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COMPUTATIONAL INTELLIGENCE FOR ANALYSING THE MECHANICAL PROPERTIES OF AA 2219 – (B_4C + H-BN) HYBRID NANO COMPOSITES PROCESSED BY ULTRASOUND ASSISTED CASTING

The computational intelligence tool has major contribution to analyse the properties of materials without much experimentation. The B_4C particles are used to improve the quality of the strength of materials. With respect to the percentage of these particles used in the micro and nano, composites may fix the mechanical properties. The different combinations of input parameters determine the characteristics of raw materials. The load, content of B_4C particles with 0%, 2%, 4%, 6%, 8% and 10% will determine the wear behaviour like CoF, wear rate etc. The properties of materials like stress, strain, % of elongation and impact energy are studied. The temperature based CoF and wear rate is analysed. The temperature may vary between 30°C, 100°C and 200°C. In addition, the CoF and wear rate of materials are predicted with respect to load, weight % of B_4C and nano hexagonal boron nitride %. The intelligent tools like Neural Networks (BPNN, RBNN, FL and Decision tree) are applied to analyse these characteristics of micro / nano composites with the inclusion of B_4C particles and nano hBN % without physically conducting the experiments in the Lab. The material properties will be classified with respect to the range of input parameters using the computational model.

Keywords: Powder metallurgy, Soft computing, ANN, Fuzzy logic, Decision tree

1. Introduction

The complex structure of Boron Carbide (B_4C) was designed during 19th century. B_4C is known as a robust material having high hardness, high cross section for absorption of neutrons, stability to ionizing radiation and most chemicals. This particle is mostly used in manufacturing various products in the industry. Hardness of the composite has increased from 60 to 118 VHN due to the addition of B_4C particles [1]. Reinforcing aluminium with SiC and B_4C nano/micro particles can lead to a more efficient material in terms of strength and lightweight [2]. In addition, the influence of adding these particles to an aluminium 7075 matrix is investigated using chevron-notch fracture toughness test method. Nano sized SiC and B_4C particle reinforced with Al 7075 aluminium nano composite were fabricated [3]. The hybrid composites like Al_2O_3 and B_4C particles are advanced class of materials used for lightweight application, having higher strength and stiffness compared to other conventional materials [4]. The performance of the materials in the military appliances, automotive and aircraft applications used these hybrid composites due to their low density and concurrent high wear resistance, strength, corrosion resistance, stiffness and thermal conductivity. The computational intelligence tools like neural networks, fuzzy logic and decision tree are able to map the relationship between the input and output parameters automatically. They have a major role in predicting and classifying material properties [5]. To predict the abrasive wear behaviour of an alloy matrix it is reinforced with B_4C particles [6]. Developed Artificial Neural Network (ANN) model based on feed forward back propagation to map the mechanical properties with different architectures to predict the experimental results [7]. Analysed the effects of these process variables on the squeeze cast A413-B_4C composites, then the effect of matrix size and milling time of the particle, apparent density and particular surface area of flake Al-Cu-Mg alloy powders were investigated both by experimental and artificial neural networks model [8]. Studied the microstructural and mechanical properties of casting Al matrix composites such as tensile strength, hardness, porosity using neural networks [9].

In this study, the back propagation algorithm of neural network and radial basis neural networks were applied to determine the stress, strain, % of elongation, impact energy, Co-efficient of Friction (CoF) and wear rate of the materials. Fuzzy logic is able to analyse the range of parameters, which are used to fix their properties. In addition, the data-mining tool like decision tool is applied to study the nature of attributes used to measure the mechanical properties of both nano and micro composites (micron sized secondary particles).

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2. Computational Intelligence tools

The computational models are very helpful to predict the characteristics of materials and to study the nature of parameters for fixing the different combination of mechanical powders. The neural network model is a network of nodes, which can map the input parameters into the output parameters using intelligent algorithms automatically. Neural Networks (NN) are important data mining tool used for classification and clustering [10]. They can process the noisy, interrelated and non-linear data easily. The decision tree model is a best reduction tool used to determine the relevant attributes, for improving the quality of the mechanical properties. Material selection is the vital role in designing the mechanical product since poorly selected material will lead unnecessary time and cost [12]. The fuzzy logic will be helpful to select the optimum material and used to fix the range of parameters of raw materials.

2.1. Back Propagation Neural Network (BPNN)

The BPNN, the automatic differential model was developed during 1970. This computational intelligence based model has two major divisions namely training and testing in the supervisor mode. This mode is similar to training the students in the class by the teacher. During training phase, the model is trained with the experimental data collected from the Lab. Each training pair has input parameters and the respective target data. The training is repeated iterations until the learning is completed based on the criteria like maximum time or the accuracy of the predictability. While testing, the trained model is applied with dependent and independent samples. Each testing sample has only the input parameters without target data. The trained system has to predict the data accurately. Dependent samples means, the same samples from the training are considered for testing. Independent samples means, samples that are not used while training set and they are completely new data.

The neural network has input layer, one or more hidden layers and output layer. It has two training phases namely forward phase and back propagation phase. In the forward phase, the input is send towards the output layer through the hidden layer. At the end of output layer, the deviation between the desired output and actual output is evaluated. If desired output correlates with the actual output, then the actual output is referred as the output of the network; otherwise, the error is propagated from the output layer towards the input layer through the hidden layer. The algorithm of BPN is given as below:

2.2. BPNN Algorithm

1. Get the size of input, hidden and output layer.
2. Initialize the weights between the inputs – hidden and hidden – output layer randomly.
3. Initialize the cumulative error as largest value.
4. While error is above desired threshold do
   - For each training sample x_p, $1 \le p \le P$,
   - Translate the input values using activation functions and transferred as input to the hidden layer
     $$f\left(x_i^k\right) = x_i^k \tag{1}$$
     where $i = 1,2\ldots\ldots n$; k = pattern index
   - Multiply the weights and the hidden node inputs to compute hidden node outputs
     $$z_h^k = \sum_{i=0}^{n} w_{ih} f\left(x_i\right) \tag{2}$$
     where $h = 1,2\ldots\ldots q$
   - Compute inputs to the output nodes
     $$f\left(z_h^k\right) = \frac{1}{1+e^{-zh}} \tag{3}$$
   - Compute the network outputs using
     $$f\left(y_j^k\right) = y_j^{'} \tag{4}$$
     where $j = 1\ldots p$
   - Compute the error between output and desired output
   - Update the connections (weights) of hidden and output nodes
     $$w_{ij}^{k+1} = w_{ij}^k + \eta\delta_j^k f\left(z_n^k\right) \tag{5}$$
     here η is a learning rate and, δ_j^k is an error term.
   - Update the weights between input and hidden nodes
     $$w_{ij}^{k+1} = w_{ij}^k + \eta\delta_h^k f\left(x_i^k\right) \tag{6}$$
5. Analyse the network performance with respect to the number of training samples, error tolerance and the training period.

