advanced data analysis techniques such as ANFIS, numerical grouping and rule sets.

ANFIS consists of six layers. The first layer is called the input layer. Input signals in this layer are transferred to other layers. Layer 2 is the fuzzification layer. Each output consists of membership degrees depending on the input values and the used membership function. Layer 3 is the rule layer; each node in this layer refers to the rules and the number created according to the Sugeno fuzzy logic inference system. Layer 4 is the normalization layer, accepting all nodes and calculating the normalized level of each rule. The 5th layer is the purification layer and the weighted result values of a rule given in each node are estimated. Layer 6 is the total layer with only one node ($\sum$). In this layer, the output value of each node is added and the actual output of the system is obtained.

3.2.2 Learning algorithm

ANFIS's learning algorithm is a hybrid learning algorithm that consists of using the least-squares method and the back-propagation learning algorithm. This learning algorithm is based on error back-propagation. There are two parts to a step in the learning process; in the first part, input samples are produced and the preliminary parameters are accepted as constant and the best final parameters are determined with the least mean square method. In the second part, the input samples are reproduced and the preliminary parameters are replaced by the gradient descent method, with the final parameters considered constant. This process is repeated later [3].

3.3 Taguchi

Taguchi design is a set of methodologies that take into account the variability inherent in the material and manufacturing processes at the design stage. Taguchi has not brought theoretical innovations to experimental design. However, it has made innovations in applications in production and has enabled the method to be accepted in the manufacturing sector with successful applications.

Traditional experimental designs are difficult to use, especially when dealing with a large number of experiments and increasing the number of processing parameters. Therefore, the Taguchi experimental design method ensures that more than one factor is taken into account at the same time, but it also ensures that the most optimum result is obtained by performing fewer experiments Design of experiment (DOE) in Taguchi is used to design the experimental run layout, to study the effect of level change in the process parameters on the output performance, because any change in the input parameters affects the output functional performance. It is important to know that all factors do not effect on the performance in the same manner [4].

3.3.1 S/N (signal/noise) ratio

Taguchi employs the signal-to-noise (S/N) ratio as its preferred sort characteristic. S/N ratio is employed as a finite value in place of a standard deviation. In its simplest form, the S/N ratio is the ratio of the mean (signal) to the standard deviation (noise). S/N ratio properties can be divided into three categories as shown in **Table 3**.

Regardless of the sort characteristic category, a higher S/N ratio comes up to better sort characteristics. Hence, the optimum degree of process variables is the degree by the highest S/N ratio.

The initiative of the Taguchi technique is to fix the sort characteristic to be optimized. The sort characteristic is a variable that has an important effect on the product class of the variation. It is the output value to be sighted. The next step is to describe noise values that can harm system performance and class. Noise values are parameters that cannot be checked or are very expensive to check. The third feature is the definition of control parameters that are considered to have important effects on quality features. Control variables are conception factors that can be adjusted and continued. The levels of each test are determined at this stage. The level number of each parameter defines the test area. The matrix experiment and the analysis procedure should be identified. First, the suitable orthogonal array for noise and check variables are selected. Taguchi has provided many standard orthogonal arrays for this aim. After choosing the proper arrays, a procedure must be defined to simulate the change in class characteristic owing to noise factors. Taguchi suggest an orthogonal array-based simulation to interpret the mean and variance of a product's output owing to alterations in noise factors. The next step is to make a matrix experiment and record the outcomes. The Taguchi technique can be employed in any situation in which there is a checkable operation. The checkable operation can be a real equipment test, mathematical equation, or computer pattern that can adequately pattern the reply of many yield or operation. After the experiments are made, the configuration of the most suitable parameter in DOE should be designated. To check up on the outcomes, the S/N ratio which is a calculation of performance to select the check levels that can deal with noise and considers both average and variability is employed as a performance criterion in the Taguchi technique. As a last step, experimental validation is made using the optimum levels predicted for the examined check variables. We can say that the Taguchi method is a powerful tool that can provide simultaneous improvements in quality and cost.

