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SIMULATION OF SURFACE MILLING OF HARDENED AISI4340 STEEL WITH MINIMAL FLUID APPLICATION USING ARTIFICIAL NEURAL NETWORK

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Abstract:
Surface roughness plays an important role in many areas and is a factor of great importance in the evaluation of cutting performance. In this paper an attempt was made to develop a model based on Artificial Neural Network to simulate surface milling of hardened AISI4340 steel with minimal fluid application. The model is expected to predict the surface roughness in terms of the fluid application parameters such as the pressure at the fluid injector, frequency of pulsing and the rate of fluid application. Such a model will be useful in the automatic control of the fluid application parameters to keep the surface roughness within the tolerance limits as required in computer assisted manufacturing. Networks with varying architecture were trained for a fixed number of cycles and were tested using a set of input / output data reserved for this purpose. The root mean square error was determined for each architecture. It was seen that a model with a 3-6–6-1 architecture gave the minimum RMSE value which could be approximated to 0.01. Accordingly this architecture was adopted for the analysis. It was also found that the predictions of the ANN model matched well with the experimental results. It is expected that such a model will be highly useful in research work connected with cutting fluid minimization during surface milling using high velocity pulsing jet of cutting fluid and to maintain the surface finish within the tolerance limits during automated hard milling operation with minimal fluid application.

Key Words: ANN, Environment Friendly, Minimal Cutting Fluid Application, Narrow Pulsed Jet, Surface Milling

1. INTRODUCTION

Conventional surface milling of hardened steel involves application of large quantities of cutting fluid. Procurement, storage and disposal of cutting fluid incur expenses and large scale use of cutting fluid causes serious environmental and health hazards on the shop floor. It also leads to problems in disposal and it has to comply with environmental legislation as well. According to the Occupational Safety and Health Administration (OSHA) regulations, the permissible exposure level for mist within the plant (PEL) is 5 mg/m³ and is likely to be reduced to 0.5 mg/m³[1]. In this context, pure dry milling is a logical alternative which is totally free from the problems associated with storage and disposal of cutting fluid. But it is difficult to implement on the existing shop floor as it requires ultra hard cutting tools and extremely rigid machine tools [2]. Ultra hard cutting tools may be introduced but the existing machine tools may not be rigid enough to accept them. In this context the best alternative is to introduce pseudo dry milling or milling with minimal fluid application [3-6]. By introducing the cutting fluid precisely at the cutting zone, better cutting performance can be achieved which will result in better surface finish, reduction of tool wear and low cutting force [7–9]. In minimal fluid application, extremely small quantities of cutting fluids are introduced as high velocity (approximately 70 m/s) tiny droplets at critical zones so that for all practical purposes it resembles like dry milling [10].

It is reported that minimal cutting fluid application can bring forth better cutting performance during turning and milling [10-12]. Research work carried out in our laboratory indicated that good cutting performance could be achieved in terms of surface finish, tool wear and cutting force when a specially formulated cutting fluid was applied on critical locations in the form of high velocity narrow pulsed jet during surface milling of AISI4340 steel with a hardness of 45 HRC by a fluid application system that can deliver cutting fluid through fluid application nozzles and offer better rake face lubrication. It is reported that the frictional forces between two sliding surfaces can be reduced considerably by rapidly fluctuating the width of the lubricant filled gap separating them [13].The scheme is environment friendly and can be easily implemented on the shop floor.

Earlier work in this research showed the fluid application parameters such as pressure at the fluid injector, frequency of pulsing and the rate of fluid application affects the surface roughness to a larger extent [11].

To improve the effectiveness of machining operations and to reduce the manufacturing costs and time, it is very important to develop modeling techniques, which will be beneficial to the metal cutting industry in the future [14].

Recently, Artificial Intelligence (AI) based models have become the preferred trend and these are applied by most researchers to develop models for near optimal conditions in machining. It is also considered as a successful approach to model the machining process for predicting performance measures through the development of an expert system which is an interactive intelligence program with an expert-like performance in solving a particular type of problem using knowledge base, inference engine and user interface. A model based on ANN is able to learn, adapt to changes and mimic the human thought process with little human interaction [15] and ANN-based approach has been successfully implemented and produced acceptable results.