2.3. Radial Basis Neural Network

Radial Basis Neural Networks (RBNN) offers a powerful framework for representing non-linear mappings from several inputs to one or more outputs [11]. RBFs are feed-forward networks consisting of a hidden layer of radial kernels and an output layer of linear neurons. The connection between input and hidden layer does not use the weighted sum of inputs. The output of the hidden layer represents basis functions, which are determined by the distance between the network input and the centre of the basis function. As the input moves away from a given centre, the neuron output drops off rapidly to zero. The output layer of RBF network is linear and produces a weighted sum of the outputs of the hidden layer. The neurons in the RBF network have localized receptive fields because they only respond to inputs that are close to their centres.

The exact interpolation called Neuron at data point (NADP) is used to map every point in the input pattern to the output layer.

Formally, the exact interpolation of Q data points in a multi-dimension space require all the D dimensional input vectors $x^k = \{x_i^k, i = 1, 2 \dots D\}$ to be mapped onto the corresponding target output y^k. Where D is the size of Input layer, the goal is to find the f function such that

$$f(x^k) = y^k \qquad \forall\ k \quad = 1 \dots\dots Q \tag{7}$$

where Q represents number of training samples. This approach requires Q amount radial basis functions. The generalization performance of RBF network relates to its prediction capability on independent test data. The algorithm given below is used to interpolate the source data exactly:

Step 1: Choose the free parameters like the spread factor, number and values of centers and the type of radial basis function. In this model, all training samples are considered as centers of RBF.

Step 2: The training pattern with D amount of features is applied to input layer X, whose size is equal to D. Then each input node (X_i; $i = 1, 2, D$) sends the input data to the hidden layer.

Step 3: At hidden layer, the distance between the input layer X and the centers is calculated by the formula:

$$\left\| X - \mu_j \right\| = \sqrt{\sum_{i=1}^{i=D} \sum_{j=1}^{j=Q} \left(x_{i,j} - \mu_{i,j} \right)^2} \tag{8}$$

where, the entire training samples is considered as center set μ in NADP model and μ_j is j^{th} centre point.

Step 4: The activation of hidden unit (ϕ) is determined by distance between the input vector and centres using any one of the RBF filter f

$$\phi_j(X) = f\left(\| \mathrm{X} - \mu_j \|\right) \tag{9}$$

The filter f may be in the form of Gaussian function, cubic function, linear function, Multi Quadric function or inverse Multi-quadric function.

Step 5: The activation of the output unit is determined by dot product between the hidden activation vector and weight vector. For convenience, an additional basis function ϕo with constant activation value of '1' can be used with unknown weight $W_{0.}$

$$y_k = \sum_{j=1}^{Q} W_{jk} \phi_j(X) + Wo\phi o \tag{10}$$

3. Decision Tree

Decision tree is a flow based chart like tree structure, where each internal node denotes a test on a parameter and the each branch represents the outcome from the test and the leaf nodes represent classes. The top most nodes are called as root node and the paths from root to leaf represents the classification rules. Decision trees classifies the given data samples from the root of the tree to the leaf node to cover every part of the tree. It is noted that Decision tree is useful because construction of decision tree classifiers does not require any domain knowledge. It can handle higher dimensional data. The learning and classification steps of decision tree induction are simple and fast [13]. The decision tree is constructed to classify the data as per the following algorithm.

Algorithm:

Step 1: Tree starts as a single node representing all the samples of data

Step 2: If the samples are all of the same class, then the node becomes a leaf and is labelled with that class.

Step 3: Otherwise computer heuristic measure for selecting the parameter that will best separate the samples into individual classes. This parameter is the test parameter at that node.

Step 4: Branch is created for each known value of test parameter and data samples are portioned accordingly,

Step 5: The above steps are repeated called recursively to the decision tree for the data samples at each partition.

Step 6: The recursive portioning stops only when any one of the following condition is true.

- All samples for a given node belong to the same class.
- There are no remaining parameters on which the samples may be further partitioned.
- There are no data samples for the branch of test parameter. In this case, a leaf node is created with the majority class in data samples

4. Fuzzy Logic

Fuzzy logic is mostly used in machine control in the Industries. The term "fuzzy" means that the values of variables are expressed in the real numbers between 0 and 1. The parameter uncertainties in the nonlinear plant can be captured effectively by utilizing the membership functions with upper and lower bounds [14]. Fuzzy Inference system (FIS) is able to map the data into logistics variables forms such as low, high, medium, very low and very high. For example, the temperature may be scaled as cold, warm and hot. This kind of mapping will be helpful to estimate the range of input parameters, which are used to control the respective control parameters.

The fuzzy control system has three stages namely input stage, processing stage and output stage. The input stage maps inputs such as motor switches, thumbwheels and so on to the appropriate membership functions and truth-values. The intermediate stage applies rules to map the input variables to the respective output variables. The rules are described as if-then rules.

For example: if (carbon weight is low) then the material strength is week. If (carbon weight is medium) then the material strength is normal. If (carbon weight is high) then the material strength is strong. The final stage maps the results into logistic variables.

5. Results and discussion

The training and testing sets were prepared individually for applying each intelligent tools like BPN, RBF, Decision Tree and Fuzzy Logic.

5.1. Computing CoF and Wear rate using BPNN

Table 1 reports the sample database for input parameters like load, B_4C content with 0%, 2%, 4%, 6%, 8% and 10% for calculating the output parameters like coefficient of friction and Wear rate for both micro and nano composites.

The neural network was designed with 3 neurons in the input layer, 12 neurons in the hidden layer and 4 neurons in the output layer. The network was trained with maximum 100 epochs as given in Figure 1.

The Correlation coefficient *R* was calculated for CoF and Wear rare of micro composites and CoF and wear rate of nano composites as 0.9978, 1.0, 0.99894 and 0.9994 respectively as given in Fig. 2(a-d) using the Equation (11), which finds the correlation between the expected value *x* and actual network value *y*.

$$r = \frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{\sqrt{\left[n\left(\sum x^2\right) - \left(\sum x\right)^2\right]\left[n\left(\sum y^2\right) - \left(\sum y\right)^2\right]}} \qquad (11)$$

Also the architecture of BPN was modified with three input neurons, 20 hidden neurons and 4 output neurons. Load, Weight % of B_4C with room temperature 30°C, 100°C and 200°C will predict the CoF and Wear rate of both micro and nano composites.