3.3.2 Analysis of variance (ANOVA)

Taguchi technique cannot judge and designate influence of individual factors on all operation, while the importance level and the contribution of individual factors can be very well specified by ANOVA [6]. Analysis of variance is a statistical

The lowest is the best.	$\frac{S}{N} : -10\log\left(\frac{1}{n}\sum_{i:1}^{n} y_i^2\right)$	In such problems, the target value of Y is zero. The smallest value represents the signal to noise ratio for its best condition.
The biggest is the best.	$\frac{S}{N} : -10\log\left(\frac{1}{n}\sum_{i:1}^{n} \frac{1}{y_i^2}\right)$	In this case, the value of Y is a non-negative measurable property with an ideal goal as infinity. The greatest value refers to the signal/noise ratio for the best case.
Nominal is the best.	$\frac{S}{N} : 10\log\left(\frac{\overline{y}}{s_y^2}\right)$	In this case, the nominal value is the target when we have a characteristic with double tolerance. So if all the parts are brought to this value, the variation is zero and the best. The target value represents the signal to noise ratio for its best condition.

y = response value, y′ = mean of the response value, s = standard deviation, and n = number of trails for given experiment.

Table 3.
S/N ratios.

instrument that is used to designate the difference or similarity between two or more data groups. ANOVA formally helps to find the significance of all main variables by comparing the mean square versus a calculation of the test faults at a specific class of confidence. The goal of experimentation is to find possible methods to reduce the deviation of the required quality as much as possible. This can be reached by identifying those parameters which play a significant role in the performance characteristic [5, 6].

4. Potential application of ANN, ANFIS, and Taguchi approaches for aluminum alloys and aluminum matrix composites

The effects of temperature, time, and the additions of magnesium and copper on the wetting behavior of Al/TiC are studied theoretically [7]. The R values of training and test sets are 0.911 and 0.903, respectively. The formulation is presented in explicit form. The proposed model shows good agreement with test results and can be used to find the wetting behavior of Al/TiC. The contribution of input parameters on the output is revealed with sensitivity analysis is shown in **Figure 5**. In the input parameters, the time and temperature have a stronger effect on the wetting of TiC system.

Effects of friction stir processing (FSP) parameters and reinforcements on the wear behavior of 6061-T6 based hybrid composites are investigated [11]. The different neuron numbers are used to determining the optimal architecture of the system. The system parameters affect the learning rate and so the prediction rate. It is obtained with 17 neurons through MSE, MAE and R values. The R^2 values of training and test sets are 0.998 and 0.995 which are quite high. The sensitivity analysis for the studied AMCs is given in **Figure 6**. The change in the applied load will be affected the wear volume loss of the composites. The applied load increases the wear in the composites.

A mathematical formulation is derived and given clearly to calculate the wear volume loss of the composites. The influence of input variables on the wear volume loss of the composites is also investigated using the prepared formulation. The wear volume loss of the composites significantly enhanced with increasing sliding distance and tool traverse and rotational speeds. A minimum wear volume loss for the hybrid composites with complex reinforcements is specified at the inclusion ratio of 50% TiC +50% Al_2O_3 because of improved lubricant ability, as well as resistance to brittleness and wear. It is clear that the formulation can be used in prediction of wear loss of the composites and so, the time and production cost can be reduced.

The effects of FSP parameters and hybrid ratio on the UTS of Al matrix (5083) hybrid composites are investigated in detail [12]. The numbers of different neurons

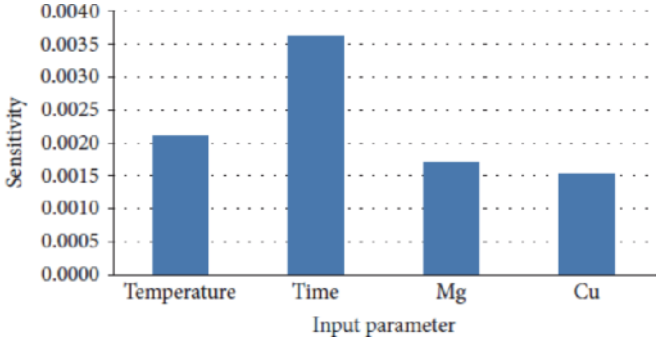

Figure 5.
Sensitivity of the input parameters for Al/TiC system.

