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Tribological analysis of laser deposited SS316L/Co27Cr6Mo functionally graded materials using adaptive neuro-fuzzy inference system

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Abstract Artificial intelligence (AI) techniques such as artificial neural networks (ANN) and neuro-fuzzy logic (FL) have found successful applications in image processing, power engineering, robotics, industrial automation, and other fields. This study utilizes the adaptive neuro-fuzzy inference system (ANFIS) modeling of machine learning (ML) to estimate the tribological properties of functionally graded materials (FGM). The FGMs were developed using a direct energy deposition (DED) technique of additive manufacturing (AM) from SS316L and Co27Cr6Mo alloys. The input data for the ANFIS modeling was obtained from Pin-on-Disc (PoD) apparatus experiments on FGM samples. The main objective of this work is to predict the tribological parameters of FGM samples by creating a data-driven predictive model called ANFIS. The findings demonstrate that ANFIS is an efficient method for estimating the wear rate of FGM samples.

Keywords: ANFIS, Co27Cr6Mo, FGM, Fuzzy logic system, SS316L, wear rate

1. Introduction

Functionally graded materials (FGMs) are widely utilized in various fields such as engineering, medical, marine, and energy sectors due to their unique properties. FGMs can be manufactured using conventional and advanced manufacturing techniques, including Additive Manufacturing (AM). Among the AM techniques, the laser deposition technique is the best Directed Energy Deposition (DED) method for producing various graded components based on user-defined process parameters.

Machine learning (ML) techniques, such as Artificial Neural Networks (ANNs), Fuzzy Logic (FL), and Genetic Algorithms (GAs), are commonly used to estimate and forecast missing data in various fields, including FGMs. Researchers from various engineering disciplines have successfully used ANFIS to infer missing data. The ANFIS technique combines ANN and FL techniques and contains two fuzzy logic models, the Mamdani and Sugeno models.

An intelligent fault diagnosis system for rotating machinery was developed using ANFIS in combination with genetic algorithm (GA) and empirical mode decomposition (EMD) to estimate and build the system (Lie 2007). In another study, the neuro-fuzzy technique was used to predict missing hydrological data of a gauging station using real-time data as input (Dastorani 2010). Vijay Kumar (2012) compared the wear rate values of Al-SiC MMC samples obtained from a pin-on-disc apparatus wear test with ANFIS-predicted values and found the ANFIS-predicted values to be 99.9% accurate. Ramesh (2013) compared the slurry erosive wear loss of cast aluminum 6061 (Al 6061) alloy with the loss predicted through back-propagation and least-square methods of the fuzzy logic model. In addition, Aldas (2014) evaluated the surface roughness of Dievar hot work tool steel samples using ANFIS modeling and found that the Gaussian membership function type produced better results than the Bell-shaped membership function. ANFIS modeling was also used to predict the influence of machining parameters on the surface roughness of carbon fiber-reinforced Al-6061 samples (Ramesh 2014).

The dry sliding wear rate of samples made through powder metallurgy using pre-alloyed Astolay 85 Molybdenum (Mo) and Distaloy AB powders was determined, and the results were compared with the empirical and ANFIS results as reported by Alambeigi (2016). The wear, wear rate, and coefficient of friction were estimated using a hybrid technique of fuzzy logic (i.e., Grey-Fuzzy) concept when load, % of coconut shell ash, and sliding distance were varied, as reported by Raju in 2017. An ANFIS model was used by Anwar (2017) to forecast the surface roughness value of BK7 glass. Zid (2018) estimated the effect of various cutting parameters on flank wear using the Taguchi method and ANFIS by studying the influence of machining parameters like cutting speed, feed rate, depth of cut, and nose radius.

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A multi-objective optimization was performed by Nwobi (2019) using ANN and ANFIS to forecast the hardness and cost outputs of age-hardened A356/CHp samples. The ANFIS model predicted a higher correlation coefficient 'R' value than ANN. Seputra (2019) used the ANFIS model to predict the density and hardness of AMC samples made through the hot press method with various compositions of 1-3 wt.% of organoclay. The hardness value enhanced from 15 to 197, and the mass density increased and achieved an optimum at 550 °C by adding a 1% weight of organoclay.

Der Jean (2019) tested the wear rate of diamond-like carbon (DLC) coatings made on SKD11 steel samples using magnetron sputtering and compared them with GA-ANFIS tribological simulations. Sosimi (2020) applied the Levenberg-Marquardt training with back-propagation neural networks technique to predict the wear rate of calcium carbonate-reinforced aluminum composites with filler particle size 150 µm.

