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Machining Parameter Optimization of Hybrid Metal Matrix Composites using Artificial Intelligence

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Abstract:
The objective of this work is to study the various artificial intelligence methods used for optimizing machining parameters while machining of hybrid metal matrix composites, by conventional and unconventional methods. A hybrid composite is formed when two or more reinforcements are added to the matrix. Hybrid Composites are manufactured by stir casting method. Machining of composites is done to create holes, slots and other features that are not possible to obtain during manufacturing of the part. Various types of machining operations are done in hybrid composites with lathe, drilling, milling and EDM machine to get the desired surface roughness, tolerance. Cutting speed, feed rate and depth of cut are the machining parameters optimized while machining in lathe with desired target like surface roughness, MRR, cutting force and tool wear. Drilling of fiber-reinforced plastics (FRP's) composites facilitates assembly of several components by means of mechanical fastening. Spindle speed, feed rate, drill type are optimized for performance characteristics thrust force, surface roughness, and tool wear in drilling operation. Spindle speed, feed rate, depth of cut is optimized for desired cutting force and surface roughness in milling operation. The influence of process parameters such as pulse on time, pulse off time, spark gap voltage, peak current, wire tension and wire feed rate on response variables such as cutting speed, surface roughness and spark gap are studied in EDM of hybrid composites. ANOVA, RSM, GRA, Taguchi method are used for optimization of various machining parameters. The AI techniques used for prediction include artificial neural network (ANNs), fuzzy logic (FL), adaptive neuro-fuzzy systems (ANFIS), decision tree, genetic algorithm (GA) and genetic programming. Fuzzy rules relate the relationship between input and output variables. Expert knowledge can be built into the system through the rule base. Fuzzy models are used for predicting the thrust force and torque for drilling hybrid composite. In adaptive neuro-fuzzy systems advantages of FL and ANNs are combined for adjusting the membership functions, rule base and related parameters for training the data set. It can continuously improve the initially obtained rough model based on the daily operating data. AI techniques are used for predicting the automatic selection of inputs and predicting surface roughness, other response variables.

Keywords: *Artificial Intelligence, Hybrid Metal Matrix Composites, Machining Parameters, Optimization.*

I. INTRODUCTION

Metal matrix composites are commonly used in automobiles and aerospace applications. Multi reinforcement composites are better replacement for single reinforcement composites. When two or more materials are added with the base material, hybrid composite is formed. Aluminium is the commonly used base material.Al6061 matrix material is suitable

January - February 2020
ISSN: 0193 - 4120 Page No. 4946 - 4949

for machining and welding applications. Commonly used single reinforcement is SiC, due to its application in brake discs, bicycle frames, aerospace and automotive industry. Al/SiC/B_4C, Al/SiC/Gr, are hybrid composites. Al_2O_3, B_4C, Gr, Mica are used as second reinforcement for hybrid composites. Al/SiC/Gr is an important hybrid composite, because a layered SiC/Gr is used in gas turbine combustor can. SiC is harder than Tungsten Carbide (WC) and Graphite particles are solid lubricant, provide high resistance to wear.

Manufacturing of these hybrid composites is done by stir casting, squeeze casting and other methods. Surface roughness determines the quality of a machined part. Cutting Speed, feed rate and depth of cut are the commonly used machining parameters for optimizing surface roughness. Tungsten Carbide (WC) and Poly crystalline Diamond (PCD) are some of the tools used for machining. Conducting full factorial experiment will be time consuming, as well as increases the cost, Taguchi orthogonal array is an alternate to complete factorial designs. Commonly used device for surface roughness measurement is Mitutoyo surf test.

ANOVA is used to analyze the difference among group means in a sample. Taguchi method is used for parameter design for conducting the experiments. Grey Relational Analysis is used for multi objective optimization problems. Response Surface Methodology are used to study the relationship between input and response, when the input factors are quantitative and few.

In this work an attempt has been made to study the various types of Artificial Intelligence techniques used by researchers to optimize the machining parameters while working with hybrid composites.

II. ARTIFICIAL INTELLIGENCE METHODS

Fuzzy Logic Controller

The fuzzy sets used to represent input and output variables are known as membership functions. The range of values considered for the variables are called universe of discourse or dimension [13]. The membership functions can have different shapes like triangular, trapezoidal, Gaussian, etc. [19]. Fuzzy model can be constructed with the help of relatively few measurements and expert knowledge can be built into the system through rule base. Prediction of output values are done by developing a model in Simulink [5]. Mamdani fuzzy model shown in fig.1 is used for modeling variable output. The thrust force and torque developed during drilling of hybrid fiber composites are predicted using fuzzy rule based artificial intelligence model [10].

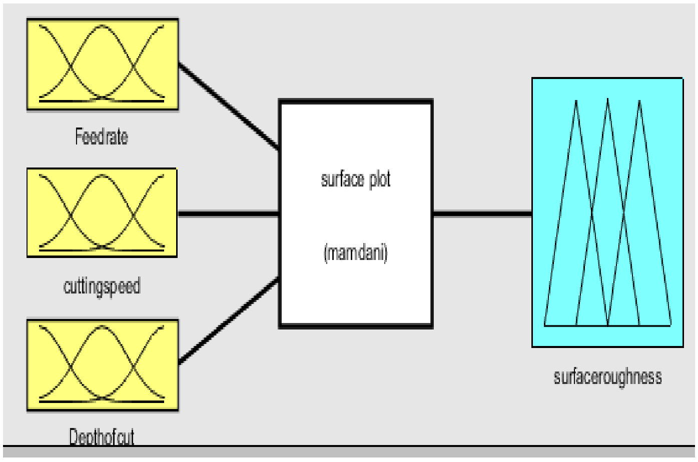

Fig.1. Mamdani fuzzy model

A system for which the relevant information is completely known is a white system; the system for which the relevant information is completely unknown is a black system. Any system between these limits is a grey system having poor and limited information [18]. Grey fuzzy logic approach offers improved grey-fuzzy reasoning grade when compared with grey relational technique.