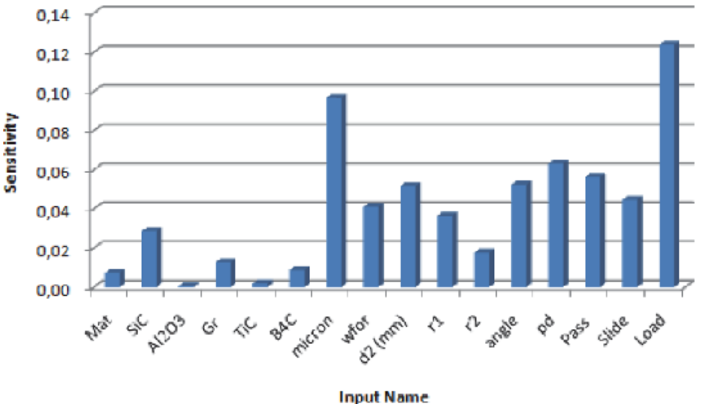

Figure 6.
Sensitivity of the input parameters for 6061 AMCs.

in one hidden layer (10–15) are used to determine the optimum model architecture. The optimal model architecture is conducted with 15 neurons. The MSE, MAE and MAPE are utilized as error-evaluation criteria, and the correlation coefficient (R) is chosen to estimate the performance of the proposed model. The maximum R and minimum error values are obtained with 15 neurons. A mathematical formulation is derived, and test results are compared with those of the model. In **Figure 7**, the error percentage of the composites is showed. The average error is 11% for training set and 4% for test set. This shows that the prediction ability of the proposed model can be accepted.

The effects of factors influencing strength, such as tool rotational and traverse speeds, and volume fractions of, carbon nanotube (CNT), aluminum oxide (Al_2O_3), graphite (Gr), silicon carbide (SiC) and zirconium oxide (ZrO_2) are also studied using the proposed formulation. Test results showed that the UTS of these composites significantly increased with increasing CNT, tool rotational and traverse speeds. In addition, the effects of complex reinforcements with different volume fractions on the 5083 AMHCs are examined. A maximum tensile strength for the hybrid composites is found at the inclusion ratio of 10% Gr + 5% ZrO_2.

The effect of different alloying elements on the ultimate tensile strength of Al-Mg_2Si composites is studied using ANN [13]. The input variables are Al, Mg, Si, copper, manganese, chromium, phosphorus, beryllium, boron, lithium, yttrium and sodium wt.% and the output is UTS in unit of MPa. Three different neuron numbers in one hidden layer (12, 13 and 14) are used. The training data set (70%) the validation data set (15%) and test data set (15%) are used. The optimal architecture is found to be 12-12-1 architecture with logistic sigmoid transfer function. The R, MSE and MAE values are used as the error criteria. The minimum MSE and MAE and the maximum R values are obtained in test set. The sensitivity of input vectors

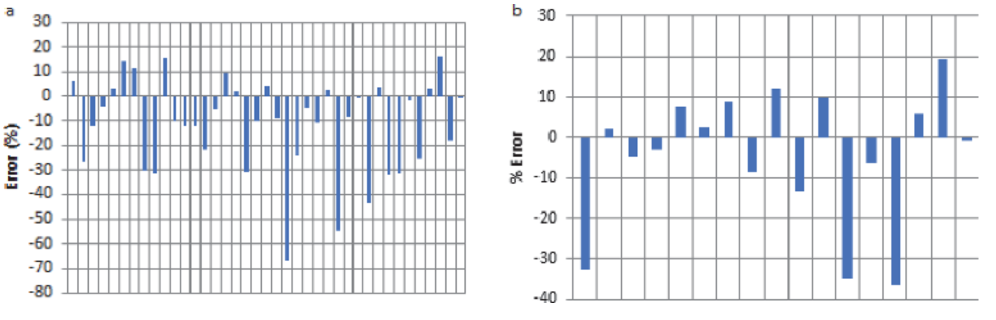

Figure 7.
Error values of the composites: (a) training set and (b) test set.