The machining behavior of Ti-6Al-4V matrix nanocomposites reinforced with 0, 0.6, and 1.2 wt.% GNPs was studied using a full factorial design of experiments. The experimental and ANFIS results were compared, as reported by Nasr (2020). Zhuang (2021) developed an ANFIS-based predictive model to predict real-time wear data of joints of cabin doors using Archard's wear model and compared it with ANFIS. A Bayesian procedure was implemented to predict the wear coefficient. Velumrugan (2021) developed an Al6061/SiC/Graphite composite and analyzed the influence of machining parameters on surface roughness through ANFIS, and a standard error of 1.67% was found.

The dry sliding wear resistance of a hybrid AlMg1SiCu alloy composite reinforced with 10% silicon carbide (SiC) and 3, 6, and 9% self-lubricant molybdenum disulfide cast via melt stir casting (MoS2) was evaluated through Box-Behnken and a pin-on-disc tribometer by Raghupathy (2021). The self-lubricant MoS2 added to the matrix material reduces weight loss and frictional coefficient. The MRR and TW of AIS steel samples were predicted for error % using ANN and ANFIS by Sada (2021), and it was found that ANN is better than ANFIS.

The hardness, tensile strength, and impact resistance of ultrasonically assisted stir-cast Aluminum-alloy-6061-hybrid nanocomposites (AMMHNCs) reinforced with graphene (C) and zirconium dioxide (ZrO2) were evaluated, and their wear behaviour was analysed. It was observed that an increase in reinforcements resulted in improved mechanical properties, whereas percentage elongation decreased. Furthermore, wear resistance was found to improve with additional reinforcements (Masooth 2022).

Sliding wear performance of carbon-reinforced polyamide composite (PA12CF20) components fabricated using fused filament fabrication (FFF) was predicted, trained and optimised using a genetic algorithm-based adaptive neuro-fuzzy inference system (GA-ANFIS) and 30 different FCCCD-based input factor combinations. As a result, improved wear performance was observed (Deepak 2023).

In this study, an adaptive neural fuzzy inference system (ANFIS) was employed to estimate the wear rate of a laser-deposited FGM sample made of SS316L and Co27Cr6Mo alloy materials using a machine learning (ML) approach. The input data was obtained from experiments performed on the same sample using a pin-on-disc tribometer with applied loads of 50, 60, and 70 N, while all other experimental parameters such as test run time (minutes), disc speed (rpm) and track diameter (mm) were kept constant. The predicted wear rate was measured in µm.

2. Materials and Methods

In this research, commercially available gas-atomised spherical powders of SS316L (Delcrome) and Co27Cr6Mo alloy (Stellite-21) were used (KENNAMETAL Inc, USA) to develop FGM samples by laser deposition. SS316L has a particle size of 150 µm / 50 µm, while Co27Cr6Mo alloy has 180 µm / 53 µm. The nominal chemical composition of Co27Cr6Mo (Co-Bal, Ni-2.6, Cr-27.5, Mo-5.4, and C-0.3) and SS316L (Ni-13.0, Cr-18.0, Mo-2.6, Fe-Bal., and Si-1.8) powders in mass% and are obtained from supplier.

The laser DED process is used to deposit FGM samples with 60*10*10 mm^3 size on the steel substrate plate using the L9 Orthogonal Array (OA) of the Taguchi method with selected process parameters of laser power (LP), powder feed rate (PFR), and scan velocity (SV) each at three levels as (LP:800,1000, and 1200 watts), (PFR:6, 9 and 12 g/min) and (SV: 0.4,0.5 and 0.6 m/min). Before sample deposition, the substrate plate is ground with 600, 800, and 1000-grit silicon oxide (SiO_2) emery papers. Acetone is used to decrease the substrate. Sample deposition was carried out in a controlled Argon gas environment with <10 ppm (parts per million) oxygen (O_2) to avoid the oxidising of FGM samples.

Laser-based DED equipment with a 2 kW Yttrium fibre laser, nozzle head, dual coaxial powder feedstocks, software cabinet, and a regulated atmosphere is used to fabricate samples. According to the CAD design, the material deposition (first layer of deposition on the substrate plate) begins with 100 % SS316L. A gradual increment in Co27Cr6Mo alloy content was done until the sample concluded with a top layer of 100 % Co27Cr6Mo alloy. The general schematic diagram of FGM is illustrated in Figure 1. The DED machine employed for specimen fabrication is shown in Figure 2. The physical laser-deposited FGM samples are shown in Figure 3 (a, b, and c). Nine FGM samples were fabricated by varying the process parameters according to the L9 of OA mentioned in Table 2. Later, a small tip of the edge of the sample was removed at one edge using the WEDM process (Make: Electronica, Model: Enova-1S), and the length of the sample after the edge was removed, as shown in Figure 4.

