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Estimation of Machine Vision and Acoustic Emission Features in Turning Nimonic75 by ANN

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Abstract: **-- Turning is an important and widely used manufacturing process in engineering industries. The study of metal removal focuses on the features of tools, work materials, and machining parameter settings. Nickel-based super alloys are widely used in aircraft industry as they are exceptionally thermal resistant and retaining mechanical properties up to 700°C. By virtue of the above they induce tool wear while machining which seriously affect the life of the component, and it is a serious concern, since it is used in critical applications. In order to monitor the tool status in turning process, tool status dependent machine vision and AE features were extracted during machining and an attempt was made to obtain a clear insight of the parameters involved. But these simpler methods of analysis did not provide sufficient information about tool status and hence there was a requirement for more sophisticated method of signal analysis. This paper is the report of an investigation of an approach for machine vision signals estimation in turning for tool status monitoring. Tool status models were defined utilizing feed forward neural networks based on back propagation algorithm. The cutting test data were provided to the designed neural networks in order to train, validate and test them. Several configurations of networks, characterized by different number of hidden layers and number of neurons in the hidden layers, were trained for carrying out the best arrangement for the status parameters prediction, in terms of resulting errors. The input neurons are the investigated parameters (Machining time, AE RMS, AE count and perimeter), in estimating vision features i.e. wear area: perimeter, machining time, AE RMS, AE count are considered as the independent variables and vice versa in order to have the performance well in multi sensory situations. This ANN model could predict the vision and AE features by knowing the input data at time t. Also, this ANN model and multisensory system were coupled for on-line monitoring of the tool status.**

***Index Terms*—Artificial neural network (ANN, Machine vision, Acoustic Emission.**

I.INTRODUCTION

Development of automated machining centers has been the focus in the realm of metal cutting in recent times. In machining, undesirable tool wear causes unpredictable machined surface roughness is inevitable. In this regard, automated tool status monitoring systems have become essential. The cost of tool failure can be significant compared to the price of a cutting tool. The use of machine vision and acoustic emission signals in the monitoring of tool status is fairly wide spread in the literature.ANN maps input and output and the supremacy of ANN is due to its capability to represent both linear and non linear relationships as well learn these relationships from the modeled data. Conventional linear models prove inadequate to handle non linear characteristics and hence ANN model is adopted for estimating the status of the tool to realize full benefit of the neural networks. To validate the obtained results as well to predict the behavior of the system (turning) under various condition of the operating range, ANN has been used since the accuracy of estimation using ANN is superior to other regression models. Monitoring system, endowed with cutting force, acoustic emission and vibration sensors, has been employed by Tiziana Segreto, et al [1], for classification of tool status in turning of Inconel 718. Sensor signals have been considered as input features to a neural network based pattern recognition system for decision making on tool condition. In order to derive and empirical model capable of predicting flank wear as a function of cutting speed and time, C. Leone [2], has developed a online prediction system using, tool wear measurement data, collected while turning Inconel 718 aircraft engine components, by using regression analysis Ra and artificial neural network paradigms. The results of the model were compared with that of ANN and stated that the accuracy of ANN prediction is better than Ra, but selection of best network configuration of ANN requires significantly longer times. On-machine tool condition monitoring by processing the turned surface images has been proposed by SamikDutta[3],have described tool wear progress using surface image features by grey level co-occurrence matrix.Further,they have estimated tool flank wear using surface image features by considering linear support vector machine based regression technique with prediction error of 4.9%.BulentKaya,et.al.,[4] have studied the key considerations for development of an online TCM system for milling of Inconel 718 superalloy. An effective and efficient strategy based on artificial neural networks (ANN) is presented to estimate tool tool status. ANN based decision making model was trained using real time acquired three axis (Fx, Fy, Fz) cutting force and torque (Mz) signals and also with cutting conditions and time. The presented ANN model

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demonstrated a very good statistical performance with a high correlation and extremely low error ratio between the actual and predicted values of tool status. In this research a prediction model using ANN for tool status estimation has been developed by Image acquisition and processing of the tool images before and after each set of experiments. Tool status is monitored (visualized) after each stages of turning and subsequently AE signals has been acquired, operation is repeated until the tool status reaches a predetermined value or threshold value.ANN as an ability to integrate the information obtained by various sources.

II. EXPERIMENTAL DETAILS

In the present study, Nimonic75, material has been chosen as work materials. Engineers have long relied upon super alloys, such as Inconel718 and Nimonic75, for their unique high temperature and stress-resistance properties. Such properties are especially critical to the aerospace industry. The chemical compositions of Nimonic75 materials are mentioned in Table1. The turning trails on Nimonic75 have been carried out in a high speed, automatic precision lathe using coated carbide tools. Here, experiments were conducted on an automatic precision Lathe and the experiments were conducted for different speed and feed combinations. The spindle speeds considered is 450 RPM.Feeds considered is 0.05, 0.06 and 0.07 mm/rev, depth of cut of 0.4mm.

Table 1: Chemical Composition of Nimonic-75

Work material	NIMONIC75
Chromium	Cr 18-21
Iron	Fe 5.00 max
Silicon	Si 1.00 max
Manganese	Mn 1.00 max
Titanium	Ti 0.2-0.6
Copper	Cu 0.5
Carbon	C 0.08-0.15
Nickel, Ni	Remainder

A. Machine vision features

Machine Vision implies "replacement of the eye and the brain in the human visual system by respectively, electronic cameras and digital computers". Such systems are now being applied routinely in industrial automation for on-line inspection. The following are some machine vision features.

