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Research Article

Artificial Neural Network Modeling of Surface Roughness in Magnetic Abrasive Finishing Process

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Abstract: Magnetic Abrasive Finishing (MAF) is an advanced finishing process in which the cutting force is controlled by magnetic field and it provides a high level of surface finish and close tolerances for wide range of industrial application. In this study the parameter that affects surface roughness in MAF process on a brass shaft of CuZn37 have been examined experimentally. These parameters are: intensity of the magnetic field, work-piece velocity and finishing time. It has been shown that the intensity of magnetic field has the most effect on finishing process, a higher intensity in magnetic field, results in a higher change in surface roughness, increasing finishing time results in decreased surface roughness and a lower work-piece velocity leads to a lower surface roughness. Finally Artificial Neural Network (ANN) prediction of surface roughness are carried out and compared with experiment. It was found that the coefficient of multiple determinations (R2-value) between the experimental and ANN predicted data is equal to about 0.999, therefore, indicating the possibility of ANN as a strong tool in simulating and prediction of surface roughness in MAF process.

Keywords: Artificial neural network, brass finishing, magnetic abrasive, surface roughness

INTRODUCTION

Magnetic abrasive finishing: Finishing is final operation involved in the manufacturing of components and is most labor intensive, time consuming and least controllable. The need of better finishing of complicated shapes made of advanced materials and high accuracy are the main factors responsible for using advanced abrasive fine finishing processes (Jain, 2002). MAF is an advanced finishing process in which the cutting force is primarily controlled by the magnetic field. It minimizes the possibility of microcracks on the surface of the workpiece, particularly in hard brittle material, due to low forces acting on abrasive particles (Jain, 2002). This process is able to produce surface roughness of nanometer range on flat surfaces as well as internal and external cylindrical surfaces (Jain *et al*., 2001). The MAF process offers many advantages, such as self-sharpening, self-adaptability, controllability and the finishing tools require neither compensation nor dressing (Chang *et al*., 2002). In MAF, the workpiece is kept between the two poles of a magnet. The working gap between the workpiece and the magnet is filled with magnetic abrasive particles, composed of ferromagnetic particles and abrasive powder. Magnetic abrasive particles can be used as bonded or unbounded. In this process, usually ferromagnetic particles are sintered with fine abrasive particles (Al2O3, SiC, CBN, or diamond) and such particles are called ferromagnetic abrasive particles (Shinmura *et al*., 1986, 1990; Chang *et al*., 2002; Jain, 2009). Finishing pressure can be controlled via magnetic field applications (Shinmura *et al*., 1993; Chang *et al*., 2002). Workpiece materials can be magnetic (e.g., steel) or non-magnetic (e.g., ceramics) and the material removal weight can be adjusted based on the size of the magnetic abrasives. Thus, MAF is a multi functional precise finishing method one can use to obtain quality surface finishes efficiently (Lieh-Dai *et al*., 2007). Shinmura *et al*. (1985a, 1987 and 1990) found that intensity of magnetic field and working gap greatly affects the surface roughness and material removal. Also they have shown that material removal and surface roughness value increase as the magnetic abrasive particle diameter increases. Jain *et al*. (2001) studied finishing of the external surface of a cylindrical workpiece and found that the working gap and circumferential speed of the workpiece are the parameters which significantly influence material removal and the change in surface roughness value. Shinmura and Aizawa (1989a) and Shinmura *et al*. (1985b) observed that for a plane, increasing finishing time up to a certain limit would result in decrease of surface roughness, after that no further improvement was noticed. Jeong-Du and Min-Seog (1995) modeled and simulated the MAF process for finishing cylindrical workpieces and concluded that the magnetic flux density increases as the air-gap length decreases. Jayswal *et al*. (2005) proposed a mathematical model for mechanics of material removal and a model for surface roughness during the MAF process. They developed a finite element code to evaluate the distribution of magnetic forces, considering magnetic flux density, type and size of magnetic abrasive particles and the working gap as the main parameters. By considering the Gaussian distribution of the ordinates of the surface profile, (Jain *et al*., 2007) modeled and simulated the surface profile obtained after MAF. This model predicts center-line average surface roughness value R_a obtained after MAF. Literature survey indicates that there are little contributions toward the simulation of the magnetic abrasive finishing process.

