Analysis of magnetic field assisted finishing (MFAF) process parameters for finishing brass workpiece using Soft-Computing Technique

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Abstract

Magnetic Field Assisted Finishing (MFAF) process is a precise nanofinishing process. Magnetorheological (MR) fluid is the main element in MFAF process. In these process two types of motion, rotational and reciprocation is provided to the MR fluid to get uniform smooth finished surface. Brass is used as the workpiece. The input process parameters are extrusion pressure, number of finishing cycles, rotational speed of the magnet, and volume ratio of carbonyl iron particle (CIP) and silicon carbide (SiC) in the medium. The output process parameter is percentage change in surface roughness. In this study the relationship between the input and output process parameters of MFAF is established using Backpropagation neural network technique. Also a close comparison has been made between the regression analysis model and neural network model of the process parameters. From the simulation results, it has been found that the neural network model yields a more accurate result than the regression analysis method. Further an optimization study has been carried out to optimize the input process parameters to get maximum output. Genetic algorithm (GA) technique is used as the optimization technique consideringregression equation model as the objective function. The optimized process parameters agree well with the experimental results.

Keywords*: Nanofinishing process, Neural Network, Genetic Algorithm.*

1Introduction

The determination of input output process parameter relationship is a key factor for controlling a finishing process. Neural network and genetic algorithms are two very efficient soft computing tools. Now a day's soft computing techniques are widely used in manufacturing processes to model the relationship between input and output parameters. Also, some statistical technique like regression analysis is used for the same purpose. Chryssolouris and Gulliot (1990) conducted multiple regression analysis and neural network methods to establish input-output relationships for machining processes and after comparing the techniques it was found that the neural network method was more accurate rather than the regression analysis.

Magnetic Field Assisted Finishing (MFAF) process is a precision finishing process where MR fluid is used as the finishing tool.The viscosity of the MR fluid changes with the applied magnetic field. MR fluid becomes viscous, changes into non-Newtonian fluid when there is a magnetic field and it became Newtonian fluid when there is no magnetic field. MR fluids are composed of abrasive particles and CIPs in carrier liquids. In the presence of magnetic field, the magnetic CIPs organize themselves in a chain or ribbon like structure along the magnetic lines of force embedding abrasive particles in between and within them. This structure of the MR fluid provides the required finishing force.

Das et al. (2012) developed a process whererotation and reciprocating motions are provided to the polishing medium by rotating magnetic field and hydraulic unit. A uniform smooth mirror like finished surface is achieved by simultaneously controlling these two motions. MR fluid is extruded through the work piece fixture under high pressure. A hydraulic unit drives two opposing piston in the MR media cylinders. So the MR fluid inside the cylinder reciprocates. At the same time, a rotational motion is imparted onto the permanent magnets surrounding the work piece fixture to rotate the MR fluid. A high velocity is obtained and a smooth mirror finished surface is achieved by combining these two motions. Figures 1 & 2 show the schematic diagram of the two motions imparted on the MR fluid.

In this study effect of various process parameters (extrusion pressure, number of finishing cycles, rotational speed of the magnet, and volume ratio of CIP/SiC in the medium) on percent improvement in surface roughness (Ra) for brass work piece has been carried out. Back propagation neural network model has been used to establish the relationship between the input and output process parameters. Also GA is used to optimize the input process parameters value to maximize the output process parameter value.