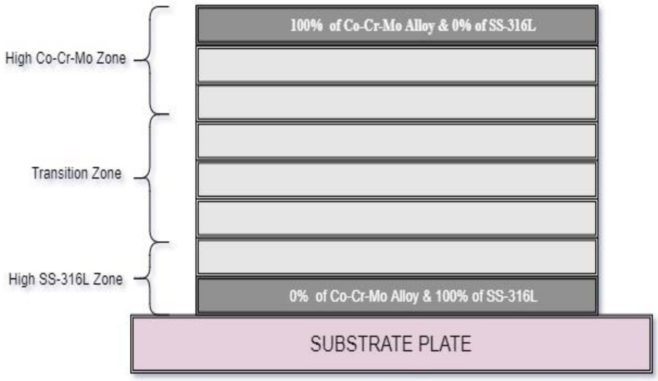

Figure 1 Schematic diagram of FGM.

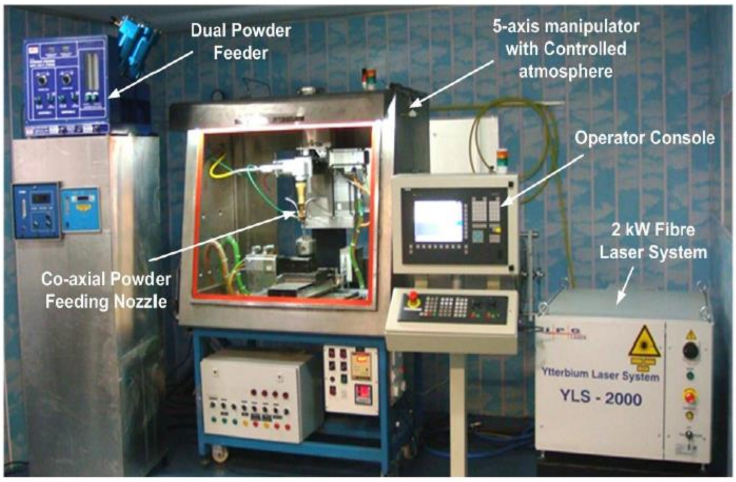

Figure 2 Direct energy deposition apparatus (Courtesy: RRCAT, Indore, MP, India).

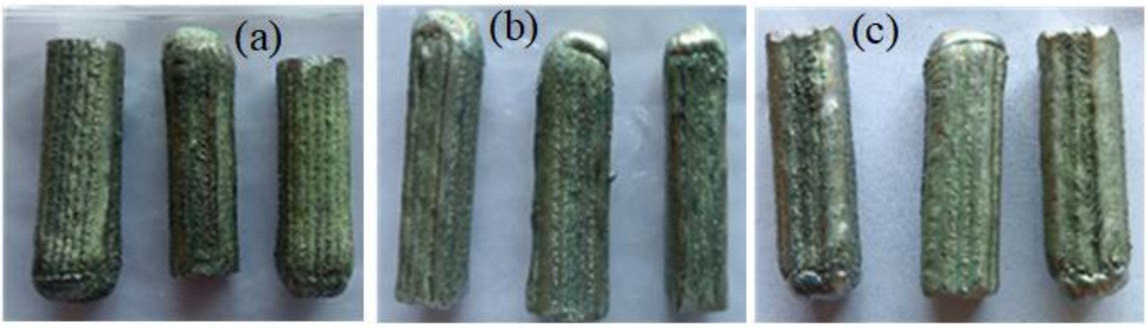

Figure 3 Nine samples (3 sets @ 3 samples each).

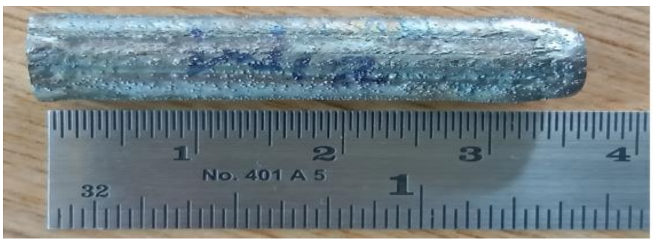

Figure 4 Length of wear test specimen (after one edge was removed on WEDM).