Artificial neural network: The ANN is a computational network that attempts to simulate the process that occurs in the human brain and nerves system during pattern recognition, information filtering and functional control (Hagan *et al*., 1996; Haykin, 1999). It uses an inductive approach to generalize the input-output relationship to approximate the desired function; such specific capacity is helpful when the case is difficult to drive a mathematical model (Chan *et al*., 2008). There has been a recent growing interest in applying Artificial Neural Network (ANN) to engineering fields for solving complex problems. The utilization of the neural network technology enables the behavior of complicated systems to be modeled and predicted based on known experimental data (Cheng *et al*., 2010; Tawakoli *et al*., 2009). Many investigators used the neural networks for prediction surface roughness parameters (El-Sonbaty *et al*., 2008; Abburi and Dixit, 2006). But on the other hand, there are no significant contributions about the employment of neural network solutions in modeling and simulation of MAF process. The objective of the present study was application of neural network solutions to predict surface roughness in magnetic abrasive finishing process. The effect of key parameters like intensity of the magnetic field, work-piece velocity and finishing time that affects performance of the process has been reported.

MAGNETIC ABRASIVE PARTICLES AIDED FINISHING OF A CYLINDRICAL SHAFT

Figure 1 and 2 shows the schematic view of the magnetic abrasive finishing and schematic of magnetic field distribution and magnetic force acting on a ferromagnetic particle respectively. The magnetic forces affect the ferromagnetic particles at position “A” outside the working gap as follows (Shinmura and Aizawa, 1989b):

$$F_x = VX_m\mu_0 H(\frac{\partial H}{\partial x}) \quad (1)$$

$$F_y = VX_m\mu_0 H(\frac{\partial H}{\partial y}) \quad (2)$$

where,

x = The direction of the line of magnetic force
y = The direction of the magnetic equipotential line
X_m = Susceptibility of the ferromagnetic particles
μ_0 = Permeability of vacuum
V = Volume of the ferromagnetic particles
H = The magnetic field strength at point “A” and $\frac{\partial H}{\partial x}$ and $\frac{\partial H}{\partial y}$ are the gradients magnetic field strength in X and Y directions

The magnetic forces represented in Eq. (1 and 2) not only concentrate the ferromagnetic particles in the working gap where magnetic field strength