The decision variables that were considered as the most influencing parameters for predicting surface roughness using ANN modeling technique were cutting speed, feed rate and depth of cut [16-20]. The machining performance is very much influenced by the fluid application parameters such as the pressure at the fluid injector, the frequency of pulsing and the rate of fluid application [21]. The machining performance is very much influenced by the fluid application parameters such as nozzle exit pressure, pulse rate and the quantity of cutting fluid. It is also clear that ANN is more successful when compared to conventional approaches in terms of speed, simplicity and capacity to learn from examples and also does not require much experimental data. In this work, a model was developed based on ANN to predict surface roughness (Ra) in terms of fluid application parameters such as pressure at the fluid injector, frequency of pulsing and the rate of fluid application during surface milling of hardened AISI4340 steel with minimal pulsed jet of cutting fluid. The predictions of the ANN model matched well with the experimental results and holds promise in research work connected with cutting fluid minimization during surface milling using high velocity pulsed jet of cutting fluid which is gaining popularity in the recent times.

2. EXPERIMENTAL DETAILS

2.1 Selection of work material

Through hardenable AISI4340 steel was selected as work material. It was hardened to 45 HRC by heat treatment. It is a general purpose steel having a wide range of applications in automobile and allied industries by virtue of its good hardenability. Plates of 125mm length, 75mm breadth and 20 mm thickness were used for the present investigation.

2.2 Selection of cutting tool

Carbide inserts with the specification AXMT 0903 PER-EML TT8020 of TaeguTec was used in the investigation along with a tool holder with the specification TE90 AX 220 - 09-L. The cutting tool inserts and the tool holder were selected as per the recommendations of M/s TaeguTec India (P) Limited who are extending their technical/material support for this research work.

2.3 Formulation of cutting fluid

Since the quantity of cutting fluid used is extremely small, a specially formulated cutting fluid was employed in this investigation. The base was a commercially available mineral oil and the formulation contained other ingredients [22]. It acted as oil in water emulsion.

2.4 Fluid application system

A special test rig was developed for carrying out the research work in hard milling with minimal cutting fluid application [23, 24]. It consists of a P-4 fuel pump (Bosch) coupled to an infinitely variable electric drive. An injector nozzle of single hole type with a specification DN0SD151 with a spray angle of 0° was used in the investigation.

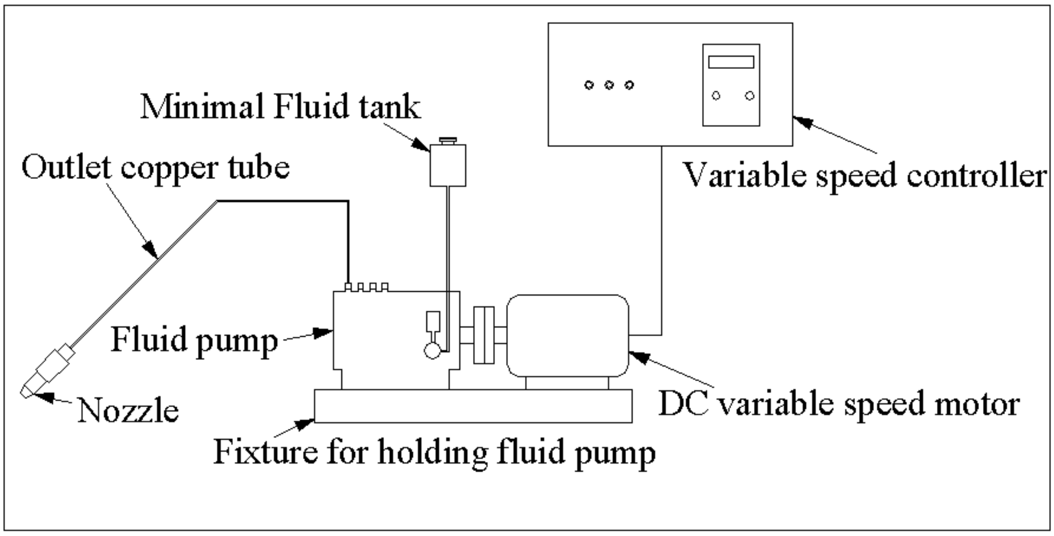

Figure 1: Schematic view of the minimal fluid applicator.