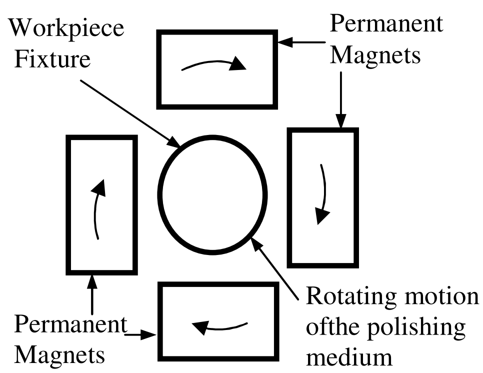

Figure 1 Schematic diagram of the rotating motion imparted on the MR fluid

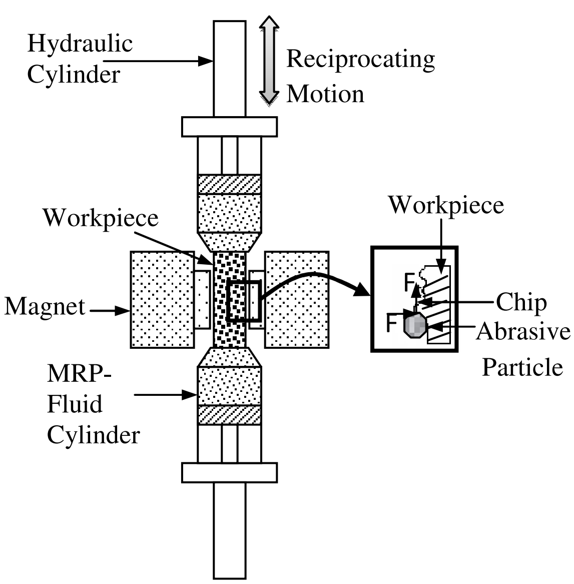

Figure 2 Schematic diagram of the reciprocating motion in MFAF set up

2 MFAF experimentation and analysis

The experiments for finishing of brass workpiece was carried out by Das et al. (2012). They designed the workpiece fixture to guide the MR fluid. To obtain the required magnetic field, outside the workpiece fixture magnet fixture (with four permanent magnets) is used. The rotational speed of magnet fixture is controlled by the motor. A variable frequency drive is used to control the rotational speed of the motor. The MRP fluid is prepared by homogeneously mixing CIP of CS grade and SiC abrasive particles with the base medium of paraffin oil (48 vol.%) and AP3 grease (12 vol.%) . Grease is used to improve the settling ability. Statistical design of experiment (DOE) techniques are used to analysethe significance of process parameters. FromDOE it has been found that most significant parameter is rotational speed of the magnet (S). Other parameters in decreasing order of significance are number of finishing cycles (N), hydraulic extrusion pressure (P) and volume ratio of CIP/SiC (R). For performing the experiments different sets of values of process parameters have been chosen. The range of input process parameters are given in Table 1 (Das et al., 2011).

Table 1: Range of process parameters in different levels (Das et al., 2012)

Sl.No	Level	P(bar)	N	S (rpm)	R
1	-2	32.5	400	20	0.34
2	-1	35	500	40	1
3	0	37.5	600	60	2
4	1	40	700	80	3
5	2	42.5	800	100	4

The relationship between the input and output process parameters is established using regression analysis. A quadratic model is considered. The plan of experiments and responses have been taken from the work reported by Das et al. (2012). The equation obtained from Regression analysis is as follows

$$\begin{aligned}\%\Delta Ra &= -886.28+38.57*P+0.41*N+1.23*S+28.49*R \\ &-4.02*10^{-3}*P*N+3.94*10^{-4}*N*S-4.64*10^{-2}*S*R \\ &-7.491*10^{-2}*R*P-0.003*R*N-0.26*10^{-2}*R*S \\ &-0.462*P^2-2.073*10^{-4}N^2-9.258*10^{-3}*S^2-3.828*R^2\end{aligned} \tag{1}$$

In this report neural network is used to determine the effect of individual process parameters on the response parameter. A three layered neural network model comprising of an input layer, output layer and a hidden layer has been modelled in C-programming language for the prediction of the output parameter i.e. percentage change in surface roughness associated with the process. There are multiple experimental points whose values have been found out to be different for the same set of input parameters, for such sets of data average of the outputs have been calculated for the output parameters and is used for the analysis.

3 Analysis of finishing process using neural network

Artificial neural network (ANN) is a soft computing tool to process information. It is inspired by the information processing capability of biological nervous system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. It is applicable in case of ANN also. ANN performance depends upon topology (architecture of neural network), connecting weights (constant value between two neurons from different layers), bias values and others (Pratihar,2009).

