Intelligent Grinding Process via Artificial Neural Networks

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Abstract. Surface roughness of the ground parts and the grinding forces are two important factors for the assessment of the grinding process. The surface roughness directly influences the functional requirements of the workpieces and the grinding forces are an important criterion for the achievable material removal rate. The establishment of a model for the reliable prediction of surface roughness and grinding forces is a key issue. This work deals with design of appropriate control strategy for prediction of grinding forces and surface roughness as one of the important indicators of the machined surface quality via applying Artificial Neural Networks (ANNs) through special sensors integrated into the machine tool. A micro-grinding process of Ti6Al4V was chosen. The model was verified by various experimental tests with different grinding and dressing parameters. It was found that the predictions made by the ANN model matched well with the experimental results.

Keywords: Artificial Neural Networks (ANNs), Micro-grinding, Surface roughness, Modeling, Intelligent grinding

1 Introduction

Mechanical micro-cutting is one of the key technologies to enable the realization of high accuracy complex micro-products made from a variety of engineering materials. Amount mechanical micro-machining process, micro-grinding has been an effective process to achieve high dimensionally accurate parts in machining process with superior surface finishes. However, modelling of the micro-grinding, especially predicting micro-grinding forces and surface roughness in a very small size is complicated and is still at its early stage. Most of the analytical models are adapted from conventional approaches but taking one or more size effects into consideration. The size effects which have been modelled to predict micro-cutting forces include ratio of feed rate to tool radius; cutter edge radius [1]; minimum chip thickness [2]; and micro-structure effect.

Research has been carried out in micro-cutting mechanics for decades and experimental studies still dominate the micro-cutting research. Limited researches, which are dealing with the fundamental understanding of the material removal mechanisms in the micro-scale (single grain-workpiece interaction), are available [3–5]. Moreover, the micro-scale numerical modelling methods are developed to describe the plastic behavior of the workpiece material at the high temperature and strain-rates linked with the grinding process. Cheng et al. [6] presented a mathematical model for the prediction of the micro-drill-grinding force. Park and Liang [7] modelled the micro-grinding forces based on the physical analysis of the process.

In all modeling studies the prediction error for the surface roughens in grinding process is very high since the grinding process is a complex process. The grinding grits on the surface of the grinding tool are stochastically distributed and it is almost impossible to find two same abrasive grit with the same shape and cutting edges, making the process very complex to be modeled. There are also several parameters which are influential in the modeling of the grinding forces and surface roughness such as: vibration, the precision of the machine tool, the tool specification, dressing parameters and other parameters which is so complicated to import all of them into the modeling process and consider their effects.

Using the ANNs is a desirable way to model such complex systems. Vrabel et al. [8] used the ANNs to predict the surface integrity in the machining process. They developed and tested a neural network which was able to predict the drill flank wear to prevent anomalies occurring on machined surface. Beatrice et al. [9] studied the ability of modeling the surface roughness (Ra) in terms of cutting parameters during hard turning of AISI H13 tool steel with minimal cutting fluid application. They showed that the ANN model can be a useful tool to select the cutting parameters for achieving desired surface finish. Tomaz Irgolic et al. [10] used the feed-forward backpropagation neural network to predict the cutting forces in milling operation. They proved that the prediction of the cutting forces with the ANNs was very reliable; the error in predicting cutting forces was smaller than 10%.

In this work several experiments at different conditions with various grinding parameters, i.e. cutting speed, feed rate and depth of cut and dressing parameters such as dressing overlap ratio and dressing speed ratio were carried out. Using the experimental data, obtained from the grinding process, two different neural networks were trained to model and predict the grinding forces and surface roughens. Finally, the models were validated and tested with some other experimental data.

2 Methodology

First the desire sensors were integrated into the machine tool for measuring the required out-put parameters during the experiments. This was an important part of this work since the errors which occur in the measuring of the outputs will directly influence the prediction of the outputs via the ANNs. To this end the titanium alloy "Ti-6V-4Al" was chosen as the workpiece material. Block samples with the dimensions of 30x20x10 mm were ground using vitrified-bonded diamond grinding pin (D46C150 V) with the diameter of 2 mm. The grinding pin was dressed using a diamond dressing roll with the diameter of 100 mm. Oil was utilized as the grinding fluid. The micro-grinding tests were carried out at different cutting speeds (v_c), dressing-speed ratios (q_d), and dressing overlap ratios (U_d) to investigate the effect of these parameters on grinding forces and surface roughness. A high-precision 5-axis CNC machining center was used for the experiments (Fig.1).