The test rig facilitated independent variation of pressure at fluid injector (P), frequency of pulsing (F) and the rate of fluid application (Q). The system can deliver cutting fluid through four outlets simultaneously so that cutting fluid could be applied to more than one location or more than one machine tool at the same time. By selecting proper settings the rate of fluid application could be made as small as 0.25ml/min. The frequency of pulsing is determined by the speed of rotation of the DC variable speed motor that drives the fluid pump.

The fluid applicator delivers cutting fluid at a rate of one pulse per revolution. This facility enables application of smaller amounts of cutting fluid per pulse. For example, if Q is the rate of fluid application in ml/min and F is the frequency of pulsing in pulses/min, fluid applied per pulse is given by Q/F. Pulsing jet aids in fluid minimization without compromising the velocity of individual particles as the pressure at the fluid injector remains constant. Pulsing jet also aids in improving the lubricating ability of the cutting fluid [13]. By varying the frequency, the rate of fluid delivered per pulse can be controlled. For example if Q is 1 ml/min and F is 1000 pulses/min and the pressure at the fluid nozzle is set at 100 bar, then fluid delivered per pulse is equal to 1/1000 = 0.001 ml while the velocity of the individual fluid particles will be approximately equal to about 70 m/s [10]. A schematic view of the fluid applicator is shown in Figure 1.

Special fixtures were designed as in Figure 2 so that the injector nozzle could be located in any desired position without interfering the tool or work during actual cutting.

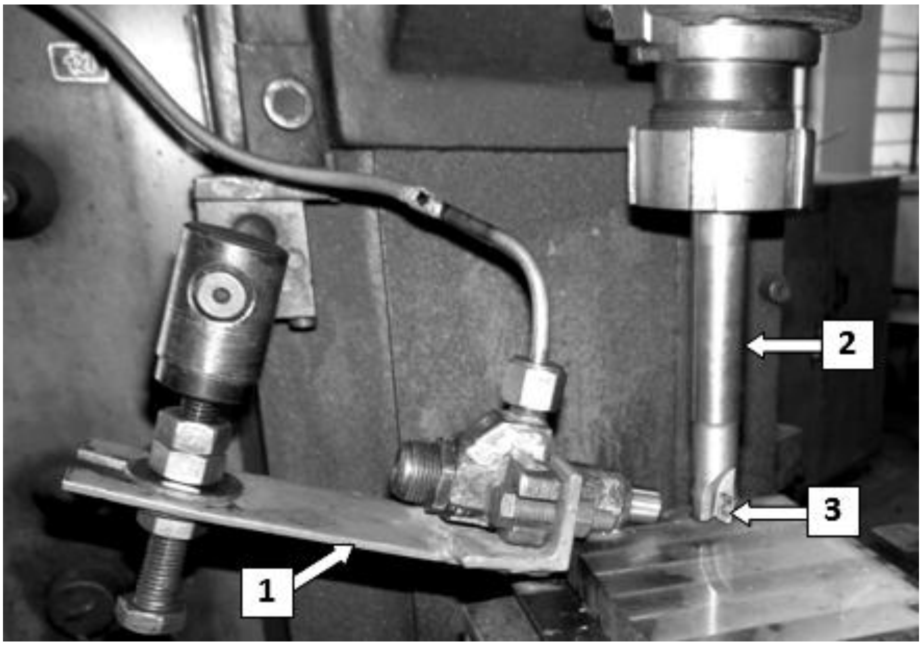

Figure 2: Fixtures for locating the fluid injector.
(1.Fixture 2.Tool holder 3.Insert)

2.5 Experimentation

A five level three factors central composite rotatable factorial design was adopted for carrying out the experiments [25]. The experiments were carried out with two replications on an HMT (model: FN1U) milling machine. A Kistler dynamometer was used for measuring cutting force. Surface finish was measured using a stylus type Perthometer (Mahr make). The cutting speed, feed and depth of cut were set in the semi finish milling range for the tool-work combinations. The cutting parameters such as cutting speed, feed rate and depth of cut were kept constant at 45 m/min, 0.09 mm/tooth and 0.3 mm respectively [11].