on UTS of Al-Mg_2Si composites is given in **Figure 8**. It is clear that Mg has more impact on UTS of Al-Mg_2Si composites because there are a linear relation between the size and morphology of the Mg_2Si phases and the mechanical properties of the composites containing Mg and Si elements. The results showed that all the data sets have quite high correlation and accuracy and therefore, the proposed mathematical function can be used in ANN studies.

The UTS of unrefined Al-Zn-Mg-Cu alloys and refined the alloys by Al-5Ti-1B and Al-5Zr master alloys are calculated with ANN [16]. There is no well-defined procedure to determine the optimal model structure, so the different neuron numbers in one hidden layer (5–20) are used with the trial and error approach. The optimal structure for this works is the 15-17-1 with logistic sigmoid transfer function. The R, MAE and MSE are used for the performance of datasets. The sensitivity results (**Figure 9**) display that the Mg element and heat treatment have the higher effect on the UTS of the Al-Zn-Mg-Cu Alloy. Because alloying elements interact with other metals and form intermetallic compounds, and these compounds are precipitated by heat treatment, resulting in high strength. The mathematical formula is obtained and the influences of scandium and carbon contents are researched using the formulation. The optimum additions of scandium and carbon rates are observed to be 0.5 Sc and 0.01 C wt.% to obtain the maximum UTS value. The prediction model with the obtained formulation has a high reliability rate.

The UTS, ductility, porosity, hardness and density of Al-Mg-Ti alloys are studied by ANN. The influences of input parameters are examined by the sensitivity

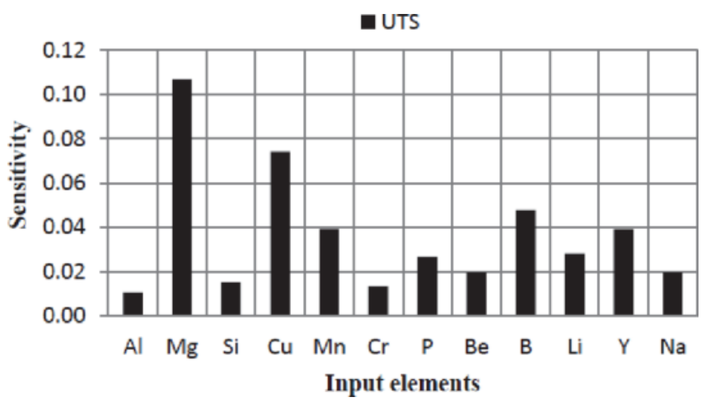

Figure 8.
Sensitivity of the input parameters for the alloy [14, 15].

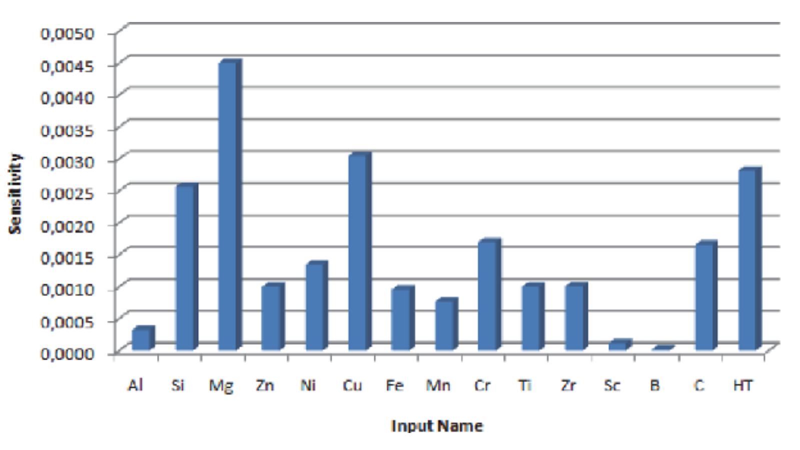

Figure 9.
Sensitivity of the input parameters for the Al-Zn-Mg-Cu alloy.

analysis. The Mg element within all input variables has the highest effect on the UTS and hardness of the alloys while the Ti element has the density and ductility. The linear correlation values for all variables are higher than 0.91 that the model accuracy is very high (**Figure 10**).