Table 1. Process Parameters

Grinding Parameters:	**Values**
Cutting Speed v_c (m/s)	6, 10, 12 and 14
Feed Rate v_{ft} (mm/min)	200 and 1000
Depth of Cut a_e (µm)	4 and 10
Width of Cut a_p (mm)	2.5
Dressing Parameters:	**Values**
Dressing Depth a_{ed} (µm)	2

Dressing Speed Ratio q_d	-0.4, +0.4 and +0.8
Dressing Overlap Ratio U_d	45, 90, 270, 305, 910, 1830

To measure the forces and surface roughness, a type 9256C2 dynamometer and a tactile surface roughness tester (Hommel-Werke model T-1000) were used, respectively. The surface roughness measurements were taken perpendicular to the grinding direction at three positions: at the beginning, at the middle, and at the end of the grinding path. A confocal microscope (µsurf mobile plus) was used to obtain the confocal pictures from the ground surface. Each test was repeated three times. Table 1 lists the utilized process parameters for the experiments.

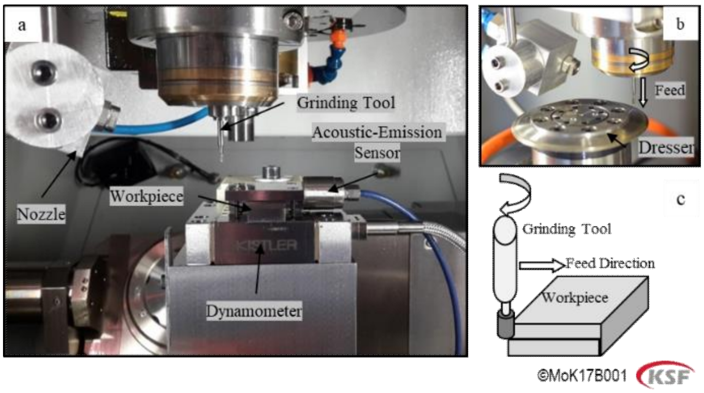

Fig. 1. a) Experimental setup, b) Dressing setup, c) Illustration of the micro-grinding process

3 Neural Networks

The appropriate architecture for the ANN was selected through a comprehensive examination of several network configurations. This was accomplished by changing the number of hidden layers and number of neurons in the hidden layers. The hidden layer plays an important role in modeling of the process via the neural networks and has an optimal quantity. The low number of the neurons in the hidden lower may cause the high Sum Square Errors (SSE) and increasing their number reduces the SSE up to a certain point that it becomes stable. After that the SSE can be fluctuated and even increases by increasing the number of the neurons [11].

A routine that utilizes a feed forward back propagation algorithm was used to develop the model as it is widely used by other researchers, since this method generally leads to the most accurate results. The feed forward back propagation is considered to be a powerful technique for constructing non-linear functions between several inputs (such as cutting speed, feed, depth of cut) and one or more corresponding outputs (such as the cutting forces). The back-propagation network typically has an input layer, an output layer and at least one hidden layer, with each layer fully connected to the succeeding layer. During learning, information is also propagated back through the network and used to update the connection weights. The following expressions give the basic relationships used for this analysis [12]:

$x_q^{[s]}$ = current output state of the qth neuron in layers.

$w_{qp}^{[s]}$= weight on the connection joining the pth neuron in layer s-1 to the qth neuron in layer s.

$I_q^{[s]}$= weighted summation of inputs to the qth neuron in layer s.

A back-propagation element therefore propagates its inputs as:

$$x_q^{[s]} = f\left(\sum_p^{[s]}(w_{qp}^{[s]} * x_q^{[s-1]})\right) = f\left(I_q^{[s]}\right) \qquad (1)$$

The MATLAB ANN toolbox was used for easily updating the value of weights and biases of the algorithm. Networks with different architecture were trained for a fixed number of cycles and were tested using a set of input and output parameters. The sigmoid function is used in this study. Fig. 2 shows a neural network structure for learning process with a sigmoid function for the hidden layer and a linear transfer function for the output layer.