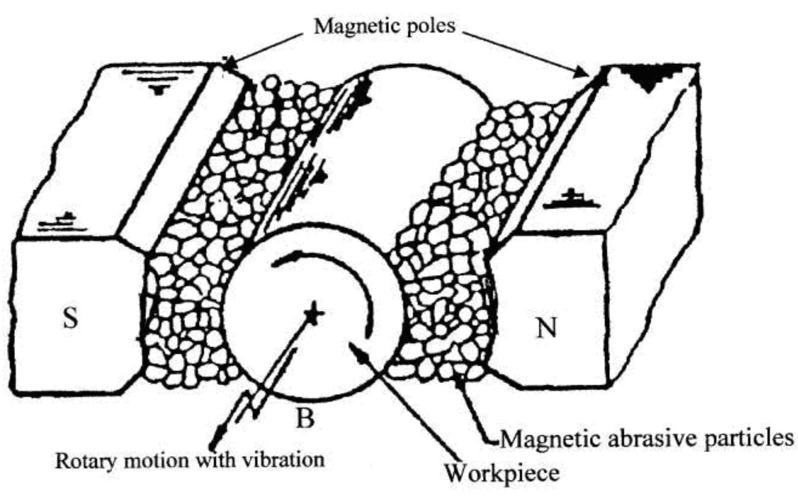

Fig. 1: Schematic view of the magnetic abrasive finishing

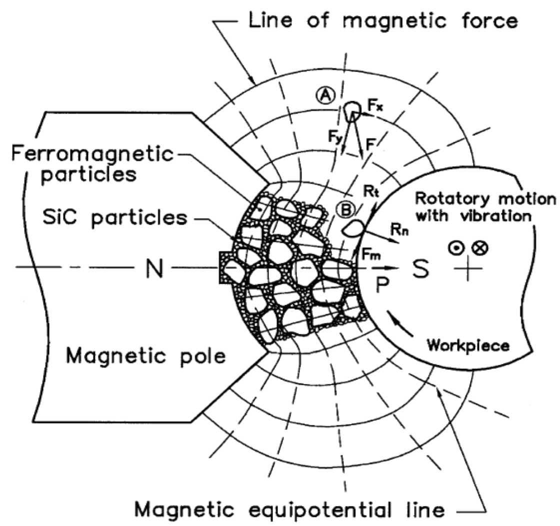

Fig. 2: Schematic view of magnetic pole, part, abrasive and magnetic particles with field lines

is superior, but also prevent the ferromagnetic particles from splashing due to workpiece rotation. The congregated ferromagnetic particles form a magnetic brush along the line of magnetic force within the working gap, which causes pressure P on the work surface. This pressure will act on the abrasive beneath the ferromagnetic particles, to generate abrasion. The abrasive cannot perform the cutting task unless it obtains abrasion pressure from the ferromagnetic particles. Eq. (3) represents pressure, P, as follows (Shinmura and Aizawa, 1989a):

$$P = [\mu_0 H^2 (1 - 1/\mu_m)]/2 \tag{3}$$

μ_m Is the relative permeability of ferromagnetic particles (Shinmura and Aizawa, 1989b).

$$\mu_m = \frac{2 + \mu_F - 2(1 - \mu_F)V_i}{2 + \mu_F + 2(1 - \mu_F)V_i} \tag{4}$$

μ_F = Specific permeability of iron constant
V_i = The relative percentage of iron (Shinmura and Aizawa, 1989b)

During finishing, the forces acting on ferromagnetic particles near the work surface are in position "B" (Fig. 2). Due to the rotation of the workpiece, a cutting resistance, R_t, will act on the ferromagnetic particles in the tangential direction of the rotational motion. Moreover, due to the magnetic field strength gradients in the working gap, the ferromagnetic particles exerts a normal force, R_n, to the work surface, while simultaneously, a magnetic force, F_m, will act on the ferromagnetic particles in the anti-direction of R_t. F_m will prevent ferromagnetic particles from flowing or dispersing out of the working gap, which ensures that the finishing process will be successful.

EXPERIMENTAL WORK

Before starting experiment, the workpiece surface finish is measured. The working gap kept constant during the experimentation. The magnetic abrasive powder, which is prepared just before each test by adding the lubricant, is fed to the finishing zone. Then the current to the electromagnets is put on. A mixture of en-butanol and etil–alchol is added to ferromagnetic and abrasive particles to form conglomerate. The conglomeration helps the magnetic abrasive particle in staying in weak bounded condition in the working gap in the initial stage. This conglomeration increases effective working time of magnetic abrasive particle before replacement. Only those abrasive particles which are in direct contact with the rotating workpiece surface, remove material by shearing (Jain *et al.*, 2001). It is suggested that due to blunting of abrasive particles, improvement in the surface finish becomes slow. Since the abrasive particles in contact with the workpiece surface wear out, the force required for cutting increases and it may exceed the holding force acting on the conglomerate (or the abrasive particles loosely held between the ferromagnetic particles). As a result, such abrasive particles are dragged outside of the magnetic zone. Also due to heat generated by friction between the abrasive particles and workpiece, lubricate bounding weakens and the particles fall out of the (Jain