Satyanarayana et al. [17] researched the influence of reinforcement and deformation on volumetric wear of aluminum matrix composites the reinforced with red mud nano-particles using ANN and regression model. Authors used the activation function of sigmoid function, the RMSE and MAPE, four input parameters, two hidden layers with seven and six neurons, one output parameter that is volumetric wear 124 data for training set and 20 data for test set in the ANN model. The R^2 and MAPE values of regression and ANN models are 0.9775 and 0.989, and 12.96 and 7.30%, respectively, and RMSE for ANN models is 0.3177. They observed that ANN approach predicted the wear rate of the composites with excellent agreement than mathematical regression model and it could be useful to decrease time, effort and cost.

The hardness, ultimate tensile strength (UTS), and yield strength (YS) of A413/B4C composites that are produced with squeeze casting route are modeled using ANN and statistical modeling [18]. Authors used the 18 data for training, 9 data for testing, the hyperbolic tangent sigmoid function (TANSIG) and the linear transfer function (PURELIN) for the activation function, the Levenberg-Marquardt algorithm (TRAINLM) and the gradient descent with a momentum BP algorithm (TRAINGDM) for the training algorithm. There are layers of three inputs, three output and 50 + 50 neurons in two hidden layers. The data are normalized within the range (0–1) before training and testing. MSE, R and prediction percentage error are used the performance criteria of the system. They observed that the optimal architecture is 3-2-2-3 (the numbers of hidden layers and neurons are 2) with Levenberg-Marquardt algorithm and the results are in good agreement with experimental values. The R is 0.96 for hardness, 0.95 for UTS and YS, and MAPE is 1.42 for hardness, 0.62 for UTS and 0.59 for YS. It can be concluded that the cost and time could be saved with the proposed model. The full design of 3^3 (three levels and three factors) factorials are used to design connection between the input and outcome variables, and the design of experiment (DOE) with ANOVA is used to determine the significance of each factor on the responses. The pressure is 70, 105 and 140 MPa, preheating temperature of die is 150, 225 and 300°C, and B_4C rate is 4, 8 and 12 wt.%, respectively. The R^2 is 95.25% and the adjusted R^2 is 93.83% that shows a high effect of the model. The squeeze pressure with contributing of about 44–46% has a powerful effect on mechanical properties, while B_4C wt.% has about 33–43% and preheating temperature of die has about 9–16%. All P-values of the response are lower than 0.005. The optimal ratio of the pressure, B_4C rate and preheating temperature of die are seen to be 140 MPa, 12 wt.% and 225°C, respectively, to obtain the maximum mechanical properties.

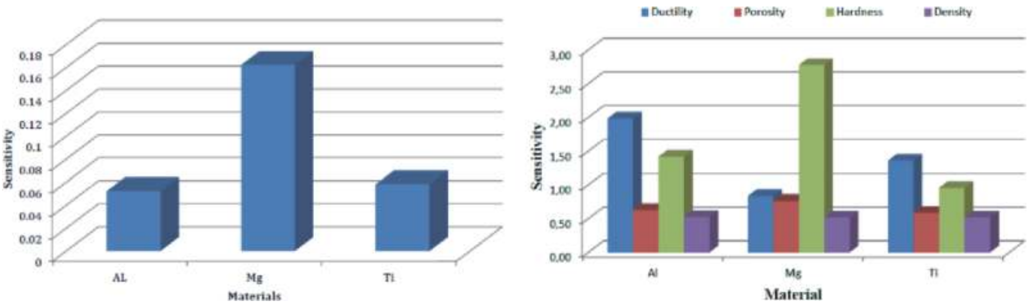

Figure 10.
Sensitivity analysis of the Al-Mg-Ti alloys.