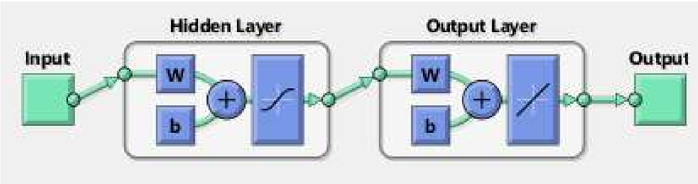

Fig. 2. The schematic of a neural network for learning

4 Results and discussion

In the modelling 80 percent of the gathered data has been chosen for training, 10 percent for validation and 10 percent for testing of the network. Different hidden layers with different number of neurons was chosen to obtain the optimal hidden layer.

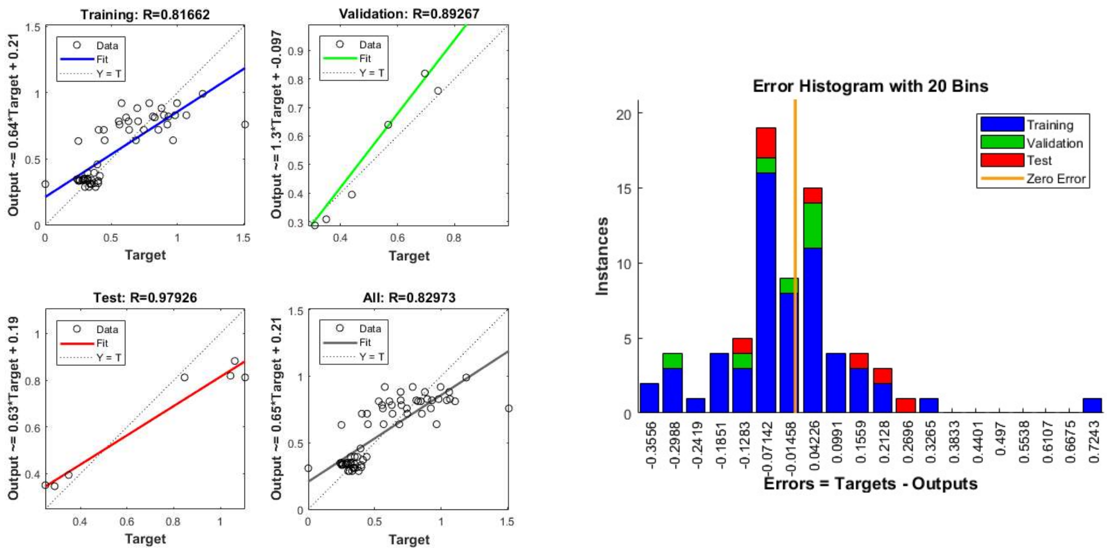

Fig. 3. left) The regression for the trained and test data for R_a, right) the Error Histogram for R_a

For modeling of the surface roughness the number of the hidden layers has been set equal to the number of the inputs and the results have been given in Fig. 3-left. As it can be seen in the figure, all the phases (training, testing, and validation) have an acceptable error which shows that the developed ANN model can precisely predict the surface roughness in the term of R_a. The training phase has an SSE of 0.82 which shows that all data are trained sufficiently. After the training the trained model has been validated with the 10 percent of the gathered data. The validation has also an acceptable error (SSE of 0.89). The model was tested furthermore with another 10 percent of the gathered data which showed a very good ability of predicting of the surface roughness via ANNs (SSE of 0.97).

Fig. 3-right represents the Error Histogram which is calculated as the difference between the targets of the neural networks and the actual outputs. The graph also shows that most of the errors in all stages are around the middle of the histogram curves which also validate the training stage. Fig. 4 shows the trend of the learning process. At the beginning of the learning process the error is high and the model correct himself by modifying the weights until a stable steady situation has been achieved. It is also clear that the all stages including training, validation and testing are approximately in the same order.

