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https://doi.org/10.5109/6793663

出版情報：Evergreen. 10 (2), pp.1061-1067, 2023-06. 九州大学グリーンテクノロジー研究教育センター
バージョン：

Prediction of Surface Roughness of Mild Steel finished with Viscoelastic Magnetic Abrasive Medium

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(Received month date, year; Revised month date, year; accepted month date, year).

Abstract: In this investigation on Viscoelastic magnetic abrasive finishing process, a deep learning model is applied to predict the change in surface roughness. A dedicated experimental setup along with the abrasive media was prepared to carry out the finishing process. Experiments were performed on mild steel to inspect the effect of several parameters such as finishing time, magnetic flux density, abrasive mesh number, magnetic tool rotational speed, feed, ultrasonic amplitude on the surface roughness. The paper aims to provide a cost-effective as well as time-effective predictive method to depict the change in surface roughness.

Keywords: Viscoelastic magnetic abrasive finishing, Surface Roughness, Artificial neural network modeling

1. Introduction

Finishing, in a manufacturing process, is employed to add an appealing texture to the workpiece. It enables us to achieve the desired surface finish, geometric structure, and accuracy through various operations that come under its umbrella. It can be classified into conventional and non-conventional finishing processes. Non-conventional finishing processes provide a multitude of advantages over the traditional processes, including better tool life and higher precision. One of the favourable non-conventional finishing processes is Magnetic Field Assisted Finishing. It employs a magnetic field generated by a temporary or permanent magnet, which provides the necessary finishing force to abrasive particles causing them to press against the workpiece, thus generating abrasion. One of its major attractions include being able to finish both internal and external surfaces with high precision and minimum surface damage. It can be further classified into three sub-categories, namely magnetic abrasive finishing (MAF), magnetorheological finishing (MRF), and Viscoelastic magnetic abrasive finishing (VEMAF). The fundamental idea behind all of these processes is the use of abrasive media which have multiple random cutting edges and no definite orientation, which finishes the surface much more efficiently when compared with a cutting tool with definite edges. In our study, we have used Viscoelastic magnetic abrasive finishing wherein Viscoelastic material is added to prevent the abrasive particles from disintegrating due to the centrifugal force of the magnetic field.

1.1 Viscoelastic Magnetic Abrasive Finishing

Li et al.[1)] first presented the technology of VEMAF, which effectively integrated the advantages of solid magnetic abrasive and abrasive flow finishing providing a whole new effective method to solve surface finishing problems of complex surfaces. In this study, an experimental setup for Viscoelastic magnetic abrasive finishing (VEMAF) was established to record and analyze the effect of process parameters on the finishing characteristics of the workpiece, followed by the analysis of this process through an artificial neural network model. A new type of polishing tool was designed and manufactured along with the Viscoelastic magnetic abrasive. This abrasive mixture comprises polymer, gel, CIP, and SIC, which, under the influence of a magnetic field, forms a magnetic brush. The strength of the magnetic field controls the finishing pressure, which affects the finishing characteristics of the workpiece. It is possible to achieve a nano-level finish of the workpiece with hardly any surface damage through this process.

1.2 Artificial Neural Networks

Neural network, also referred to as Deep Learning, is an approach to Artificial Intelligence that is applied to almost all engineering applications. A neural network, a massively parallel distributed processing system, is a simplified model of our biological neuron system. Neural networks learn by training over the training data, and their accuracy is measured by testing them over the testing data or validation data, with the use of various metrics and scores. They are particularly fundamental in explaining non-linear relationships between the process parameters. They enable obtaining complex connections between dependent and independent variables with the application of activation functions. Neural networks are encouraged because of their tolerance to high levels of noise and non-linearities in the datasets. The promptness and quickness of the operation of neural networks in terms of working and producing accurate results can be seen both in software and in real-time in hardware. This is one of the many reasons they're implemented and preferred over other conventional multiple regression models. Three key features define a neural network; topology, functionality, and learning. Topology refers to the quantity of nodes in each layer and the interconnection between these nodes. Functionality entails the transfer function and the cost function of network outputs. Learning refers to the way in which the network trains itself, which is determined by parameters such as the learning rate. A neural network has various types, but the most commonly used is the back-propagation network. Back-propagation works by feeding the input to the entire network (input layer, hidden layers and the output layer) and predicting an output. The error in the output is then computed and this error is back propagated upon which the network is fine-tuned to minimise this error in the next iteration. The number of iterations is defined by the parameter 'epochs,' and the aim of running multiple iterations is to ensure that after every iteration, the loss/error is decreasing, which proves the efficiency of the neural network.