The process parameters and experimental variables Al5059/SiC/MoS_2 composites are optimized by ANN and Taguchi [19]. The five input and the six output variables and 27 data are used in the ANN model for training and testing. The performance of output variables is determined by R^2 which is 98.12% surface roughness, 98.63% for temperature, 96.98% for radial force, 98.54% for feed force, 99.34% for material removal rate (MRR) and 98.71% for tangential force. The L27 orthogonal array (three levels and five factors) with "smaller is better" criteria for Taguchi design is performed. The optimum S/N ratios for surface roughness are found to be 5% SiC, 40 cutting speed of 1000 rpm, μm particle size, 200 mm/min feed and 0.5 mm depth of cut, respectively. For the temperature, all values are the same but cutting speed are 500 rpm. The optimum values varied for radial force, feed force, material removal rate and tangential force. The significance and influence of process variables on the quality are studied analysis of variance (ANOVA). Authors reported that the best important variable in all input parameters on the milling operation is silicon carbide addition (wt.%) in the composite followed by the feed rate, depth of cut, cutting speed and particle size of SiC.

Al2219 alloy reinforced with TiC+Al_2O_3 + Si_3N_4 is produced by squeeze method [20]. The melt temperature, die temperatures, stirring speed, feed rate and stirring time (min) are varied. To optimize the mechanical properties of hybrid composites, a statistical investigation is performed by ANFIS-gray wolf optimizer (ANFIS-GWO) and ANFIS-K-nearest neighbor (ANFIS-KNN) algorithms. They observed that the optimization results predicted the most suitable process parameters to obtain aluminum hybrid composites with high mechanical properties, and experimental and optimization results showed an optimal combination of hybrid and process parameters.

The flow stress values of 6061 Al-15% SiC metal matrix composites are predicted by an ANFIS [21]. The hot compression tests are applied to composites at various strain rates and temperatures. In the used ANFIS model, there are 17 rules with 17 membership functions (MF) which is Gaussian type for input MF, and linear parameters are 68 and non-linear parameters are 102. The samples of training and checking data are 88 and 12, respectively. The percentage mean error (PME) and RMSE are used to performance criteria. The predicted PME value of the flow stress by the ANFIS is less than 1.4%. Author declared that ANFIS with a hybrid learning algorithm can accurately be estimated the flow stress for the composites. In order to find the number of hidden nodes, there is not any way to obtain a highly system performance. The flow stress of 6061 Al-15% SiCp for plastic deformation can.

The impact resistance (IR) of Al-epoxy laminated composites by 2, 5 and 10-layers and has notch tip configuration with crack divider and crack arrester is predicted using ANFIS [22]. The experimental results of 126 are conducted for ANFIS model. The structure of ANFIS is obtained by seven input variables and the triangular and Gaussian membership functions (MFs). In this ANFIS model, the system is trained using 103 data and tested using 23 data. The best R^2 value of the Gaussian MFs model is 97.73% for training set, and the minimum R^2 value is 91.95% in the test dataset with the triangular MFs model. They concluded that both models had high R^2 values and strong potential, and IR of Al-epoxy laminated composites could be predicted by highly accurately with the proposed model under the given condition.