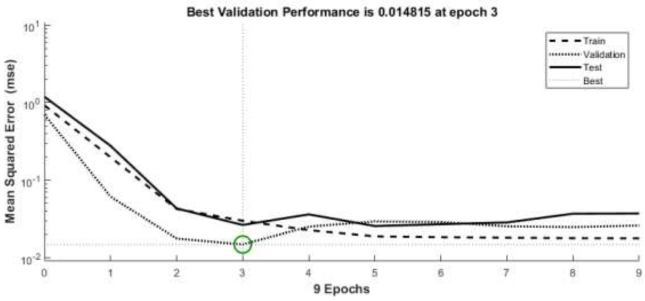

Fig. 4. the modeling trend versus the learning Sycle for R_a

To model the grinding forces first the number of neurons in the hidden layer has been set to 10 and the errors have been listed in the Fig. 5-left. The results show that the ANN also can precisely predict the grinding forces with an acceptable error. The histogram graph also shows that most of the errors in all stages are around the middle of the histogram curves which validate the training stage (Fig. 5-right).

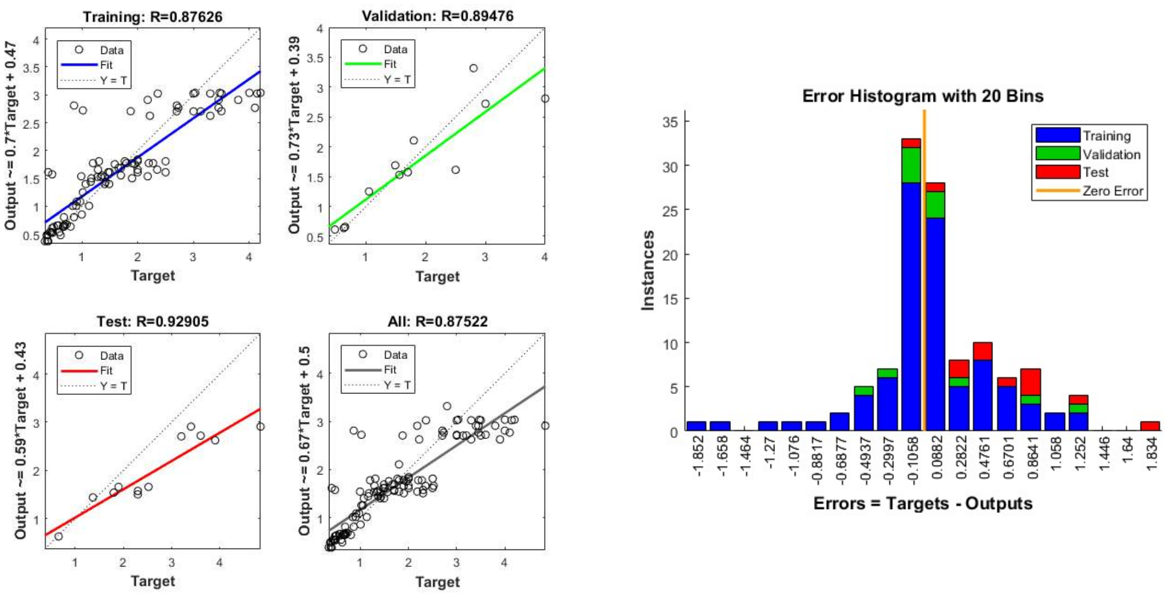

Fig. 5. left) The regression for the trained and test data for the grinding forces with 10 neurons in hidden layer, right) the Error Histogram for the grinding forces

Conclusion

A neural network with different structures was designed and trained to predict the grinding forces and surface roughness of micro grinding of titanium. The cutting forces and surface quality was measured via integrated sensors into the machine tool. It was observed that the accuracy of the training phase as well as testing highly depends on an optimized number of the neurons in the hidden layer. The results showed that the ANNs are capable to model the grinding forces and surface roughness of titanium material with an acceptable accuracy. The results of this study can be used to monitor the process online. As a future work it is suggested to use acoustic emission as an additional sensor to online monitor the process, enabling the prediction of the surface roughness with the help of ANNs.

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