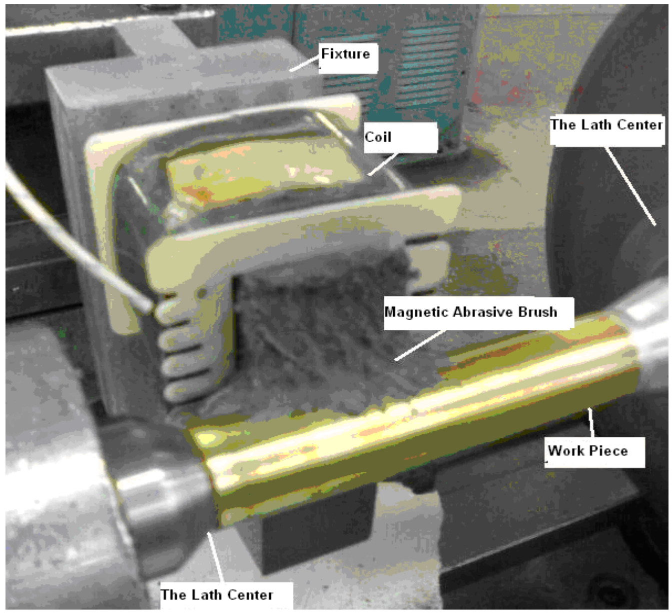

Fig. 3: Experimental setup

Table 1: Experiment conditions

Work piece material	Brass CuZn37
Work piece dimension (mm)	Ø22X 95 L
Working Gap (mm)	1
Work piece speed (m/s)	0.82-1.15
Current (A)	1.7, 2 and 2.5
Ferromagnetic particles weights (g)	5
Ferromagnetic Particles hardness (kg/mm^2)	780 - 940
Ferromagnetic Particles density (g/cm^3)	8.7
Abrasive particles weight SiC (g)	4
Abrasive particles hardness (kg/mm^2)	2800
Abrasive particles density (g/cm^3)	3.1
Specimen rotational velocities (rpm)	1000 (1.15 m/sec), 710 (0.82 m/sec)
Test duration (min)	20, 30
Number of specimen tested	12

et al., 2001). When needed fresh supply of magnetic abrasive particle is constantly added to maintain its finishing efficiency. The general setup of experiment is shown in Fig. 3. Magnetically excited coils, around which copper wire of 0.7mm diameter was wound 750 turns, produced the magnetic field. A fixture was designed and manufactured to fix the magnet to the lath machine. A cylindrical brass CuZn37 was used as workpiece. The unbonded magnetic abrasive applied is a mechanical mixture of ironic ferromagnetic particles and SiC abrasive with en-butanol as a cohesive between particles. Ferromagnetic particle mesh size of 220 and SiC with the mesh size of 200 has been used. Table 1 presents the experimental conditions. A TR240 model Time Group Inc system machine with 8 mm measuring length (probe movement length) was used to measure the surface roughness (R_a).

ARTIFICIAL NEURAL NETWORK

For training of the ANNs the experimental results is used that are obtained from experimental work. The back-propagation learning algorithm is used in a feed-forward, single hidden layer network. In the majority of neural networks no transfer function for input layer are considered, so neurons in input layer have no transfer function (Haykin, 1999). Tangent sigmoid (Tansig) transfer function is used as the activation function for the hidden layer. The transfer function used is presented in Eq. (5). The values of the training and test data were normalized to a range of (-1, 1).

$$Tangsig(z) = 2(1 + \exp(-2z)) - 1 \quad (5)$$

That z is the weighted sum of the input. Computer program has been performed for the ANN simulation and data pattern from experiments were used for the training of the network. Five numbers of available data were randomly selected and used as test data set. Statistical methods, Mean Square Error (MSE), Root-Mean-Squared (RMS), Absolute fraction of variance (R^2), coefficient of variation in percent (cov) values, were used for comparison. Error during the learning is called RMS and defined as follows:

$$RMS = (1/p\sum_j \left|t_j - o_j\right|^2)^{1/2} \quad (6)$$

Table 2: Statistical values of train process

Neurons	MSE	RMS	R2	cov
3	0.011468	0.107089	0.99256	19.07876
4	0.002869	0.053564	0.99638	9.542826
5	8.88E-05	0.009421	0.999888	1.678503
6	0.003304	0.057485	0.995828	10.24139
7	0.006404	0.080023	0.991884	14.25679
8	0.003226	0.056795	0.995928	10.11849
9	0.000744	0.027276	0.999064	4.859539
10	0.011311	0.106351	0.985574	18.94741

In addition, R^2 and coefficient of variation in percent (cov) are defined as follows, respectively:

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \quad (7)$$

$$\text{cov} = \frac{RMS}{o_{mean}} \times 100 \quad (8)$$

where,
t = Target value
o = Output value
p = Pattern
O_{mean} = The mean value of all output data (Bechtler *et al*., 2001). The performance of the network can be evaluated by the Mean Square Error (MSE), which is defined as:

$$MSE = 1/p \sum_j \left| t_j - o_j \right|^2 \quad (9)$$

Inputs and outputs are normalized in the (-1, 1) range as Eq. (10):

$$v_n = 2\,(v_R - v_{Min})/(v_{Max} - v_{Min}) - 1 \quad (10)$$

Variants of the algorithm used in the study are scaled conjugate gradient (SCG), Pola-Ribiere Conjugate Gradient (CGP) and Levenberg-Marquardt (LM). Statistical parameters that assessed the neural network are shown in Table 2. The coefficient of multiple determinations (R2-value) obtained for L-M algorithm is 0.999888 which is satisfactory.

RESULTS AND DISCUSSION

Results from experimental work: Effects of different process parameters (finishing time, magnetic field intensity and circumferential speed of the workpiece) on surface roughness are studied. R_a is defined as the difference between the surface finish value before MAF and after MAF. This R_a value is always found to be positive hence surface finish is improved in all cases. A small area was marked on workpiece for measuring initial surface finish before MAF and final surface finish after MAF.

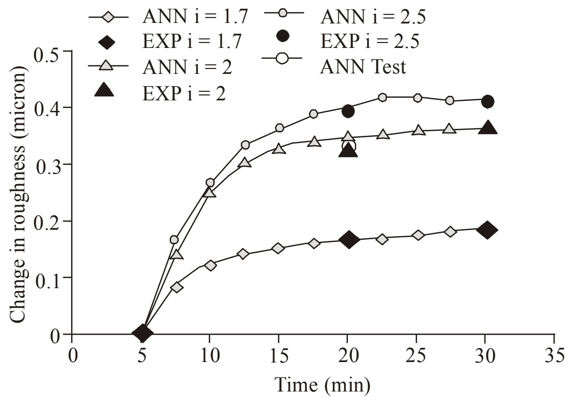

Fig. 4: Change in surface roughness with finishing time for circumferential speed of 0.82 m/s

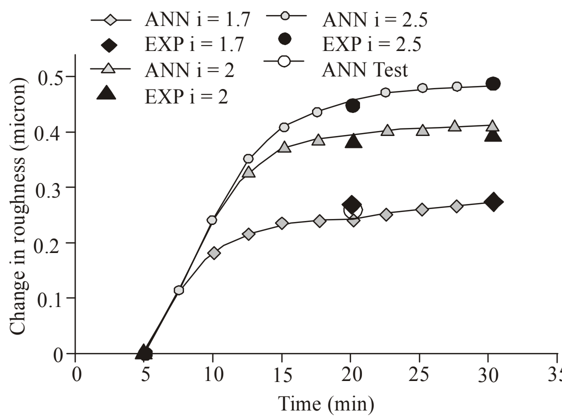

Fig. 5: Change in surface roughness with finishing time for circumferential speed of 1.15 m/s

Effect of coil current and circumferential speed on surface roughness: Surface roughness variation for different finishing times for two different circumferential speeds of 0.82 and 1.15 m/s and three different coil current of 1.7, 2 and 2.5 a (magnetic force acting on magnetic abrasive particles) are shown in Fig. 4 and 5. As the finishing time and coil current increases, magnetic abrasive brush is more engaged with the workpiece and micron chipping increases, hence the surface roughness improves and a higher material removal achieved. As it is evident, from the above figures up to certain period of time depending on current (i.e., finishing force) a high rate of change in surface roughness can be seen, after that no further improvement was noticed, this could be due to the fact that at the beginning of the process the abrasive particle are much sharper than towards the end of process.