Kandpal et al. [23] optimized the EDM process parameters of AA6061/10% Al_2O_3 aluminum matrix composites casted by stir casting method using Taguchi route with ANOVA. The three factors with three levels in design of experiment section are set thus orthogonal array of L9 "larger is better" criteria is selected chosen. The input parameters are current and time of pulse and duty factor and the output factor is material removal rate (MRR). Authors declared that the current is

Method	Advantages	Disadvantages
ANN	Function approximation Data classification Data processing System control The solution of nonlinear problems Prediction Explicit formulation Storing information throughout the network Ability to work with missing knowledge Having error tolerance Having distributed memory Gradual deterioration Machine learning Parallel processing ability Detecting all possible interactions between variables	Training for each problem Large volumes data requirement Hardware requirement Failure to explain the behavior of the network Determining the appropriate network structure (topology) Difficulty displaying the problem to the network Not knowing the training time of the network Problem must be numerical Extremely addictive to data and applications Selecting of appropriate input variables
ANFIS	Numerical grouping Rule setting Prediction Better learning ability A much smaller convergence error Fewer adjustable parameters Parallel computation A well-structured knowledge representation A better integration Linguistic expressiveness of inaccurate inputs and system outputs Adaptability The ability to process information simultaneously Calculation to be efficient Working with linear techniques To be successful with optimization and adaptive techniques Continuity guarantee of the output Suitable for mathematical analysis There is no vagueness Reaching to the target faster The solution of nonlinear problems Function approximation Data classification Data processing System control	Training for each problem Hardware requirement Large volumes data requirement Selecting of appropriate input variables Low accuracy when there are not enough training data Cannot handle multiple output systems Long run time when the number of membership functions is large
Taguchi	Experimental design (system, tolerance, parameter) The possibility of calculating the inter-factor interactions not possible in the experimental design by changing one factor at a time Showing which factor is important Finding all available compositions	High fault tolerance Difficulty of calculating the effects of unexpected changes in experimental conditions Randomization, repetition and blocking of experiments Exponentially increasing the size of the experiments with the number and levels of factors Difficulty in explaining the high level of interactions

Table 4.
Advantages and disadvantages of the model.

the most affecting parameter on material removal rate and the optimal variables are 14 A for pulse current, 200 μs for the pulse on time and 50% for duty factor to obtain the maximum MRR.

The wear behavior (SWR: specific wear rate) of LM25/fly ash composite materials produced with stir casting route is optimized using Taguchi design of experiment with ANOVA [24]. The experimental design is carried out by the orthogonal array of L27 (three levels and four factors) "smaller is better" criteria in which sliding speed, load, reinforcement and sliding distance are input factors. The change in load compared to the other input variables would more be affected the SWR. Authors observed that the used optimization model reduced the specific wear rate and confirmed the increasing of wear resistance of the composites by the proposed optimum parameters. They also said that the Taguchi method is useful in optimizing the specific wear rate.

Table 4 shows the advantages and disadvantages of the model used. It is clear that each method has different advantages and disadvantages. ANN, ANFIS and FL techniques use the experimental results but Taguchi is used for the experiment design which provides the maximum output with the minimum experiment.

Table 5 shows the decision matrices for ANN, ANFIS and Taguchi approaches. In the decision matrices, weighting factor (WF) is designated using the information in **Table 4**. The score values where ANFIS has the highest score value are close each other. For example, ANN runs with higher data volume compared to ANFIS. This shows why ANN has the score 3 while ANFIS has the score 4. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method is used for the more detailed analysis in shown in **Table 6**.

The main purpose of TOPSIS, which is a multi-criteria decision making method, is to enable the organization, interpretation and analysis of information in decision making. TOPSIS method reveals the distances to positive and negative ideal solutions, revealing ideal and non-ideal solutions. In the TOPSIS, the parameters are normalized (Eq. (1)), calculated weighted normalized matrix (Eq. (2)), ideal the best and worst values, Euclidean distance from ideal best and worst (Eqs. (3) and (4)), and performance (Eq. (5)), respectively, using following equations;

$$\overline{X}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j-1}^{n} X_{ij}^2}} \tag{1}$$

$$V_{ij} = \overline{X}_{ij} \, x \, W_j \tag{2}$$

$$S_i^+ = \left[\sum_{j-1}^{m} \left(V_{ij} - V_j^+ \right)^2 \right]^{0.5} \tag{3}$$

$$S_i^- = \left[\sum_{j-1}^{m} \left(V_{ij} - V_j^- \right)^2 \right]^{0.5} \tag{4}$$

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{5}$$

WF	**1**	**5**	**4**	**2**	**3**	**Score**
Method	**Time**	**Features**	**Predicting**	**Volume**	**Design**	
ANN	3	5	5	3	1	57
ANFIS	3	5	5	4	1	59
Taguchi	4	3	3	5	5	56

Table 5.
Decision (score) matrices.