Most commonly used method for the training of neural network is Backpropagationalgorithm which is actually backward propagation of errors. It is a supervised learning method (Rojas, 1996).This technique internally adjusts the weight values to approximate the nonlinear relationship between the input and output.

The Backpropagation neural network works in two steps: Feedforward and Backpropagation. In the first step i.e. Feedforward step inputs are provided to the input layer and the effect is passing through the hidden layer and it produces an output through the output layer. The actual output of the network then compared with the expected output and the error is computed for every output neuron. The output error signals are then fed back to the hidden neurons. This process is then repeated until each neuron in the network has received an error signal that describes its relative contribution to the overall error.

In the second step i.e. Backpropagation of the errors of each neuron is used to update the connection weights. The Backpropagation algorithm works based on steepest gradient descent method (Haykin, 1984).

3.1 Simulation procedure

One three layered feed forwarded neural network model with four inputs, one output and ten hidden nodes is employed for the input–output process parameter mapping and the neural network is trained for 30 samples of the data spanning over the ranges set up by Table 1 earlier. The inputs to the neural network are hydraulic extrusion pressure (P), number of finishing cycles (N), rotational speed of the magnet (S), and volume ratio of CIP/SiC (R) and the responses are recorded in terms of the % Δ Ra. A random no. generator is used to initialize the synaptic weights and thresholds associated with various neurons. In order to decide the structure of the neural network the rate of convergence is checked by changing the associated learning rate and momentum rate.

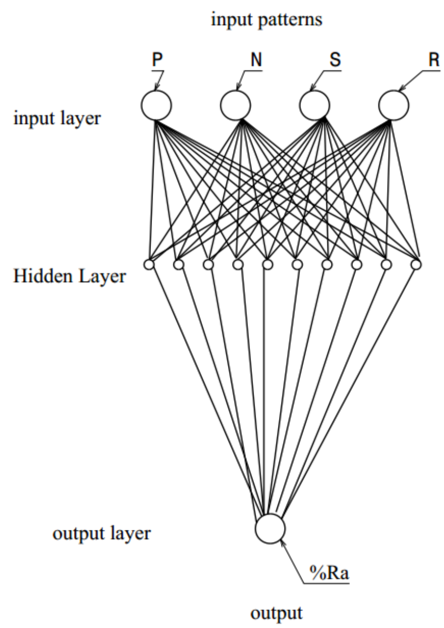

Figure 3 Schematic diagram of structure of neural network

The data for training purpose is taken from the experiments already carried out by Das et al. (2012). During the training process the data in the training set is presented to the network in an epoch-by-epoch basis i.e. complete presentation of the entire training set to the network. For a given training set, training of the neural network may be performed either in the incremental mode or in the batch mode of training. In the incremental mode of training the weight updating of the associated neuron is performed after passing each set of training data from the epoch while in the batch mode of training the weight updating is performed after the presentation of all training samples that constitute an epoch. When compared incremental mode is found less local storage requirementfor each synaptic connection and also helps the network from being trapped in the local minima. However, the batch mode is known to provide a more accurate estimate of the gradient vector.

In the present work, another method known as the *active learning* is used. During the training process, initially all patterns in the training set is presented to the network and the corresponding error parameter (sum of squared errors over the neurons in the output layer) is found for each of them. Then the pattern with the maximum error is found and this is used for updating the synaptic weights. Once the weights are updated, all the training patterns are again fed to the network and the pattern with the maximum error is then found. This process is continued till the maximum error in the training set becomes less than the allowable error specified by the user. This method has the advantage of avoiding a large number of computations, as only the pattern with the maximum error is used for changing the weights. This method also avoids the problem known as thrashing (when weights are changed using a particular pattern from the training data, the error for some other pattern may change to a higher value than the allowable value.