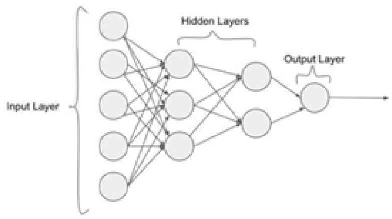

Fig. 1 General Artificial Neural Network Architecture

In recent times, the application of neural networks has been found in precision manufacturing, and it is being implemented to analyse various machining phenomena along with machining quality. Numerous researchers have utilized neural networks for the prediction of surface roughness parameters in other finishing processes. However, on the other hand, there is very little contribution of significance in the employment of neural network architectures in the modeling and simulation of the VEMAF process. The purpose of this research is to employ a neural network to analyse, and predict the surface roughness in a Viscoelastic magnetic abrasive finishing process. The impact of process parameters, namely finishing time, magnetic flux density, abrasive mesh number, magnetic tool rotational speed, feed and ultrasonic amplitude on the corresponding surface roughness has been analysed.

2. Related Work

After the invention of magnetic field assisted finishing process in early 20th century, many researchers have since developed various novel ideas to improve the key parameters, and many publications have been introduced in this field some of which are outlined below:

Earliest technique of Abrasive finishing in a Magnetic Field was outlined by Baron, Y.M[2]. Process principles and the influence of abrasive particle size on the surface finish was demonstrated by Shinmura et al.[3] on ceramic bars, using diamond-coated abrasive particles. Fox et al.[4] presented a technique and investigated experimentally the application of this technology. A pole rotating system for internal magnetic abrasive finishing, was proposed by Yamaguchi & Shinmura[5] which characterised in-process abrasive behaviour by the magnetic field, acting on the magnetic abrasive. Singh et al.[6] measured experimentally the forces acting on their workpiece. They also found out the percentage contribution, of various experimental operating factors, on the forces and change in surface roughness. Srinivas et al.[7] studied the effect of various process parameters in the viscoelastic magnetic abrasive finishing arrangement using Ansys Maxwell.Li et al.[8] established a mathematical model of interfacial debonding while using coupling agents and also determined the effect of these agents on change in surface roughness. Li et al.[9] developed a new d surfaces in face milling process, by means of a feed-forward back-propagation neural network model. Their work could help achieve the desired surface roughness profile geometry by appropriately determining the cutting conditions. Djavanroodi F.[11] examined the effectiveness of back-propagation neural network models for predicting the surface roughness variation in the MAF process. Numerous researchers have also utilized neural networks for the prediction of surface roughness parameters (Petri et al.[12], Singh et al.[13], however, no concrete employment of ANN has been seen in the VEMAF process. Therefore, in order to optimise VEMAF through a machine learning technique, in our study, we have employed an artificial neural network model to predict the change in surface roughness. magnetic finishing media for the magnetic abrasive finishing process on rotary surfaces. El-Sonbaty et al.[10] analysed and anticipated the connection between cutting conditions and comparing fractal boundaries of machine

3. Experimental Setup

The schematic diagram of the Viscoelastic magnetic abrasive finishing operation is illustrated in fig. 2. A CNC tapping and drilling machine was used for the experiment, consisting of a polishing tool, ultrasonic generator, Viscoelastic magnetic abrasive polishing medium, workpiece, and fixture, as shown in fig. 3.