A Tribometer (Make-DUCOM, Bengaluru, India) was employed to conduct the wear test on laser-deposited samples following ASTM G-99 standards by using defined test conditions listed in Table 1; Each sample is weighed in grams (g) before the wear test with electronic weighing equipment (Make-OHAUS, USA) having 10^{-4} accuracies.

Table 1 Test parameters of experimentation on Pin on Disc for the wear test

Pin Material	Pin Length (mm)	Pin Diameter (mm)	Load (N)	Speed of Disc (rpm)	Track Diameter (mm)	Distance Travelled by Pin (Km)	Calculated time to run the test (min.)
FGM Sample	40±2	10±1	50,60,70	500	50	3.5	38.20

3. Adaptive Neuro-Fuzzy Inference System

In 1993, Jang proposed the adaptive neuro-fuzzy inference system (ANFIS). It is one of the soft computing techniques machine learning algorithms use to predict the solution for various complex nonlinear problems. By combining neural networks and fuzzy inference techniques, ANFIS abstracts nonlinearity. It refers to a system's local linear input-output relationship, represented by a set of 'if-then' rules. The first order's Takagi-Sugeno model (TSM) trains adaptive fuzzy logic. The TSM employs a combination of least squares and back-propagation gradient descent algorithms to train a data set. Figure 5 depicts the entire structure of the trained model.

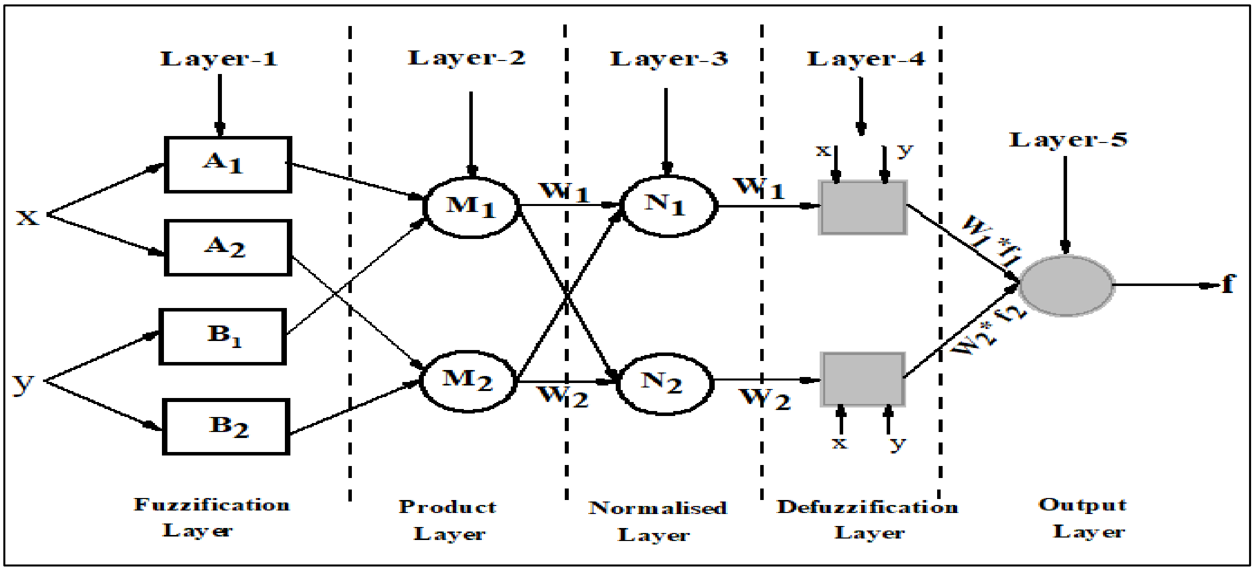

Figure 5 The general architecture of ANFIS [Ragupathy (2021); Sada (2021)].

It has 'fixed' (layer-2,3 and 5) and 'adaptable' (layer-1 and 4) layers from Layer-1 to Layer-5. The x and y are the two inputs, and f is the final output. The description of the individual layer is as follows *Layer-1.* Each node 'i' in this layer is an adaptive node with a node membership function Gaussian, triangular, trapezoidal, etc. (here, a triangular membership function was used). This layer's output O_i^1, is obtained by Eqn-1 and Eqn-2.

$O_i^1 = \mu_{Ai}(x)$, i=1,2…. (1)

and $O_i^1 = \mu_{Bi}(y)$, i=1,2…. (2)

Where O is the final output, which is a linguistic member.