3. ARTIFICIAL NEURAL NETWORK

3.1 Selection of Network Architecture

An appropriate architecture for the artificial neural network was selected through an exhaustive examination of a number of network configurations. This was accomplished by changing the number of neurons in the hidden layer and the number of hidden layers. Normalization of input data was carried out using the equation 1,

$$x_i = \frac{0.8}{d_{\max} - d_{\min}} \left(d_i - d_{\min}\right) + 0.1 \tag{1}$$

Where $d_{\max}$ is the maximum value of the input/output data, $d_{\min}$ is the minimum value of the input/output data, and d_i is the i_{th} input/output data [26]. A sigmoidal function as shown in Equation 2 was used as transfer function in this model.

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

A back propagation algorithm, which adjusts weights according to the gradient descent method, was used to minimize the difference between the desired and actual output of the network. A routine which utilizes a feed forward back propagation algorithm was used in developing this model [27]. Networks with varying architecture were trained for a fixed number of cycles and were tested using a set of input and output parameters. Even though researchers are free to test at any number of hidden layers with any number of nodes for each hidden layer, the number of hidden layers and the nodes in each hidden layer are subjected to the complexity of the mapping, computer memory, computation time and the desired data control effect. Too many nodes result in a waste of computer memory and computation time, while too few nodes may not provide the desired data control effect [28]. For the best prediction result, the guidelines given by Zhang et al. [29] was preferred, where the recommended number of nodes for the hidden layer are ‘‘n/2”, ‘‘1n”, ‘‘2n”, and ‘‘2n + 1” where n is the number of input nodes. Since the number of input variables is 3 for this study, the recommended number of nodes in the hidden layer are (3)/2 = 1.5 ≈ 1, 1(3) = 3, 2(3) = 6, and 2(3) + 1 = 7. Therefore, by limiting the trial-and-error process with two hidden layers, this study applied to eight different network structures, which are 3–1–1, 3–3–1, 3–6–1, 3–7–1, 3–1–1–1, 3– 3–3–1, 3–6–6–1 and 3–7–7–1, as described in Figure 3 and Figure 4 were selected for prediction of surface roughness.