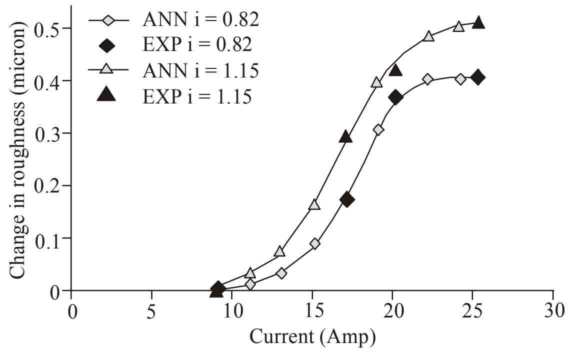

Fig. 6: Change in surface roughness with coil current for finishing time of 30min at different workpiece velocities

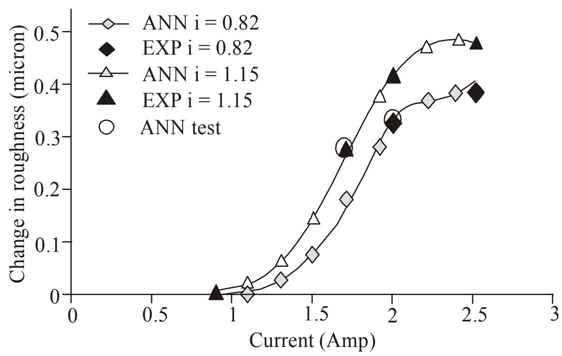

Fig. 7: Change in surface roughness with coil current for finishing time of 20 min at different workpiece velocities

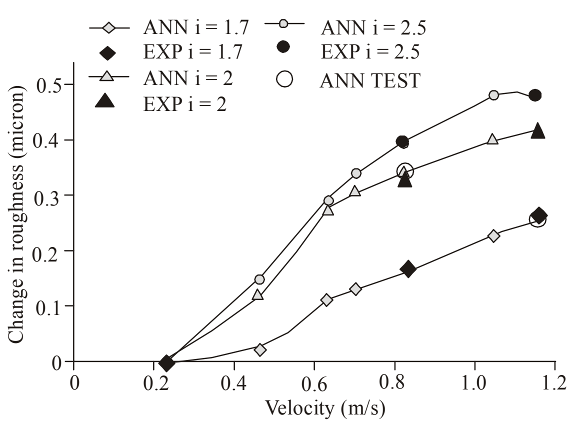

Fig. 8: Change in surface roughness with work piece velocity at different coil current for finishing time of 20 min

Another reason can be, because as the time passes the number of abrasive particle decreases and little particles replace would occur, hence chipping is lower and gradient of surface roughness decreases. Figure 4 and 5 also, shows that at a specific time and coil current, there is higher change in surface roughness for higher workpiece speed (cutting velocity) than the lower

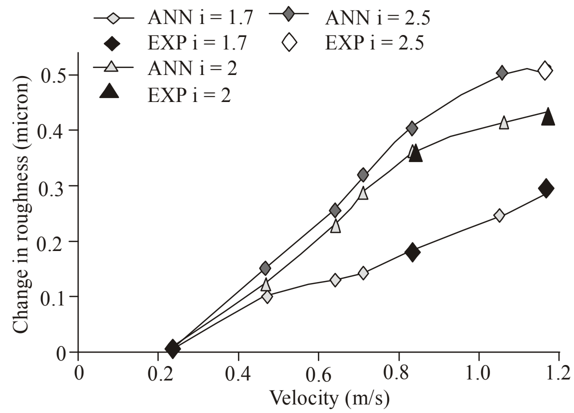

Fig. 9: Change in surface roughness with work piece velocity at different coil current for finishing time of 30 min

workpiece speed. This is because the at higher workpiece speed number of the grains coming in contact with the workpiece increases.

Effect of coil current and finishing time on surface roughness: Surface roughness variation for different coil current at two different finishing times is shown in Fig. 6 and 7. At low coil current due to lack of magnetic force, the change in surface roughness is low but, as the current of coil increases, the intensity of magnetic field (magnetic force acting on magnetic abrasive particles) increases and magnetic abrasive brush toughness increases (a higher force for holding particles in the direction of field) and can take deeper cuts to remove more amount of material from the workpiece so the variation of surface roughness increases. And so finishing improves. This effect will further escalate with the increase in finishing time and circumferential speed. Highest value of change in surface roughness is at coil current range of 1.7-2 A.

Effect of coil current and finishing time on surface roughness: In general, material removal increases with increase in circumferential speed Fig. 8 and 9. As the workpiece speed increases, magnetic abrasive brush is more engaged with the workpiece and micron chipping increases, hence the surface roughness improves and a higher material removal achieved.