WF	0.05	0.4	0.2	0.15	0.2	Volume and design (min)			Volume and design (max)		
Method	**Time**	**Features**	**Predicting**	**Volume**	**Design**	**Si^+**	**Si^-**	**Ci**	**Si^+**	**Si^-**	**Ci**
ANN	3	5	5	3	1	0.014	0.043	0.754	0.038	0.024	0.391
ANFIS	3	5	5	4	1	0.007	0.044	0.861	0.039	0.021	0.354
Taguchi	4	3	3	5	5	0.043	0.014	0.245	0.024	0.038	0.608

Table 6.
TOPSIS matrices.

The ideal best and worst values are the determining of the minimum or maximum values in the given ranges. The Ci values show the ranks of ANN, ANFIS and Taguchi methods. The maximum and minimum Ci values for the minimum data volume and design and the maximum data volume and design are observed at ANFIS and Taguchi approaches, respectively. This explains that if the analysis of broad features such as the solution of nonlinear problems, data classification, data processing, system control, or prediction will be performed, ANFIS or ANN techniques should be applied. If an experiment design with different variables will be executed, the Taguchi method should be used. So, experiment variables and its effects with less experimental study can reveal easily.

5. Conclusion

The key parameters are determined by executing the artificial neural network (ANN), adaptive-neuro fuzzy inference systems (ANFIS) and Taguchi with ANOVA. The nonlinear problems, the function approximation, data classification, data processing and system control etc., in engineering applications of AMCs can be easily carried out by soft computing approaches. Although many different methods are used for this purpose, we can say that the most popular and the most widely used methods are Taguchi, ANN and ANFIS approaches due to factors such as the minimum error, maximum accuracy, fast, cost, and time in forecasting, decision analysis, optimization, modeling and solution of complex problems and etc. One of the most important tasks in ANN and ANFIS is the determination of the number of layers, neuron, hidden layer, learning algorithm, and transfer function because there is no well-defined procedure to find the optimal parameter settings and network architecture. These variables affect the learning and forecasting abilities of the system with high accuracy. In the ANN, datasets must be normalized. ANFIS has the advantage to combine both ANN and Fuzzy knowledge. So ANFIS is more precise in term of efficiency even though ANN may outperform ANFIS model. ANFIS algorithm has a hybrid learning approaches in its structure. This helps the algorithm to be faster and more precise in term of efficiency than most of ANN algorithm.

The models have an important advantage coming from their ability to generate mathematical equations that can be easily programmed and used in applications in the production process. The theoretical analysis of material parameters is quite complicated due to various factors. The explicit formulations are proposed using these methods for estimating the parameters of composites. The training requirement for ANN includes large amounts of data, but this does not apply to ANFIS. The calculations can be made with the mathematical formulation obtained from the ANN which is an important advantage of ANN compared to the other methods. ANFIS and Neural Networks must be trained for each problem. The compatibility of experimental and theoretical results is researched by MSE, MAE, MAPE, RMSE, R and R^2 criteria because the minimum error criteria and maximum correlation coefficient are expected. The sensitivity of input parameters on the output in the stated studies, and the decision and TOPSIS matrices for three approaches are derived and discussed. Also, the advantages and disadvantages of the methods are tabulated. It can be concluded that ANFIS and ANN approaches can be used to solve the many complex problems with minimum error, control system, detect the interactions between variables, reach the target faster, predict and optimize the results with the maximum accuracy. The Taguchi is an experimental design method and provides the optimum results with fewer experiments using multiple results at the same time. The system, parameter and tolerance design is the special interest of the Taguchi.

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