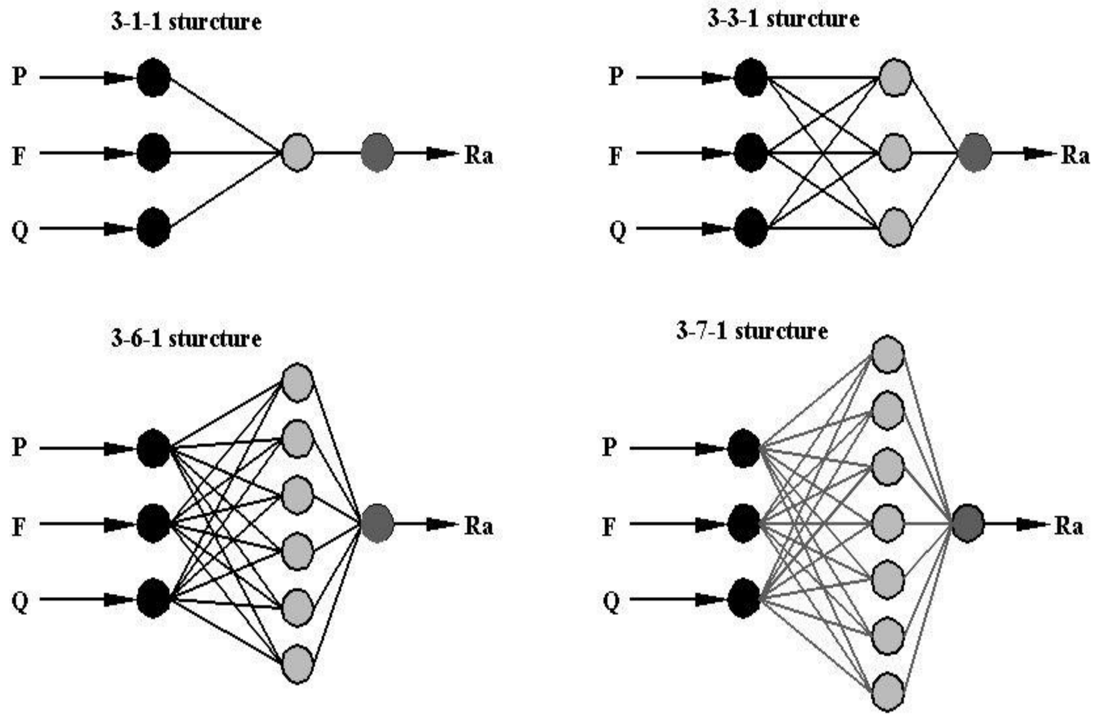

Figure 3: ANN network structure model with a single hidden layer.

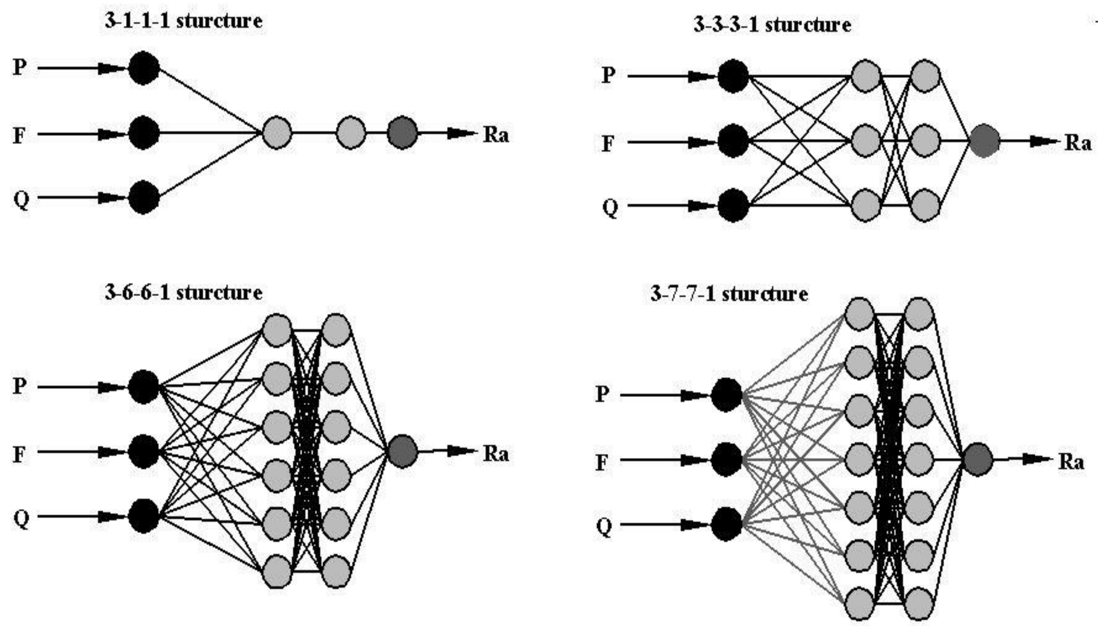

Figure 4: ANN network structure model with a two hidden layer.

An error tolerance of 0.001, learning rate of 0.5 and momentum factor of 0.1 were assigned while training the model. The model was trained using the set of experimental data available in Table I.

Table I: Data used for training the ANN model.