Table 2 shows the expected experimental value, actual output of the network and % of error of all output parameters of both micro and Nano composites.

TABLE 1

Sample database

Sample No.	Load	Al	B_4C %	Micro composites		Nano composites	
				CoF	Wear rate	CoF	Wear rate
1	4.00	0.40	2.00	0.35	1.22	0.35	0.85
2	4.00	0.40	4.00	0.33	1.15	0.30	0.85
3	4.00	0.40	6.00	0.30	0.97	0.28	0.63
4	4.00	0.40	8.00	0.28	0.66	0.25	0.56
5	4.00	0.40	10.00	0.30	0.82	0.30	0.71
6	8.00	0.54	2.00	0.51	1.45	0.40	1.22
7	8.00	0.54	4.00	0.45	1.26	0.39	1.15
8	8.00	0.54	6.00	0.43	1.12	0.36	0.74
9	8.00	0.54	8.00	0.41	0.93	0.35	0.78
10	8.00	0.54	10.00	0.44	1.08	0.38	0.90
11	12.00	0.56	2.00	0.51	1.74	0.41	1.37
12	12.00	0.56	4.00	0.48	1.41	0.40	1.26
13	12.00	0.56	6.00	0.46	1.23	0.38	1.12
14	12.00	0.56	8.00	0.43	1.19	0.37	1.01
15	12.00	0.56	10.00	0.43	1.23	0.39	1.12
16	16.00	0.60	2.00	0.53	1.93	0.40	1.78
17	16.00	0.60	4.00	0.49	1.82	0.39	1.67
18	16.00	0.60	6.00	0.48	1.30	0.39	1.19
19	16.00	0.60	8.00	0.43	1.23	0.37	1.16
20	16.00	0.60	10.00	0.48	1.38	0.38	1.31

5.2. Radial Basis Neural Network

The RBFN network model was designed with 3 input neurons, 58 hidden neurons and 4 output neurons. Nearly 45 samples were collected with load, length, % B_4C content as input parameters and stress, strain, % of elongation & impact energy as output parameters.