In Layer-2, each node is a fixed node mentioned by M_1 and M_2 and performs a fuzzy 'AND' product function for the incoming data from Layer 1. The output of this layer was described as W_1 & W_2, obtained by the product of M_1 and M_2 with the outcome of the first layer using Eqn-3.

$O_i^2 = \mu_{Ai}(x) \text{ X } \mu_{Bi}(y)$, i=1,2…. (3)

Where W_1 & W_2 have enhanced strengths of two inputs

In layer 3, each node in this layer is a fixed node mentioned by N_1 and N_2. The normalised enhanced strength was calculated from the earlier layer by the ratio of ith rule enhanced strength (W_i) to the sum of ith rule-enhanced strengths ($\sum W_i$), given by Eqn-4 as,

$O_i^3 = \overline{w}_i = \frac{W_i}{\sum W_i}$, i=1,2…. (4)

Further, in Layer-4, each node is an adaptive node, a resultant part of the fuzzy rule function of Eqn-5 and contributing to the overall output.

$O_i^4 = \overline{w}_i * f_i = \overline{w}_i * (p_k x + q_k y + r_k)$, i =1,2…. (5)

where, $f_i = p_k x, q_k y, and\ r_k$ and $also\ p_k, q_k, and\ r_k$ are the linear parameters.

Finally, in Layer- 5, the summation of all normalised outputs is mentioned in a single fixed node in this layer mentioned as f; a defuzzification process is conducted using the Eqn-6,

$$O_i^5 = \sum_{i=1}^{n} \overline{w}_i * f_i = \sum_{i=1}^{n} \overline{w}_i * (p_k x + q_k y + r_k), \quad i = 1,2.... \quad (6)$$

3.1. ANFIS through MATLAB

The flow diagram below depicts the step-by-step procedure for running the ANFIS application via the MATLAB (version 2018b) interface. ANFIS's basic structure begins with input data. It proceeds to input membership functions (MFs), then input MFs to rules, next rules to output characteristics, later output MFs, and finally, single-valued output (Vijay Kumar 2012).

In this work, the FGM samples were loaded in three steps (50, 60, and 70 N) at a constant disc speed (500 rpm) and track diameter (50 mm). The obtained experimental data results (average wear rate in µm / N / m, applied load in newtons, and time in minutes) are utilised for training and testing the network. The step-by-step procedure is shown in Figure 6. The inputs are applied load and time, while the wear rate is the output. Finally, the experimental and ANFIS results are compared.

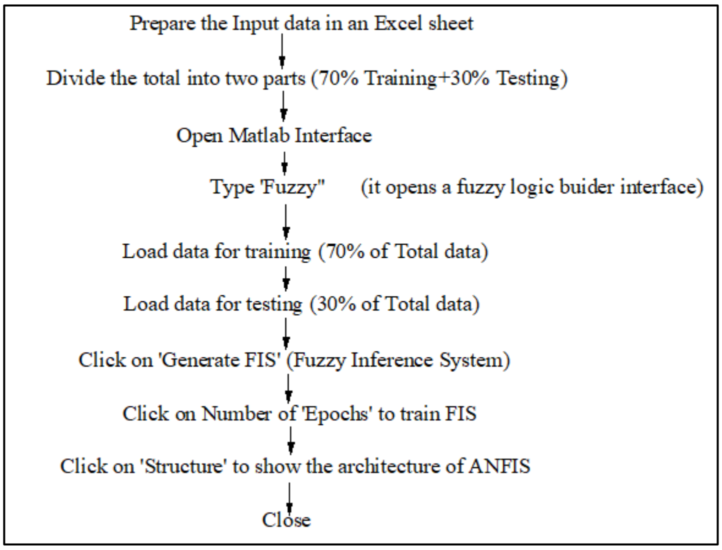

Figure 6 Step-by-Step procedure of ANFIS in MATLAB interface.

4. Results and discussion

A trained machine learning algorithm (ANFIS) was used in this study to estimate the wear rate (in µm / N / m) of laser-deposited functionally graded material samples. With given experimental inputs and outputs, the ANFIS can predict the desired outcome. Figure 7 depicts the fuzzy logic function object used to determine the number of inputs (here, two inputs were taken). Figure 8 explores the training and testing data in a fuzzy interface, where 'bubbles' represent 70 % of training data and 'dots' represent 30 % of testing data.