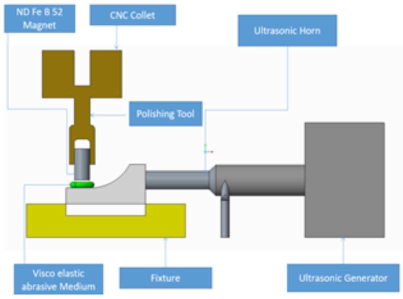

Fig. 2 Schematic Diagram of Setup

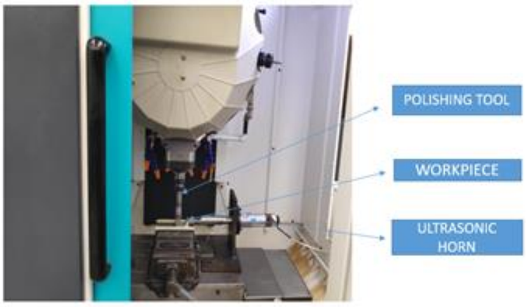

Fig. 3 CNC Machine Setup

The polishing tool is shown in fig. 4, it consists of a mild steel tool holder having a length of 95 cm and an outer diameter of 20 mm. The top of the tool holder holds the polishing tool to the spindle of the CNC machine. An N52 permanent magnet with a diameter of 20 mm and a height of 20 mm is used to generate magnetic field, which provides magnetic force. This force helps build a magnetic abrasive brush which generates abrasion pressure. The distribution of flux densities generated during finishing, for 3 different working gaps, through Ansys Maxwell Anosoft is as shown in fig. 5. The flux densities measured using Gauss Meter are shown in fig. 6. The readings are 3.11 T, 2.99 T, 2.8T, and 2.59 respectively. Ultrasonic generator used for the present research work produces fixed frequency ultrasonic waves of 25kHz and can produce ultrasonic waves ranging from 11µm to 99 µm as shown in fig. 7 . The viscoelastic abrasive was taken of 3 sizes, 400 microns, 600 microns and 800 microns. We could not take up bigger sizes because when experimented with abrasives of 1000 microns, scratches were observed. This could possibly be due to their deposit on the workpiece surface, which is not removable[14-17].

For the preparation of a flexible magnetic abrasive brush, a Viscoelastic medium was prepared. First, a polymer was prepared with silicon base oil mixed with boric acid with the further addition of lewis acid and NH_4CO_3. Separately hydrocarbon oil was mixed with aluminium stearate and heated to 100°C to produce a gel, and the mixing of polymer and gel at 50°C resulted in the preparation of the Viscoelastic medium. Mixing CIP and SiC with this medium resulted in the final Viscoelastic magnetic abrasive medium, as shown in fig 8. This medium helps reduce the segregation of the CIP and abrasive mixture in the absence of a magnetic field. Since we are using a permanent magnet in the current experiment, hence the particles will not have any tendency to get segregated. A viscosity test of the final medium was done and came out to be 954 mPa-S. It was also assumed that throughout the finishing operation there wasn't any appreciable change in the viscosity of the medium[18-22].

Nine different samples of mild steel have been used in the experiment and subjected to three cycles of operation to study the effect of process parameters on surface roughness. The pictorial view, same for each workpiece, is shown in fig. 9. For each experiment the workpiece was mounted on a vice which was bolted on the machine table. A closed-loop magnetic field was formed between the magnetic pole and the ferromagnetic workpiece. This led to the formation of a magnetic abrasive brush responsible for cutting action until the desired finish as shown in the fig. 10 was obtained[23-26].

Fig. 4 Polishing Tool

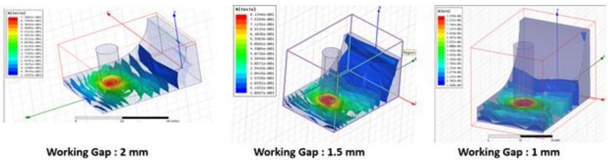

Fig. 5 Flux density simulation for different working gaps

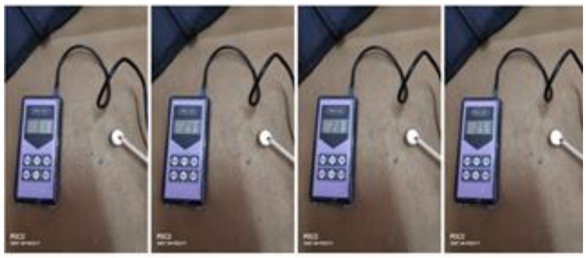
Fig. 6 Flux Density measurement

Fig. 7 Ultrasonic Generator (Fixed Frequency)