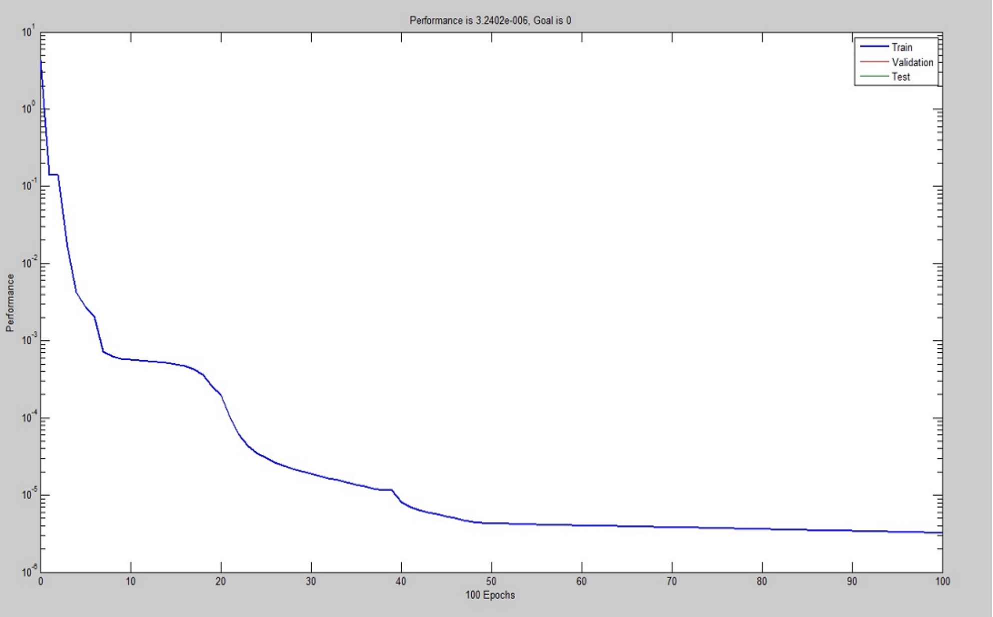


Fig. 1. BPNN training

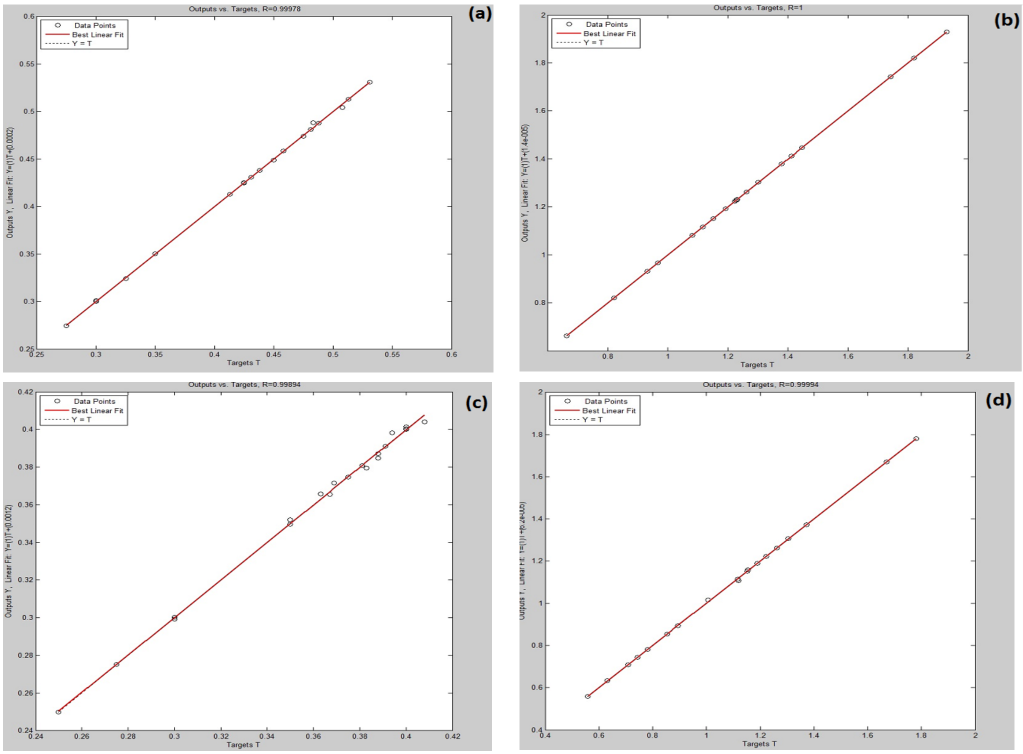
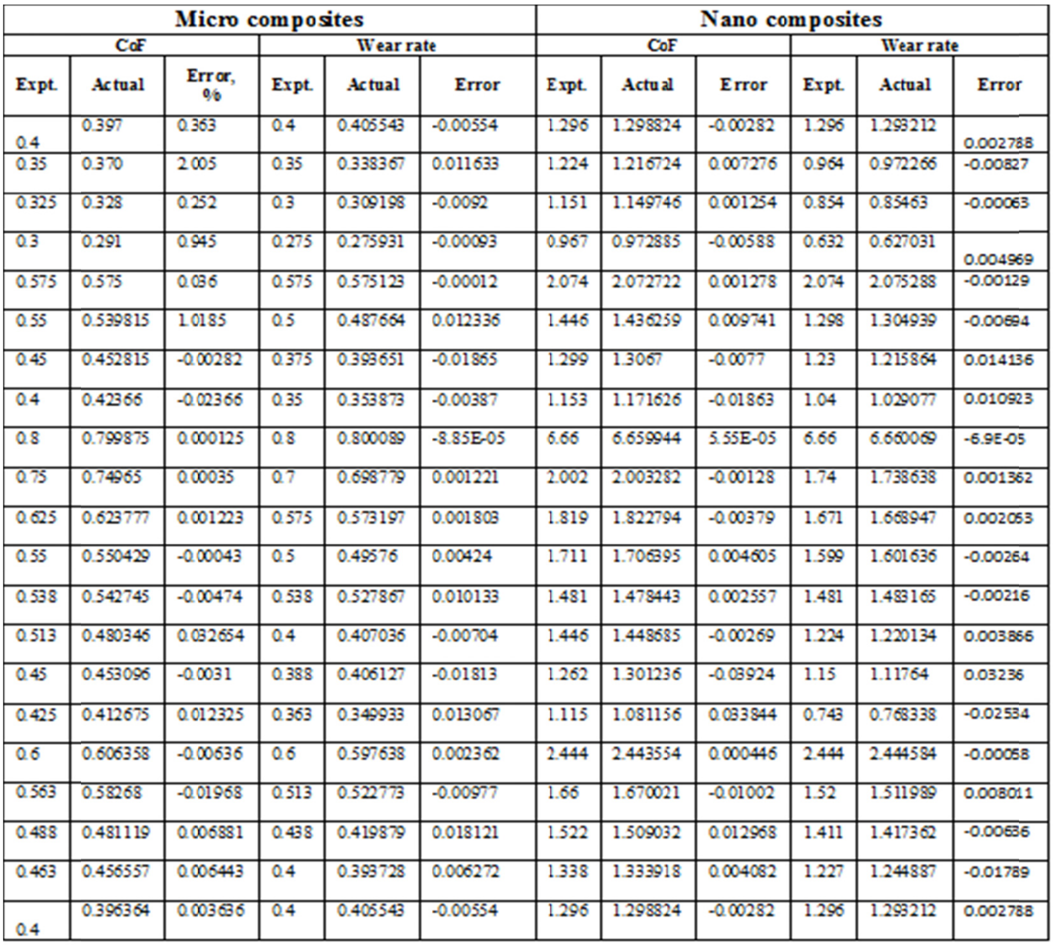


Fig. 2. Correlation coefficient for (a) CoF of micro composites (b) Wear rate of micro composites (c) CoF of nano composites (d) Wear rate of nano composites

TABLE 2

Temperature based CoF and Wear rate for Al2219-B_4C composites



Micro composites						Nano composites					
CoF			Wear rate			CoF			Wear rate		
Expt.	Actual	Error, %	Expt.	Actual	Error	Expt.	Actual	Error	Expt.	Actual	Error
0.4	0.397	0.363	0.4	0.405543	-0.00554	1.296	1.298824	-0.00282	1.296	1.293212	0.002788
0.35	0.370	2.005	0.35	0.338367	0.011633	1.224	1.216724	0.007276	0.964	0.972266	-0.00827
0.325	0.328	0.252	0.3	0.309198	-0.0092	1.151	1.149746	0.001254	0.854	0.85463	-0.00063
0.3	0.291	0.945	0.275	0.275931	-0.00093	0.967	0.972885	-0.00588	0.632	0.627031	0.004969
0.575	0.575	0.036	0.575	0.575123	-0.00012	2.074	2.072722	0.001278	2.074	2.075288	-0.00129
0.55	0.539815	1.0185	0.5	0.487664	0.012336	1.446	1.436259	0.009741	1.298	1.304939	-0.00694
0.45	0.452815	-0.00282	0.375	0.393651	-0.01865	1.299	1.3067	-0.0077	1.23	1.215864	0.014136
0.4	0.42366	-0.02366	0.35	0.353873	-0.00387	1.153	1.171626	-0.01863	1.04	1.029077	0.010923
0.8	0.799875	0.000125	0.8	0.800089	-8.85E-05	6.66	6.659944	5.55E-05	6.66	6.660069	-6.9E-05
0.75	0.74965	0.00035	0.7	0.698779	0.001221	2.002	2.003282	-0.00128	1.74	1.738638	0.001362
0.625	0.623777	0.001223	0.575	0.573197	0.001803	1.819	1.822794	-0.00379	1.671	1.668947	0.002053
0.55	0.550429	-0.00043	0.5	0.49576	0.00424	1.711	1.706395	0.004605	1.599	1.601636	-0.00264
0.538	0.542745	-0.00474	0.538	0.527867	0.010133	1.481	1.478443	0.002557	1.481	1.483165	-0.00216
0.513	0.480346	0.032654	0.4	0.407036	-0.00704	1.446	1.448685	-0.00269	1.224	1.220134	0.003866
0.45	0.453096	-0.0031	0.388	0.406127	-0.01813	1.262	1.301236	-0.03924	1.15	1.11764	0.03236
0.425	0.412675	0.012325	0.363	0.349933	0.013067	1.115	1.081156	0.033844	0.743	0.768338	-0.02534
0.6	0.606358	-0.00636	0.6	0.597638	0.002362	2.444	2.443554	0.000446	2.444	2.444584	-0.00058
0.563	0.58268	-0.01968	0.513	0.522773	-0.00977	1.66	1.670021	-0.01002	1.52	1.511989	0.008011
0.488	0.481119	0.006881	0.438	0.419879	0.018121	1.522	1.509032	0.012968	1.411	1.417362	-0.00636
0.463	0.456557	0.006443	0.4	0.393728	0.006272	1.338	1.333918	0.004082	1.227	1.244887	-0.01789
0.4	0.396364	0.003636	0.4	0.405543	-0.00554	1.296	1.298824	-0.00282	1.296	1.293212	0.002788

As stated in the algorithm of RBF, the number of hidden neurons is equal to the number of training samples. Hence the hidden layer size is 58. The linear filter is selected to process the hidden neurons output. The optimum value of centre width is fixed as 2.0. The RBFNN was tested and the output parameters of both micro and nano composites like Stress, Strain, the % of elongation and Impact Energy (J) were measured as given in Figure 3(a-d) respectively.