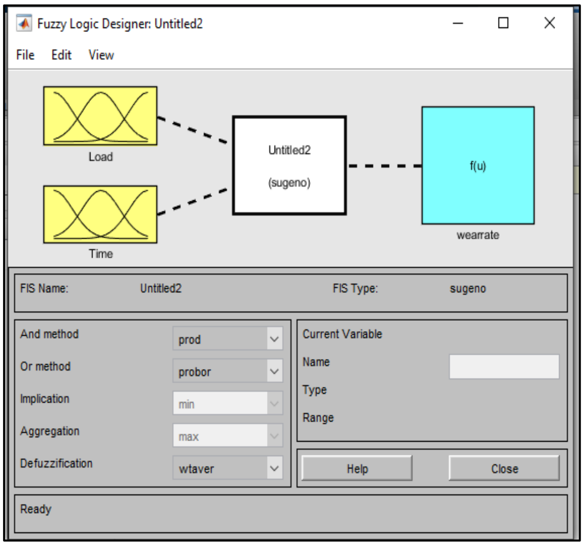

Figure 7 Fuzzy Logic Designer.

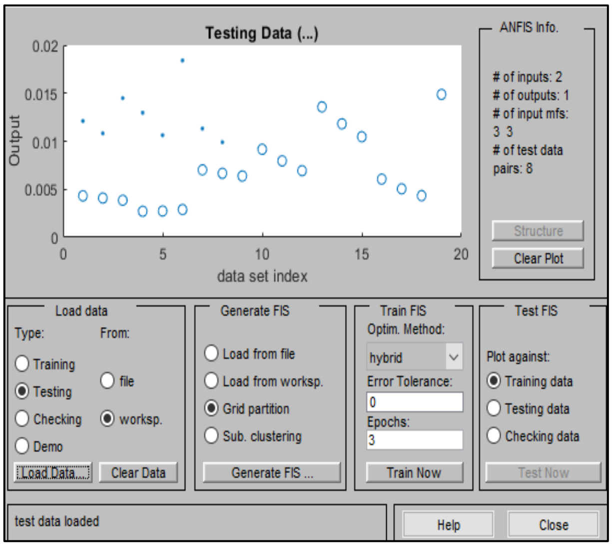

Figure 8 Training and Testing data loaded.

A Fuzzy Interface System (FIS) was created using the given inputs. A hybrid training FIS combining back-propagation and the least mean square (LMS) in ANFIS was used to train the algorithm. The multiple numbers of epochs must be performed to calculate the training error. The training error was reduced from 3.2749E10^{-3} to 3.2741E10^{-3} after 50 epochs, as shown in Figure 9. After 100 epochs, the error was reduced to 3.2661E10^{-3}, as shown in Figure 10. The MFs generated for both the inputs are 3 and 3, 3 X 3 = 9 rules were developed to forecast the output wear rate.

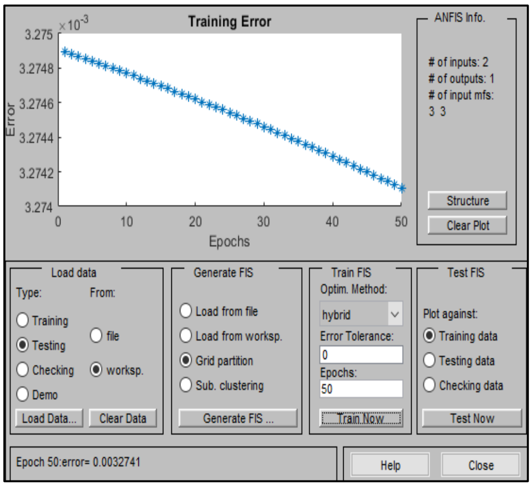

Figure 9 Training Error at 50 Epochs.

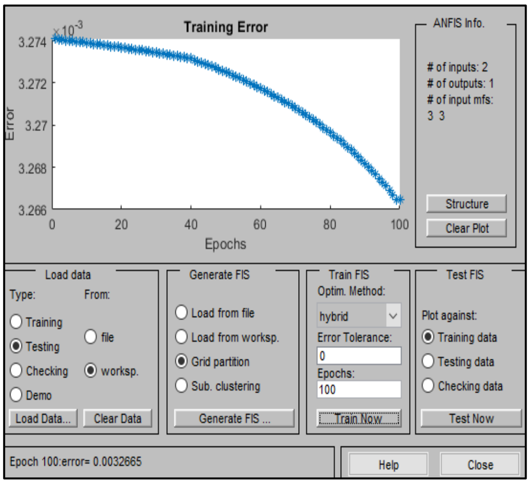

Figure 10 Training Error at 100 Epochs.