Results of ANNs: The ANN was built and trained in MATLAB^{TM} environment. The back-propagation learning algorithm is used in a feed-forward, single hidden layer network (Hagan *et al*., 1996; Haykin, 1999). Figure 10 shows the architecture of the ANN used for the surface roughness variation prediction. In this, the Coil current, finishing time and workpiece speed are the inputs data and the surface roughness

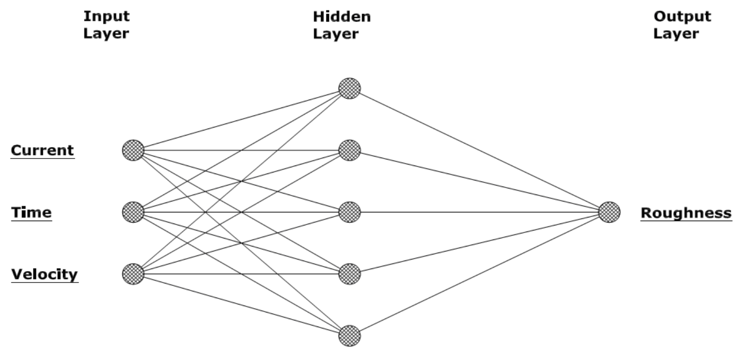

Fig. 10: Architecture of the multi-layered perceptron networks

Table 3: Statistical values of test process for surface roughness

No	D: NN	D: EXP	Error (ANN and EXP) %
3	0.021145	0	....
11	0.260245	0.28	7%
23	0.343447	0.33	3%
34	0.004228	0	…………..

variation is the actual outputs. Experimental data are used for training and testing the network. There is no strict rule for design of the ANN structure. However, the number of neurons in the hidden layers is critical to determine the complexity level of the function. In order to calculate the surface roughness, mathematical formulations can be derived from the resulting weights and the activation functions used in the ANN. As the regression coefficients obtained from both the training and testing of the ANNs were extremely good it is believed that the results thus obtained would be accurate. As expected the best approach which performed minimum errors is the LM algorithm with 5 neurons (Haykin, 1999). Levenberg-Marquardt (LM) Back-Propagation training was repeatedly applied until satisfactory training is achieved. The configuration 3-5-1 appeared to be the most optimal topology for this application. It would have also been possible to optimize topology of the neural network, by utilized multi-objective genetic algorithms for training of the neural network. In this method the number of nodes in the hidden layer, the architecture of the network, the weights can be taken as variables and a Pareto front can be constructed by minimizing the training error along with the network size (Pettersson *et al*., 2009; Sardinas *et al*., 2009; Bhattacharya *et al*., 2009).

The regression curves of the output variable surface roughness variation for the test data set are shown in Fig. 4 to 8. It should be noted that some of the data were completely unknown to the network and it was used for testing the network. Table 3 shows the comparison of the ANN and Experimental results. Neurons in input layer have no transfer function. Tangent sigmoid transfer function has been used.

$$f(E_i) = 2/(1+\exp(-2\times \mathrm{E}_i)) - 1 \tag{11}$$

where, E_i is the weighted sum of the input.

It can be seen that for such neural network model, simulation results display a very good agreement with available experimental data for a wide range of operational parameters of MFA process.

CONCLUSION

Magnetic abrasive finishing, usually involves a number of process parameters, also little contributions has been made toward the simulation of the magnetic abrasive finishing process. In this study, the effectiveness of using neural network solutions for modeling and prediction of surface roughness variation in magnetic abrasive finishing process is comparatively evaluated. A Levenberg-Marquardt with Back-Propagation algorithm was used to simulate the process. For such neural network model, simulation results display a very good agreement with available experimental data.

From magnetic abrasive finishing process parameters considered in this study, the intensity of current which results the intensity of magnetic field (magnetic force acting on magnetic abrasive particles) has the most effect on finishing process. The best result obtained for surface roughness variation is the case of 2.5 A and the velocity of 1.15m/s and the finishing time of 30 min, the variation in surface roughness is about 0.52 micron.

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