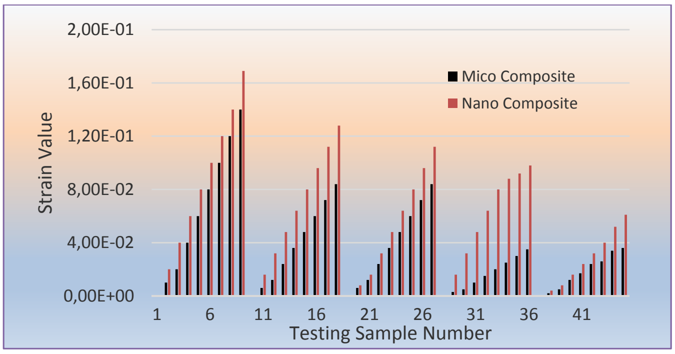


Fig. 3(a). Strain value of micro and nano composites

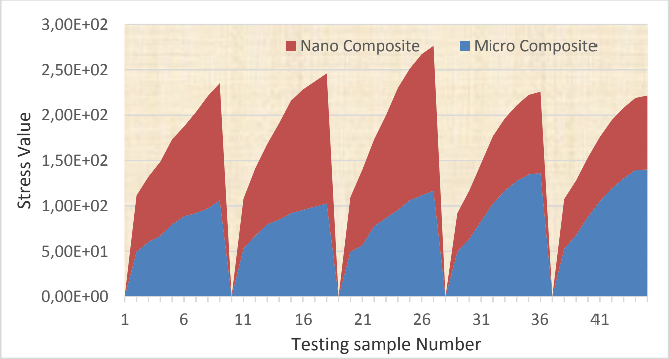


Fig. 3(b). Stress value of micro and nano composites

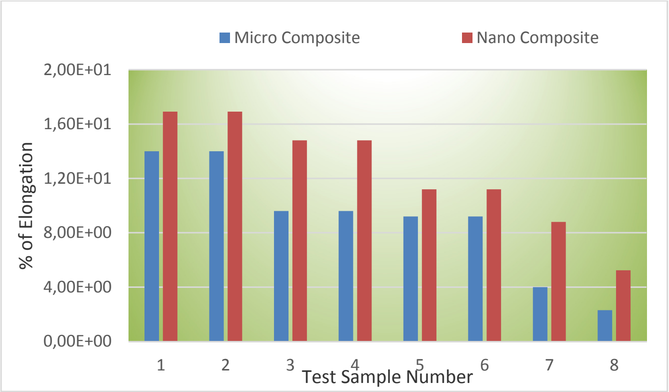


Fig. 3(c). % of Elongation of micro and nano composites

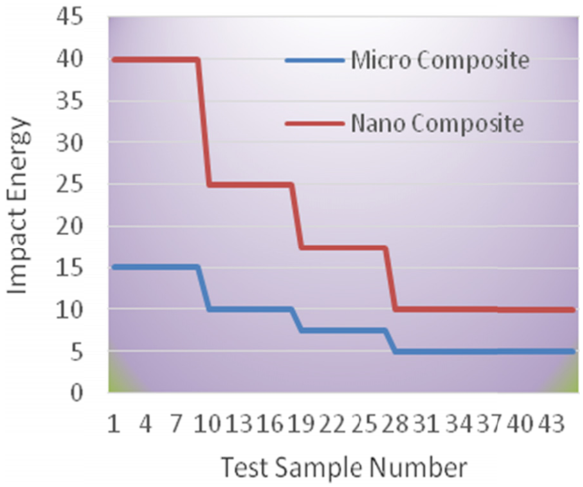


Fig. 3(d). Impact Energy of micro and nano composites

5.3. Decision tree

The input attributes like Load, Al and B_4C particles with 0%, 2%, 4%, 6%, 8% and 10% content are analysed to predict the output parameters CoF and Wear rate individually and shown in Figure: 4(a-d). For example, the load attributes classifies left sub tree for the value less than 6 and right sub tree for the value greater than 6. Again the second input attribute value less than or equal to 3 generates left sub tree and greater than 3 generates right sub tree. Further the attribute B_4C categories left sub tree and right sub tree for the value less than 3 and greater than or equal to 3 respectively. Again in the right sub tree, B_4C is categories as left and right sub trees for the value less than 5 and greater than or equal to 5 respectively.

If the load is greater than 6 and B_4C% is less than 3 then the CoF value is predicted as 0.51733. Similarly to predict CoF value as 0.44189, the input parameter load is greater than or equal to 6 and B_4C% is greater than 5. Figure 4(e-f) reports the decision tree construction to predict the CoF and WR respectively for both Micro and Nano composites.

The complete decision tree for all output parameters is shown in Figure 4(g) and the respective detailed algorithm to construct decision tree is given in Figure 4(h). This kind of analysis will be helpful to study the strength of input parameters to get the required output parameters.

5.4. Fuzzy Logic

The Load, Weight % of B_4C with Nano Hexagonal boron nitride % will find the CoF and Wear rate. The sample experimental data is reported in Table 3 and Table 4. The Fuzzy Inference System (FIS) reads the raw data in non-fuzzy data (Crisp Data) and maps into range form (Fuzzy data) using fuzzification.

Then it evaluates the input and generates the output, which in turn will be converted into Crisp Output using fuzzification using this FIS model the relationship among the parameters can be studied easily. The sample Fuzzy system is given in Figure 5. Figure 6 shows the designed FIS, which gets 3 input parameters and 2 output parameters. The values of input parameters are fuzzyfied using triangular-shaped membership function and the output parameters are fuzzyfied (Equation 12) using trapezoidal function (Equation 13).