Fig. 8 Viscoelastic Abrasive Medium

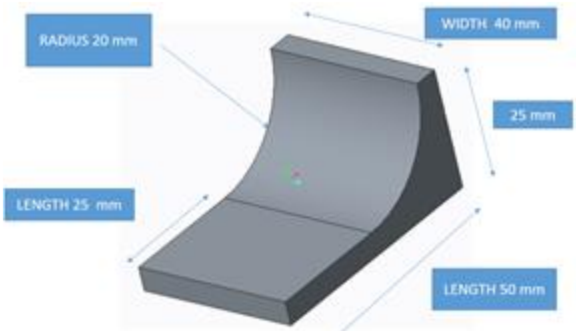

Fig. 9 Pictorial view of the workpiece

Fig. 10 Finished Specimen

4. Model development

4.1 Data Set

After completion of the experiment with several combinations of process parameters, i.e. finishing time, magnetic flux density, abrasive mesh number, magnetic tool rotational speed, feed and ultrasonic amplitude, the output in terms of surface roughness for each experiment was recorded. Instrument used for recording the surface roughness is known as TalySurf as shown in fig.11. The characteristics of change in surface roughness (ΔRa) were analyzed for 27 observations using neural network modeling. The input variables of the training dataset were standardised to ensure that all the variables were analysed over the same range of values. This was necessary because while an input variable like magnetic flux density has values less than one, another input variable, namely abrasive mesh number, has values in hundreds. Therefore, to prevent the higher values of one variable from influencing the model more strongly, than the one with much smaller values, standardisation was deemed necessary. The utility class used to perform this preprocessing of the dataset is StandardScaler. StandardScaler standardises all the values of all the variables in the range of -1 to 1. Therefore, every variable now impacts the output variable genuinely, and the model can now justly analyse the correlation of each input variable with the output variable. Once the training input variables have been standardised, utilising the same mean and standard deviation, the input variables of the testing dataset are also standardised. However, not all variables have been passed on as input variables to our neural network. Once we defined the correlation factor between various variables and the outfit, we found out that two variables out of the six were having very low correlation values and therefore were eliminated during the feature selection process. Therefore, our neural network was fed four input variables, namely magnetic flux density, abrasive mesh number, magnetic tool rotational speed, and feed, along with the output variable change in surface roughness[27-28)].

Table 1. Input Variables

Variable	Values Taken
Magnetic Flux Density (Tesla)	0.7208, 0.8134, 0.8875
Abrasive Mesh Number	400, 600, 800
Magnetic Tool Rotational Speed (rpm)	480, 600, 720
Finishing Time (mins)	6, 9, 12
Feed (mm/min)	12, 18, 24
Ultrasonic Amplitude (μm)	15, 30, 45

Fig. 11 TalySurf Instrument

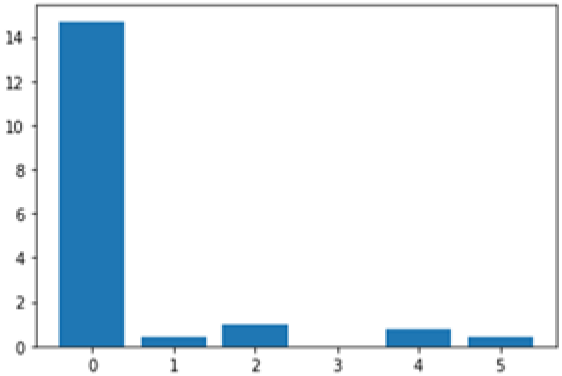

Fig. 12 Correlation Graph

4.2 Neural Network Architecture

The architecture of our model was determined through experimentation. The model consisted of 4 layers comprising the input layer, 2 hidden layers, and one output layer. Components of the model are as follows:

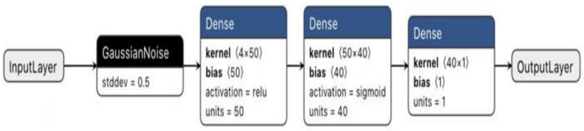

Fig. 13 Model Architecture

Table 2. Model Hyperparameters

Optimiser	Adam
Loss	Mean Squared Error
Metrics	Mean Squared Error
Batch Size	1
Epochs(Iterations)	100

Training a neural network on a small dataset can lead to overfitting which reduces the learning abilities of the network by manifolds. Adding noise to such a dataset regularises the data and helps in reducing overfitting. Gaussian noise, also known as white noise, has a mean of zero and standard deviation of one. Thus, to reduce overfitting and train the model well on our small dataset, we have introduced Gaussian noise in our input layer, by adding the Gaussian Noise layer.