4 Optimization of the finishing conditions

To optimize the process parameters GA is used. GA is based on natural genetics and natural selection. Darwin's survival of the fittest principal is implemented on this algorithm. Here fitness function is first derived from the objective function and then it is used in genetic operations. Reproduction, crossover, mutation are main three genetic operator. These genetic operators are used to operate the populations of points, evaluated from the objective function. Using these operators a new population is created. The process is repeated until it meets the termination criteria (Deb, 2011). The algorithm of genetic algorithm is as follows (Pratihar,2009):

Step 1: Random population of initial solutions are generated.
Step 2: The fitness function of the objective function for each solution is calculated.
Step 3: The population of solutions is then modified using the different genetic operators. First, reproduction operator is used to generate a mating pool consists of good solutions. Then from the existed solutions new solutions are created using crossover operator. Next, mutation operator is used. If the solutions are trapped in a local minimum mutation operator can help the solutions to jump to the global minimum.
Step 4: Step 2 and 3 are repeated until the algorithm meets its termination criteria.

In this study single objective optimization is carried out considering $\%\Delta$Ra of brass workpiece (Eq. (1)) as the objective functions in the MATLAB Optimization Toolbox. Optimization Toolbox provides widely used algorithms for standard and large-scale optimization. These algorithms solve constrained and unconstrained continuous and discrete problems. The toolbox includes functions for linear programming, quadratic programming, binary integer programming, nonlinear optimization, nonlinear least squares, systems of nonlinear equations, and multi-objective optimization.

A real coded GA has been used to obtain the optimum $\%\Delta$Ra. Stochastic uniform selection,scattered crossover and constraint dependent mutation have been used as the selection(reproduction), crossover, and mutation operators respectively. Maximization of $\%\Delta$ Ra was carried out using the input output relationship obtained from the regression analysis as the objective function. The variable bounds are taken same as the range of variables in Table 1. The population size of 100 is considered for the GA technique.

5 Results and discussion

Experiments have already been conducted to study the effects of variable process parameters on the $\%\Delta$Ra (Das et al., 2012).The experimental results have been compared with those obtained from the theoretical model. Though for some of the parameters the response obtained from the regression analysis and neural network model show some deviation but the nature of curve obtained from the two are almost same for wide range of operating conditions.

5.1 Characterization of the experiments

Using the experimental procedure described $\%\Delta$ Ra has been computed for various machining conditions and the effect of various process parameters have been computed as follows

5.1.1 *Effect of hydraulic extrusion pressure*

Figure 4 show that percentage change in surface roughness of brass increasewith increase in hydraulic extrusion pressure. Shear force helps in removing surface undulations. Shear force increasesdue to high pressure thus improving the surface finish.

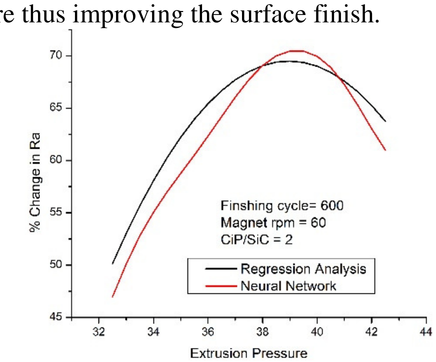

Figure 4 Effect of extrusion pressure on the % Ra of brass

But as the pressure reaches a certain value the shear force attain saturation. So, the % change in Ra decreases after a certain value of hydraulic extrusion pressure. The experimental result validates the theoretical result.

5.1.2 *Effect of number of finishing cycles*

Figure 5 shows that % change in Ra increases with increasing number of cycles. But withincreasing number of cycles, surface finish achieved a saturation value. At first with more number of cycles % change in Ra increases.After some cycles the height of the peaks gets reduced and peak area increases which is hard to remove. So after certain period percentage change in Ra reached a saturation point. The trend of both graph is similar and both supports the experimental results.

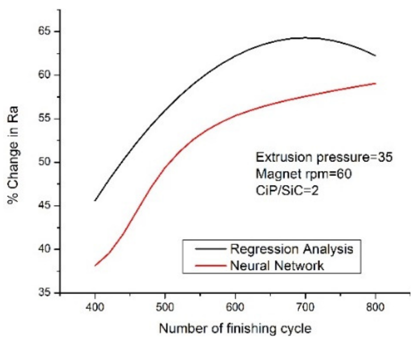

Figure 5 Effect of the number of finishing cycles on % Δ Ra of brass

5.1.3 Effect of Rotational speed of the magnet

As shown in Fig. 6, increasing the rotational speed of the magnet also increases the percentage change in surface roughness because with higher rotational speed the abrasive speed also increases. So the material removal rate increases. Hence the percentage change in surface roughness also increases. But after a certain period with increasing rotational speed % change in Ra saturates.