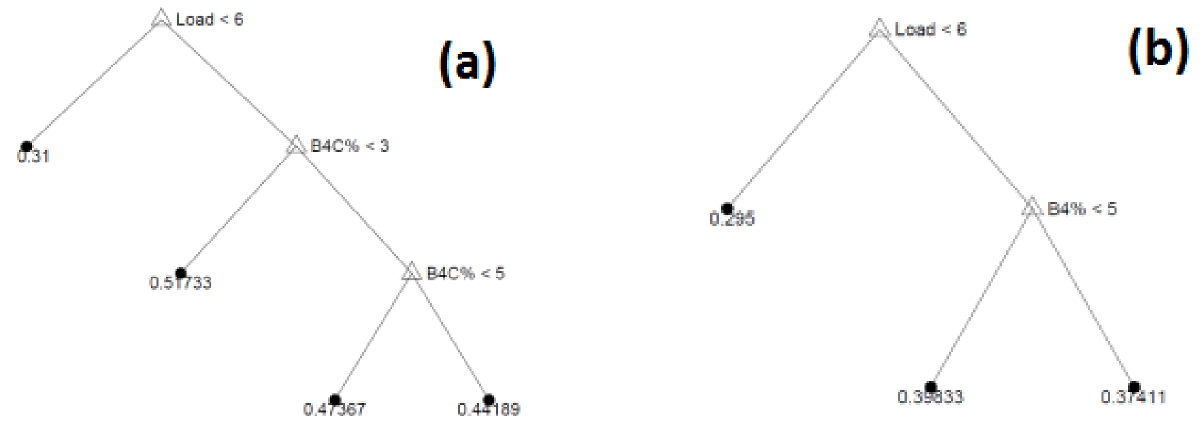


Fig. 4(a-b). Decision tree to predict CoF of (a) micro composites (b) nano composites

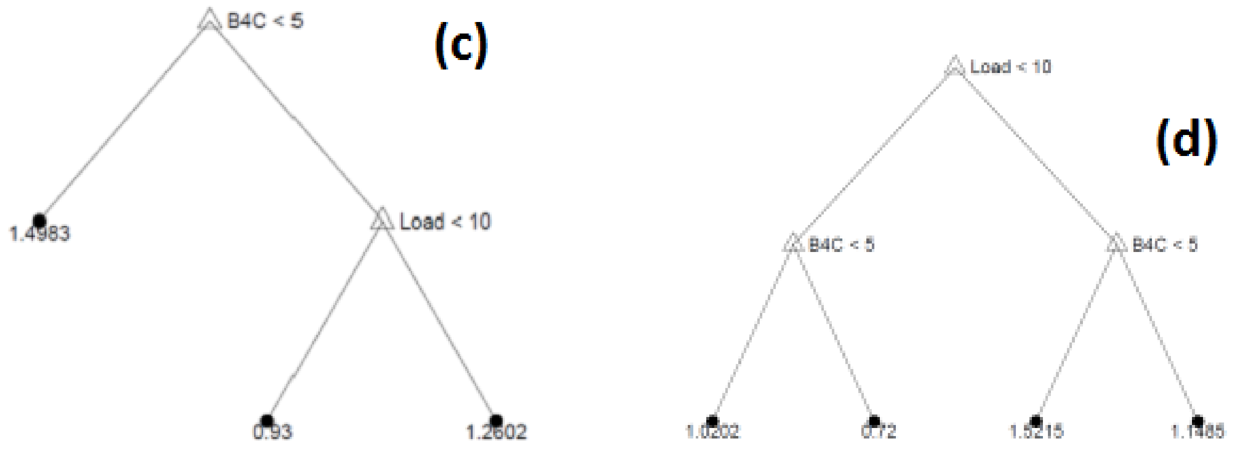


Fig. 4(c-d). Decision tree to predict wear rate of (c) micro composites (d) nano composites

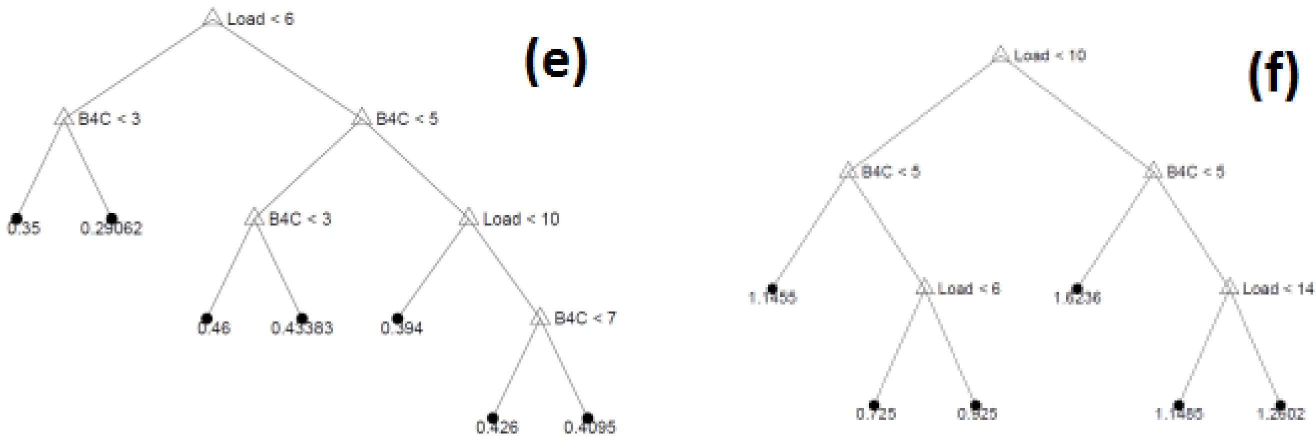


Fig. 4(e-f). Decision tree to predict micro and nano composites of (e) COF (f) wear rate

5.4.1. Member function

The input parameters load, B_4C weightage and Nano hBN % uses triangular-shaped membership function. The triangular curve is a basic function of a vector, *x*, and depends on three scalar parameters such as *a*, *b*, and *c* as given below.

$$f(x,a,b,c) = \max\left(\min\left(\frac{x-a,}{b-a},\frac{c-x}{c-b}\right),0\right) \tag{12}$$

The parameters *a* and *c* locate the "feet" of the triangle and the parameter *b* locates the peak.

i) Load:

The minimum and maximum value for load are 4 and 16 respectively in the raw data.

$$\text{Membership value} = \begin{array}{r} Low \\ Medium \\ High \end{array}\begin{pmatrix} -0.8 & 4 & 8.8 \\ 5.2 & 10 & 14.8 \\ 11.2 & 16 & 20.8 \end{pmatrix}$$