Figure 11 shows the structure of the current investigation as developed in the ANFIS model. Layer-2 displays eighteen input membership functions (inputmfs) built at two inputs of layer-1, represented by 'white dots'. The third layer was the normalised layer, which consists of 81 (9X9) rules represented by 'blue dots'. Layer-4 demonstrated an individual output membership function, and Layer-5 combines these output membership functions (outputmfs) to form the final output.

The rule viewer obtained at input parameters of load=50 N and time=1151 minutes is shown in Figure 12, and the output of wear rate is -0.00189 X 10 3 µm / N / m. Likewise, the wear rate was 0.0128 X 10^{-3} at an input load of 60 N and a time of 1151 minutes. Similarly, Figure 13 and Figure 14 show the input load of 60 and 70 N and the wear results. The results show that increased applied load causes an increase in wear rate.

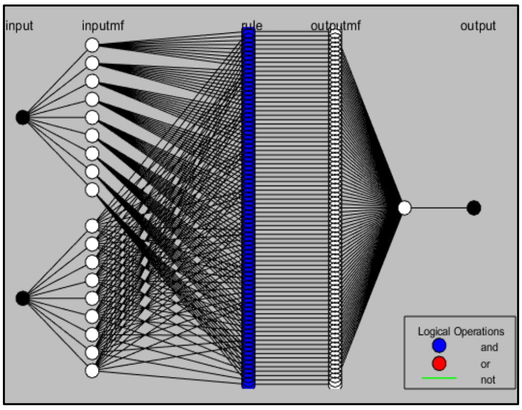

Figure 11 The structure developed in ANFIS.

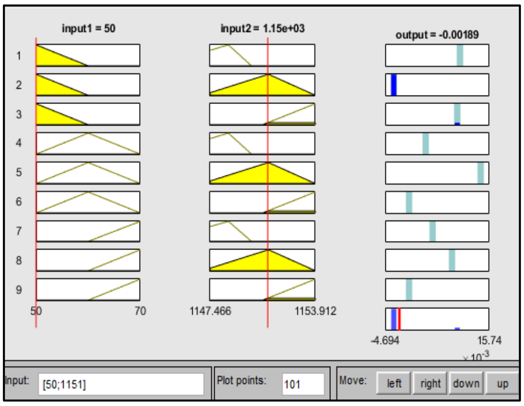

Figure 12 Rule viewer at 50 N load.

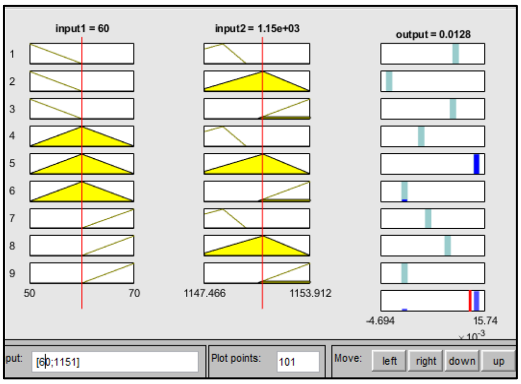

Figure 13 Rule viewer at 60 N load.

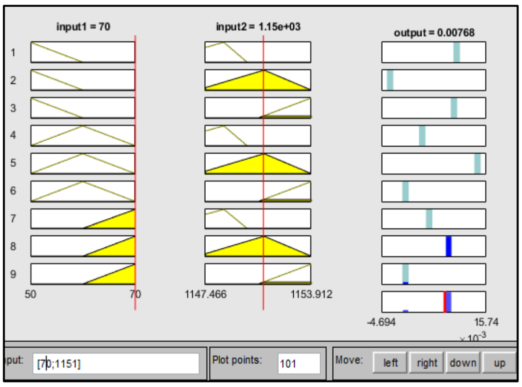

Figure 14 Rule viewer at 70 N load.

Figure 15 was the graph obtained from ANFIS. It explains the influence on output (wear rate in µm / N / m) when only one Input-1 (load in newtons) was given. At the first input (load=50 N) was applied, the wear rate was extremely low, but when the load was increased from 50 to 60 N, a rapid linear increment in wear rate was observed. Later, from 60 to 70 N of load application, it was seen that the wear rate slowly and linearly decreased. Figure 16 shows the influence of the second input (time in minutes) on output (wear rate in µm / N / m) in ANFIS. The wear rate rapidly increased at the initial stage (1147 to 1148 minutes) and was constant (1150 to 1151 minutes) for a brief period. Later, the wear rate was reduced rapidly when the time led to a maximum of 1154 minutes.