Sl. No	Pressure at the fluid injector (P), bar	Frequency of pulsing (F), pulses/min	Quantity of cutting fluid (Q), ml/min	Surface roughness (Ra), µm
1	60	350	3.5	0.675
2	90	350	3.5	0.591
3	60	650	3.5	0.88
4	90	650	3.5	0.627
5	90	350	8.5	0.514
6	60	650	8.5	0.87
7	90	650	8.5	0.564
8	100	500	6	0.4
9	75	250	6	0.615
10	75	750	6	0.711
11	75	500	2	0.851
12	75	500	10	0.82
13	75	500	6	0.527
14	75	500	6	0.545
15	75	500	6	0.516
16	75	500	6	0.532
17	75	500	6	0.536

In order to understand whether an ANN model is producing good predictions, the test data that has never been presented to the network were used to check its ability to predict. The statistical methods of Root Mean Square error (RMSE), Coefficient of determination (R^2) and Mean Error Percentage (MEP) have been used for making comparisons [30]. These values are determined using the following equations:

$$\text{RMSE} = \left(\left(\frac{1}{p}\right) \sum_j |t_j - o_j|^2 \right) \quad (3)$$

$$R^2 = 1 - \left(\frac{\Sigma_j |t_j - o_j|^2}{\Sigma_j (o_j)^2}\right) \quad (4)$$

$$\text{MEP} = \frac{\Sigma_j \left(\left(t_j - o_j\right)/_{t_j}\right) \times 100}{p} \quad (5)$$

Where t is the target value, o is the output and p the number of samples.

The root mean square error was determined for each architecture. Table II shows the RMS error value for the network structures.

Table II: RMSE values for the network structures.

Sl. No	Layer configuration	Error tolerance	Root Mean Square error
1	3-1-1	0.001	0.2782
2	3-3-1	0.001	0.0506
3	3-6-1	0.001	0.03197
4	3-7-1	0.001	0.02356
5	3-1-1-1	0.001	0.28033
6	3-3-3-1	0.001	0.02383
7	**3-6-6-1**	**0.001**	**0.011816**
8	3-7-7-1	0.001	0.013456

It is seen that a model with a 3-6–6-1 architecture gave the minimum RMSE value which could be approximated to 0.01. Accordingly this architecture was adopted for the analysis.

3.2 Model validation

The test patterns used for validating the ANN model during milling with minimal fluid application and its comparison with experimental results is shown in Table III. It is seen that there is good agreement between the predictions by the ANN model and the experimental results.

Table III: Comparison of the predictions by the 3-6-6-1 ANN model with the experimental results.

Sl. No	Pressure at the fluid injector (P), bar	Frequency of pulsing (F), pulses/min	Quantity of cutting fluid (Q), ml/min	Surface roughness (Ra), μm		Error %
				Experimental results	Prediction by ANN	
1	60	350	8.5	0.817	0.811	0.73
2	50	500	6	0.84	0.8308	1.09
3	75	500	6	0.521	0.5318	2.07
4	100	500	6.706	0.3904	0.3871	0.84

4. RESULTS AND DISCUSSIONS

In the present analysis fluid application parameters such as pressure at the fluid injector, frequency of pulsing and the rate of fluid application during surface milling of hardened AISI4340 steel with minimal pulsed jet of cutting fluid were considered to develop the ANN model to predict average Surface roughness (Ra). It was found that the network structure with 3-6-6-1 configuration gave the best prediction of performance with a coefficient of determination as high as 0.997, the standard error of 0.011 percent and Mean error percentage of 0.93.
This study has considered eight different ANN network structures which are 3–1–1, 3–3–1, 3–6–1, 3–7–1, 3–1–1–1, 3–3–3–1, 3–6–6–1, and 3–7–7–1 and it was found that the 3–6–6-1 structure has given the best prediction. It was also observed with ANN models that the predictions with considerable accuracy is possible even with smaller number of training data.

5. CONCLUSION

The ANN model developed can be used to fix the fluid application parameters to achieve desired surface finish and to maintain the surface finish within the tolerance limit during automated surface milling of hardened AISI4340 steel with minimal fluid application. The area of fluid minimization using high velocity pulsing jet of cutting fluid is gaining popularity in recent times due to its enhanced lubricating ability. The new scheme can be well acceptable to the industry as it does not require any major changes in the existing setup for its implementation on the shop floor and is totally free from problems associated with procurement, storage and disposal of cutting fluid.

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