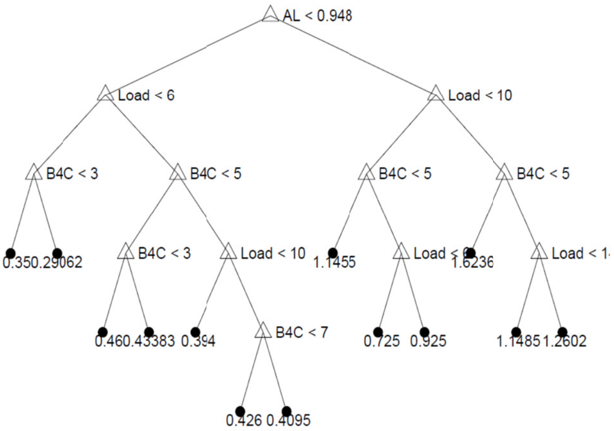


Fig. 4(g). Complete tree for COF and wear rate of both micro and nano composites

ii) B_4C Weightage

The minimum and maximum value for B_4C are 0 and 6 respectively in the raw data.

$$\text{Membership value} = \begin{array}{r} Low \\ Medium \\ High \end{array} \begin{pmatrix} -2.4 & 0 & 2.4 \\ 0.6 & 3 & 54 \\ 3.6 & 6 & 84 \end{pmatrix}$$

iii) Nano Hexagonal boron nitride %

The minimum and maximum value for hBN % are 0 and 200 respectively in the collected raw data.

$$\text{Membership value} = \begin{array}{r} Low \\ Medium \\ High \end{array} \begin{pmatrix} -80 & 0 & 80 \\ 20 & 100 & 180 \\ 120 & 200 & 280 \end{pmatrix}$$

The output parameters of FIS use the trapezoidal function whose curve is a function of a vector, *x*, and depends on four scalar parameters *a*, *b*, *c*, and *d* as given by:

$$f(x,a,b,c) = \max\left(\min\left(\frac{x-a,}{b-a},1,\frac{d-x}{d-c}\right),0\right) \tag{13}$$

The parameters an and *d* locate the "feet" of the trapezoid and the parameters *b* and *c* locate the "shoulders." This model classifies the input data into low, medium and high using the inference rules as given below:

iv) Coefficient of Friction (CoF)

The minimum and maximum value for CoF are 0.2000 and 0.9688 respectively in the collected raw data.

$$\text{Membership value} = \begin{array}{r} Low \\ Medium \\ High \end{array} \begin{pmatrix} -0.1075 & 0.2 & 0.5075 \\ 0.2769 & 0.5844 & 0.8919 \\ 0.6613 & 0.9688 & 1.276 \end{pmatrix}$$

v) Wear rate

The minimum and maximum value for wear rate are 0.1490 and 14.950000 respectively in the collected raw data.

$$\text{Membership value} = \begin{array}{r} Low \\ Medium \\ High \end{array} \begin{pmatrix} -5.771 & 0.149 & 6.069 \\ 1.629 & 7.55 & 13.47 \\ 9.03 & 14.95 & 20.87 \end{pmatrix}$$

1. if Al < 0.948 then node 2 else node 3
2. if Load < 6 then node 4 else node 5
3. if Load < 10 then node 6 else node 7
4. if B_4C < 3 then node 8 else node 9
5. if B_4C < 5 then node 10 else node 11
6. if B_4C < 5 then node 12 else node 13
7. if B_4C < 5 then node 14 else node 15
8. fit = 0.35
9. fit = 0.290625
10. if B_4C < 3 then node 16 else node 17
11. if Load < 10 then node 18 else node 19
12. fit = 1.1455
13. if Load < 6 then node 20 else node 21
14. fit = 1.62362
15. if Load < 14 then node 22 else node 23
16. fit = 0.46
17. fit = 0.433833
18. fit = 0.394
19. if B_4C < 7 then node 24 else node 25
20. fit = 0.725
21. fit = 0.925
22. fit = 1.1485
23. fit = 1.26017
24. fit = 0.426
25. fit = 0.4095

Fig. 4(h). Decision tree for regression

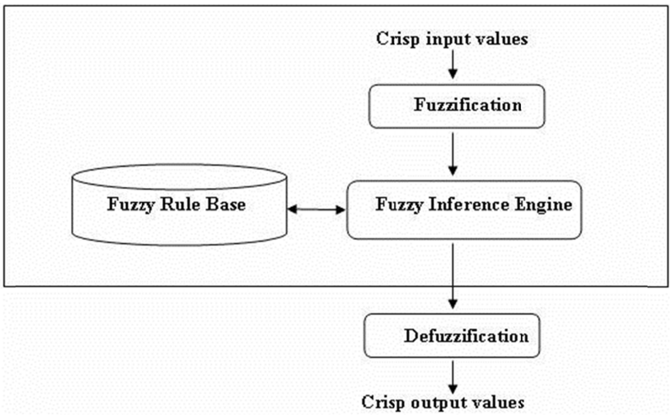


Fig. 5. Fuzzy Inference Model

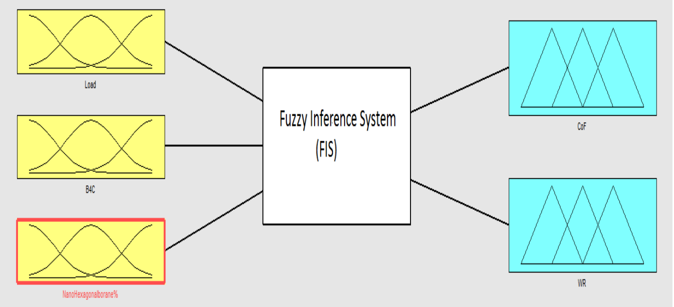


Fig. 6. FIS to predict CoF and Wear rate

TABLE 3

CoF for load, B_4C weightage and Nano hBN %

Sample No.	Load	B_4C weightage	hBN %	Nano based CoF
1	4	2	200	0.450
2	4	4	200	0.375
3	4	6	200	0.625
4	8	0	100	0.600
5	8	2	100	0.425
6	8	4	100	0.387
7	12	2	200	0.525
8	12	4	200	0.483
9	12	6	200	0.783
10	16	2	200	0.550
11	16	4	200	0.500
12	16	6	200	0.817

TABLE 4

WR for load, B_4C weightage and Nano hBN %

Sample No.	Load	B_4C weightage	hBN %	Nano based WR
1	4	4	100	0.4098
2	4	6	100	1.2684
3	4	2	200	1.0788
4	8	6	100	1.4923
5	8	2	200	1.3020
6	8	4	200	1.1176
7	12	0	0	1.8890
8	12	2	0	1.1153
9	12	4	0	0.9685
10	16	2	200	3.1250
11	16	4	200	2.3470
12	16	6	200	4.4769

5.4.2. Inference Rules

The following relationship among the parameters is studied as given below to construct FIS

- If load increases then the CoF and Wear rate decreases.
- The change in CoF and WR are directly proportional to the Nano hBN %
- If B_4C increases then the CoF and WR will also increase