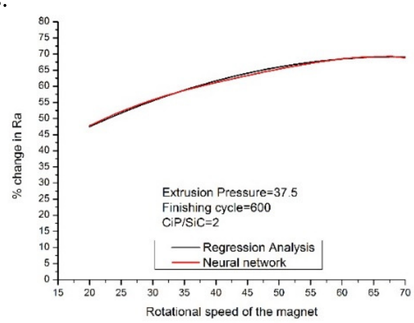

Figure 1 Effect of rotational speed of magnet (rpm) on % change in Ra of brass

The main reason behind this with increasing rotational speed the bonding strength between CIP particles and abrasives get loosen due to centrifugal force (Jha and Jain, 2004). So the abrasives lost their ability to abrade the workpiece. As a result % change in Ra saturates. Both graphs shows same trend and also support the experimental data.

5.1.4 Effect of volume ratio

As shown in Fig. 7 with increase involume ratio of CIP/Abrasive the % change in Ra also increases. With increasing volume ratio the no. of CIP particles also increases so the force acting on the abrasive particles also increases. As a result material removal increases which in turnincreasesthe % change in Ra. But after some certain value with increasing volume ratio % change in Ra decreases due to high concentration of CIP than abrasive particle. So the decrease in abrasive particle reduce the material removal rate. Here the trend of both graph is similar. The experimental results also same as the obtained results.

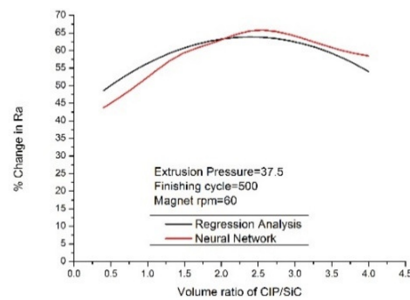

Figure 7 Effect of the volume ratio on % change in Ra of brass

5.2 Optimization of the process parameters

Single objective optimization on %change in Ra has been carried out separately using the eqn.1 obtained from regression analysis. Because of the non-linear nature of the models and the existence of upper and lower limits on parameter values GA based optimization has been preferred. The optimization problem is formulated as

Maximize: *% Change in Ra*

Where *% change in Ra* is given by eqn. (1).

Hydraulic Extrusion Pressure (P)∈[32.5 42.5] bar
Number of Finishing cycle (N)∈[400 800] cycles
Rotational speed of the magnet (S)∈[20 100] rpm
Volume ratio of CIP/SiC (R)∈[0.34 4]

Table 2 Optimized values of input parameter and output parameter obtained through MATLAB genetic algorithm toolbox

Input parameters				Output
P (bar)	N	S (rpm)	R	% Δ Ra
38.7	652.3	68.4	2.2	71.3

6Conclusions

In MFAF process input-output relationship was established implementing the Backpropagation neural network model and regression analysis. Obtained results from these two models were compared. It has been found that the neural network model and regression analysis model both showed same behaviour as the experimental model. The neural network model was more precise than the regression analysis model.

Also Genetic algorithm is used to optimize the process parameters. After optimizing the process parameters it was found that in case of brass the percentage change in surface roughness is maximum (nearly 72 nm) when the approximate value of hydraulic extrusion pressure, number of finishing cycles, rotational speed of the magnet and volume ratio of CIP/SiC is 39 bar, 673, 68 rpm, and 2 respectively. It is nearly same as the experimental result (Das et al., 2012).So we can use genetic algorithm for process optimization.

For future work instead of Backpropagation algorithm radial basis function neural network can also be used. Genetic algorithm can be used to tune neural network model, which will help the neural network model to predict more accurate results.

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