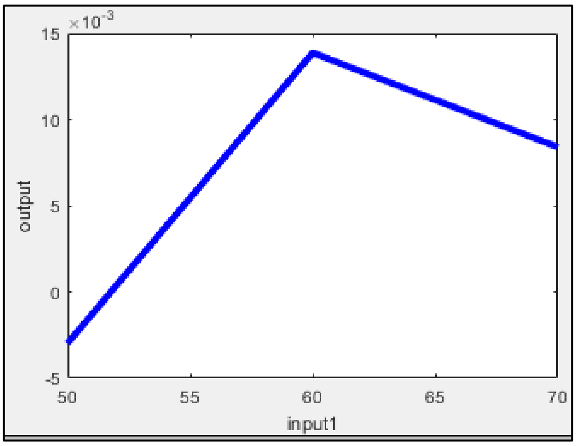

Figure 15 Graph with the load as input.

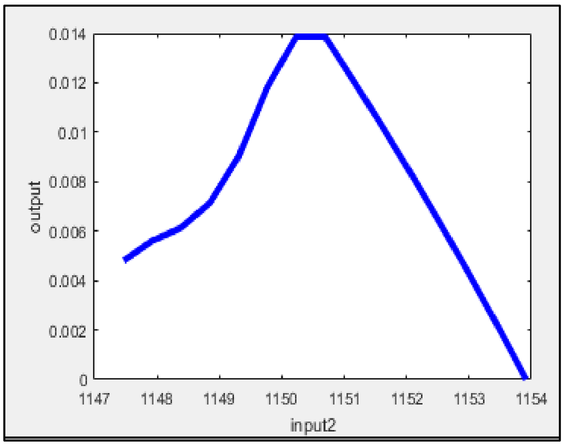

Figure 16 Graph with time as input.

Figure 17 depicts the surface generated in ANFIS when the wear rate is predicted using two inputs (load and time) and their impact on output (wear rate). According to the graph, a gradual increase in output was observed when input -1 (load in newtons) was given from 50 to 60 N. A regular decrease in output from 60 to 65 N is later stable from 65 to 70 N. When input-2 (time in minutes) was increased, the wear rate also increased. From the results of the ANFIS analysis, it is concluded that the time to conduct the wear test influences the wear rate of the sample more than the load applied.

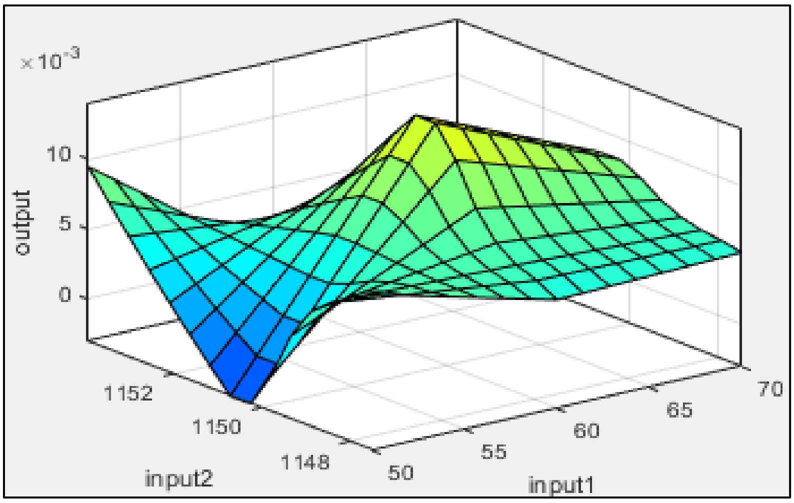

Figure 17 Surface generated in ANFIS with two inputs.

5. Conclusions

The mechanical properties of laser-deposited FGM samples of SS316L and Co27Cr6Mo alloy were evaluated using a pin-on-disc setup under various loads, and the experimental data was used to train and validate an ANFIS model. The results demonstrate that the ANFIS model accurately predicts wear test values, indicating its potential for future use in predicting wear behavior. The ANFIS model is preferred in this case due to its ability to overcome the major limitation of ANNs (black box problem), using a hybrid training function (ANN and fuzzy logic) following 'IF-THEN' rules. The study shows that at a load of 50 N, the wear rate was minimal, but it increased linearly when the load was increased to 60 N. Between 60 and 70 N, the wear rate gradually decreased. The ANFIS model's second input (time in minutes) has a significant impact on the wear rate output (µm/N/m), with wear increasing substantially between 1147 and 1148 minutes before stabilizing between 1150 and 1151 minutes. The wear rate then quickly dropped until 1154 minutes.

Ethical considerations

Not applicable.

Conflict of Interest

The authors declare that they have no conflict of interest.

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