The criteria considered for best performance are lower surface roughness and flank wear, and higher material removal rate. In grey-fuzzy analysis, multi-objective optimization problem is converted into a single objective optimization by grey relational analysis technique and uncertainties in grey output are reduced by fuzzy logic [20]. The steps involved in fuzzy logic approach are fuzzification of input data, rule inference and defuzzification process. A larger value of grey

January - February 2020
ISSN: 0193 - 4120 Page No. 4946 - 4949

relational coefficient indicates better performance characteristic and will be equal to one. Surface roughness reduces with an increase in cutting speeds. Increase in feed rate increases surface roughness, due to increase in tangential force and heat generation [1].

Artificial Neural Network

One of the best known biological neural networks is human brain**.** Backpropagation algorithm provides several advantages when compared with other networks and has been proven successful in different applications. ANN is used to learn the collected data. ANN based predictive model outperforms other techniques due to robustness and high learning accuracy [6]. The general architecture of 3 layered multilayer perceptron (MLP) is shown in fig.2

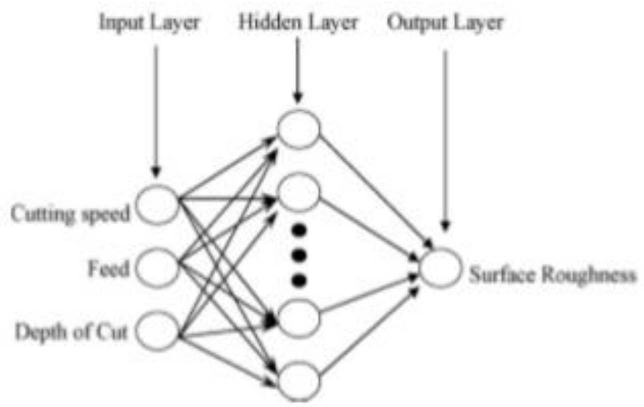

Fig.2. Configuration of neural network

Fuzzy Adaptive network (FAN) has learning ability of neural network and linguistic representation of complex, vague phenomenon. FAN continuously improves the initially obtained rough model with the help of daily operating data. FANs are five-layered representation of corresponding fuzzy inference rules [14]. FAN structure for surface roughness is shown in fig.3

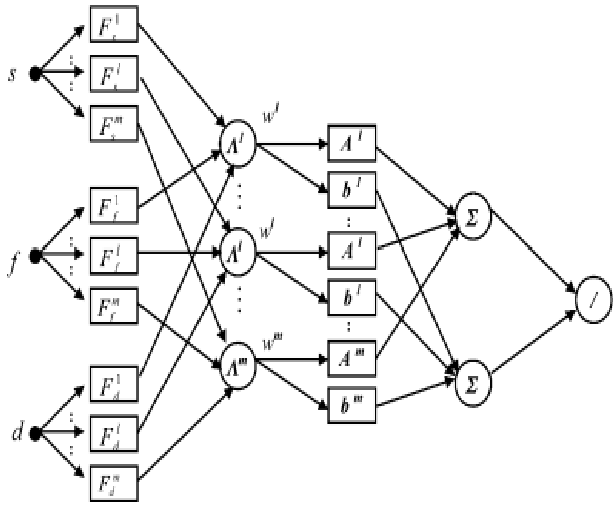

Fig.3. FAN structure for surface roughness

A feed-forward ANN trained with Levenberg-Marquardt algorithm is used for predicting cutting force in turning. The ANN consists of 4 input neurons (depth of cut, cutting speed, feed rate and cutting edge angle) and one output neuron for resultant cutting force [15].

Decision tree

Decision tree is known as white box model as it provides clear view of what is happening inside the model, whereas ANN and ANFIS are known as black box model, because outcome of these predictive models are comprehensible but not for understanding the internal operations. Classification And Regression Trees (CART algorithm) is used for development of predictive model, generation of regression and classification model [16].

Genetic Algorithms

Genetic algorithms and programming are used to generate high quality solutions to optimization problems. A genetic algorithm performs multiple directional and robust searches in complex spaces by maintaining a population of potential solutions. The steps involved in GA process are parameter setting, initialization process, and evaluation [17]. Training time is normally higher with GA, but GA helps in automatic selection of important inputs and number of Membership functions for predicting surface roughness. GA-ANFIS and ANN results are better than genetic algorithm programming [12].

III. CONCLUSION

Inclusion of graphite as an additional reinforcement reduces the cutting force in Al/SiC$_p$ composite. Grey-fuzzy analysis is used for converting multi-objective optimization problem into single-objective optimization problem. Grey fuzzy logic approach offers improved grey-fuzzy reasoning grade when compared with grey relational technique. FAN network is designed to model vague and not well-defined systems, suitable for modeling large amount of data. ANN outperforms other techniques due to robustness and high learning accuracy. Artificial Intelligence Methods have prediction potentials for non-experimental patterns also, consumes lesser time, and gives higher accuracy. AI can be used for eliminating unnecessary, time consuming measurements. AI methods can be successfully adopted for prediction of surface roughness, cutting force, thrust force, torque and tool wears.

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