5. Results and Discussion

A seven-fold cross-validation approach was used, which utilised the entire data set for model evaluation. The data set, of 27 data points, was split into seven mutually exclusive data sets. The neural network was trained with six of the seven datasets and tested on the test set, each of the seven times any six datasets were used for training while the remaining one was utilised for testing. Cross-validation is an evaluation technique primarily used for a small dataset. This is necessary for two reasons :

1. To avoid overfitting by preventing the model from learning a particular training data which it is trained upon. This results in overfitting and does not result in a successful model.

2. To enable the model to be able to predict unseen data with a low error, which can otherwise be an issue because if the model is training only on a particular part of the dataset then it is completely unaware of the rest of it, and since the dataset already is small, the training dataset is even smaller. Hence, the learning curve of the model can be quite small. Instead, through cross-validation, depending on the number of chosen folds, the model is trained on all different kinds of data points and tested on all the others, and therefore is fit enough to be able to deal with external data.

Fig. 14 Seven fold cross-validation

The result was evaluated through two metrics, namely the mean absolute error and the R^2 value (coefficient of determination).

Mean absolute error is the mean of the difference between the predicted values and the experimental values. It is calculated using the following equation :

$$MAE = \frac{\Sigma\,(y_{pred} - y_{exp})}{N}$$

In which y_{pred} and y_{exp} are predicted, and experimental values respectively, and N indicates the number of data points.

Coefficient of determination helps in determining the amount of variance of the dataset that the model is able to understand and learn. It is calculated through the following equation :

$$R^2 = 1 - \frac{\Sigma\,(y_{exp} - y_{pred})^2}{\Sigma\,(y_{exp} - y_{mean})^2}$$

Table 3. Result Metrics

Mean Absolute Error	0.032
R2	0.62

Modeling Results of the Neural Network for the testing data :

Table 4. Network Prediction on testing data

S.No.	MFD	AMN	MTRS	FEED	Experimental ΔRa	Predicted ΔRa
1	0.814	600	720	18	0.076	0.066
2	0.72	800	720	12	0.007	0.0025
3	0.72	400	480	24	0.008	0.0039
4	0.887	400	720	12	0.1077	0.1007
5	0.814	600	720	12	0.064	0.0632
6	0.814	400	600	18	0.104	0.1028
7	0.72	600	600	12	0.108	0.1063
8	0.887	800	600	12	0.142	0.141
9	0.887	800	600	24	0.18	0.148

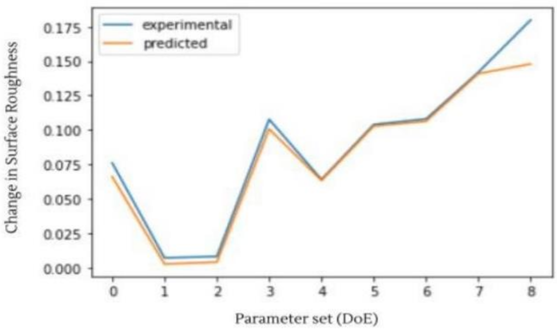

Fig. 15 Graphical Depiction of the experimental and predicted test dataset

6. Conclusion

As a consequence of the above-mentioned results, it seems suitable to conclude that :

1. The efficacy of this neural network model in predicting the change in surface roughness for Magnetic Abrasive Finishing has been affirmed.
2. A suitably trained network effectively blends optimal input conditions for Magnetic Abrasive Finishing.
3. Feature selection, in the case of datasets with large variances, is a key component of data preprocessing in order to effectively train a model.
4. Adding noise to a neural network model training on a small dataset can lead to regularization and help lessen overfitting.
5. Flux density varies depending upon the distance between the magnet and the area to be machined.
6. The base for flux density values has been set as 0.5 because upon lowering the flux density below this value, scratches were observed.
7. Maximum flux density has been adopted for Mild Steel because most of the machining zone came under the influence of maximum flux density.

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