The above constraints were implemented by Fuzzy inference system by:

1. If (Load is Medium) and (B_4C is High) and (Nano hBN % is Medium) then (CoF is Medium) (WR is Medium)
2. If (Load is High) and (B_4C is Medium) and (Nano hBN % is Medium) then (CoF is Medium) (WR is Low)
3. If (Load is High) and (B_4C is High) and (Nano hBN % is Medium) then (CoF is Medium) (WR is Medium)
4. If (Load is Medium) and (B_4C is High) and (Nano hBN % is High) then (CoF is High) (WR is Medium)
5. If (Load is Medium) and (B_4C is Medium) and (Nano hBN % is High) then (CoF is Medium) (WR is High)
6. If (Load is Low) and (B_4C is Low) and (Nano hBN % is Low) then (CoF is Medium) (WR is Low)
7. If (Load is Low) and (B_4C is Low) and (Nano hBN % is Medium) then (CoF is Medium) (WR is Low)
8. If (Load is Low) and (B_4C is Medium) and (Nano hBN % is Medium) then (CoF is Low) (WR is Low)
9. If (Load is Medium) and (B_4C is Medium) and (Nano hBN % is Medium) then (CoF is Medium) (WR is Low)
10. If (Load is Medium) and (B_4C is Medium) and (Nano hBN % is Low) then (CoF is Low) (WR is Low)
11. If (Load is Medium) and (B_4C is Low) and (Nano hBN % is Low) then (CoF is Low) (WR is Low)
12. If (Load is Low) and (B_4C is Medium) and (Nano hBN % is Low) then (CoF is Low) (WR is Low) (1)
13. If (Load is Low) and (B_4C is Low) and (Nano hBN % is Medium) then (CoF is Medium) (WR is Medium) (1)
14. If (Load is Low) and (B_4C is Medium) and (Nano hBN % is Medium) then (CoF is Low) (WR is Low) (1)
15. If (Load is Low) and (B_4C is Low) and (Nano hBN % is High) then (CoF is High) (WR is Medium) (1)
16. If (Load is Low) and (B_4C is High) and (Nano hBN % is High) then (CoF is Medium) (WR is Medium) (1)
17. If (Load is High) and (B_4C is High) and (Nano hBN % is High) then (CoF is High) (WR is Medium) (1)
18. If (Load is High) and (B_4C is High) and (Nano hBN % is Low) then (CoF is Medium) (WR is Medium) (1)
19. If (Load is High) and (B_4C is Low) and (Nano hBN % is Low) then (CoF is High) (WR is Medium) (1)
20. If (Load is Low) and (B_4C is High) and (Nano hBN % is Low) then (CoF is Low) (WR is Low) (1)
21. If (Load is Low) and (B_4C is Low) and (Nano hBN % is High) then (CoF is High) (WR is Medium) (1)
22. If (Load is Low) and (B_4C is High) and (Nano hBN % is High) then (CoF is Medium) (WR is Medium) (1)

TABLE 5

Fuzzy variables of Input and Output parameters

Parameter	Low			Medium			High		
Load	–0.8	4	8.8	5.2	10	14.8	11.2	16	20.8
B_4C	–4	0	2.4	0.6	3	54	3.6	6	84
hBN %	–80	0	80	20	100	180	120	200	280
CoF	–0.1075	0.2	0.5075	0.2769	0.5844	0.8919	0.6613	0.9688	1.276
WR	–5.771	0.149	6.069	1.629	7.55	13.47	9.03	14.95	20.87

5.4.3. Evaluation using FIS

The values of fuzzy variables Low, Medium and High of input and output variables are given in the Table 5. These statistical measures used in this model will be helpful for analysing the nature of parameters deeply.

For example the inference rule is

- If (Load is Low) and (B_4C is High) and (Nano hBN % is High) then (CoF is Medium) (WR is Medium)
- According to this rule, if the Load value is 2 (Low), B_4C is 70 (High), Nano hBN % is 250(High) then the predicted output values of FIS are CoF 0.5844 (Medium) and WR 7.5495(High)
- Thus the fuzzy variables are related with the respective crisp values which helps to understand the relationship between the range of input and parameters is analysed while preparing the composites.

6. Comparison among the soft computing tools

The scope of all computational tools is not unique. Each one have different functionality and the objective or the outcome of the tool is different. With respect to the nature of the scenario, capability or the strength of the tool, learning period, error accuracy the proper soft computing tool will be selected as per the Table 6.

7. Conclusions

The developed computational intelligence tools in this work is used to study the properties of materials. Each tool has different purpose. Hence, with respect to nature of scenario, number of samples required learning period and expected accuracy, the type of tool can be chosen.

- The Neural networks in the form of BPNN and RBFN can act as prediction tool to predict the CoF and wear rate, stress, strain, % of elongation, Impact Energy parameters without conducting the experiments physically in the Lab.
- Among these prediction tools BPNN and RBF, RBFNN is the optimum tool for prediction due to more accuracy and less training time.
- The decision tree is able act as classification tool to analyse the relationship among the input attributes to find the respective output parameters. Using data fixing tool like fuzzy logic, the mechanical properties can be classified easily in the abstract form like low, medium and high. The Fuzzy Inference System (FIS) can map the given crisp data into fuzzy fed form to determine the range of input parameters relevant to the properties of materials.
- The computational tools are able to simplify the manufacturing process of micro and nano composites and prove that the nano composites can yield more strength and lifetime of the materials.

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TABLE 6

Comparison among various soft computing tools

Name of the tool	Nature of the tool	Strength of architecture	Epochs required for learning	Error Accuracy
BPN tool	Act as Prediction tool to predict COF and WR parameters	Light weighted architecture (Hidden neurons 12)	100 epochs	Minimum error accuracy is 0.010923
RBF tool	Act as Prediction tool to predict Stress, Strain, the % of elongation and Impact Energy (J)	With heavy weighted architecture (50 to 100 neurons), used as prediction tool to predict the output parameters.	Single epoch since there is no backward phase	Minimum error accuracy is 1.04E-11
Decision Tree Tool	Act as classification tool to classify the attributes Load, Al and B_4C with respect to the CoF and WR	Maximum 2 to 3 levels for each CoF / WR for individual Micro/Nano composites. 3 to 4 levels for both composites. 6 levels for both outputs while combining both composites	Single Iteration to construct the tree structure	Classification accuracy Minimum fitness value is 0.394
Fuzzy logic tool	Act as data fixing tool used to fix the range of parameters while composite preparation	Architecture 3 input nodes and 2 output nodes	5 iterations required to define the member functions of 3 input and 2 output variables	Fuzzy value in terms of Low, High and Medium

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