Area and Perimeter

It is assumed that an un calibrated image contains pixels that are 1 unit by 1 unit in size. Therefore, the area of any pixel is 1 unit squared and the perimeter is 4 units. In this case, the area of a blob is the sum of the pixels in the blob. The perimeter is the total number of pixel sides in the blob, as shown in Fig.1.

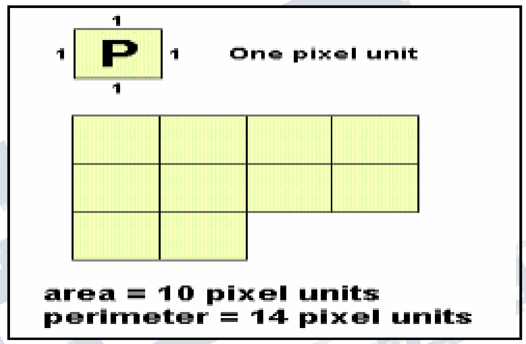

Figure1.Wear area and perimeter

B. Acoustic emission features

AE sensors "listen" to structures and materials to detect AE activity. AE sensors are vital links between the test structures and the analysis instrumentation, and their performance is critical to the success of every test. An Acoustic emission sensor converts the mechanical energy carried by the elastic wave into an electrical signal; the sensor is more properly termed a transducer is as shown in Fig.2

Figure 2.AE sensor

RMS: This is a measure of power in a signal. In Acoustic emission work the AE signal from the sensors is squared (this

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makes all values positive), the square root is then taken and some signal averaging is applied. The resultant RMS signal is of low bandwidth and can be sampled at a relatively low frequency of 100 Hz. **Counts, N**, The number of times the signal amplitude exceeds the preset threshold. Refers to the number of pulses emitted by the measurement circuitry if the signal amplitude is greater than the threshold.

III. RESULTS AND DISCUSSIONS

For developing ANN's, the Neural Network Toolbox of Matlab® was used and the Levenberg-Marquardt back propagation algorithm was chosen. For training and validating the network the input pattern had to be divided in two sets, one for each phase. The Matlab® toolbox was programmed to divide the input pattern as: the 70% for training the network and the 30% for validating it. After these two first phases, the ANN's giving the lowest MSE was chosen as the right predictive instruments. In particular, performance status monitoring data of experiments were utilized and ANN architecture provided the best results for wear area prediction; while the best network for prediction is the 4-12-1 network. When the work piece material is nimonic75 the network has an optimal architecture based on 4-12-1 configuration. The topologies of artificial neural networks are shown in Fig.3and Fig.4

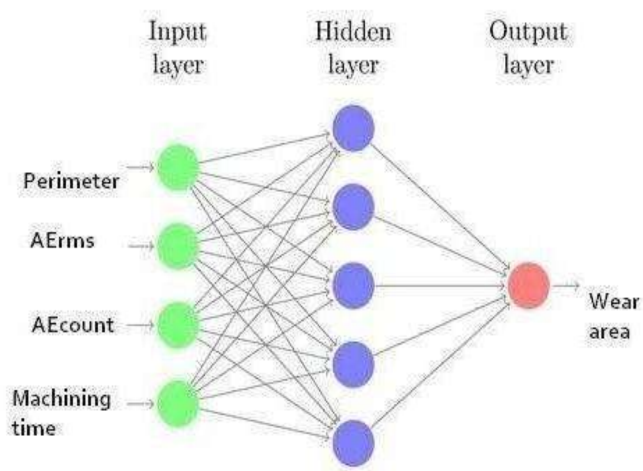

Figure.3Topologies of the ANN for prediction of Machine Vision parameters

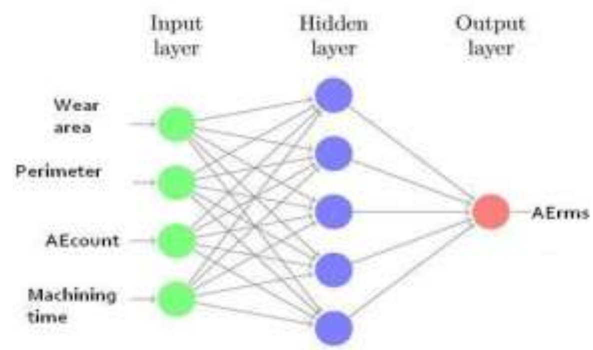

Figure.4Topologies of the ANN for prediction of Machine Vision parameters

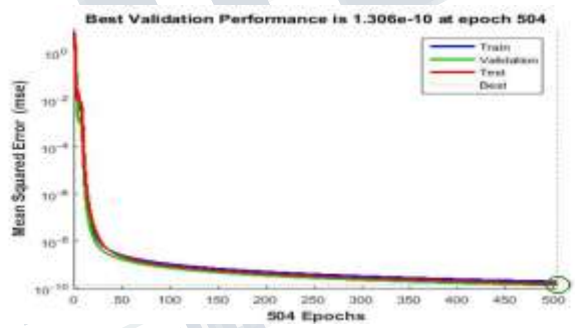

Figure.5 Performance plot for ANN

The test curve is similar to curve obtained during validation and indicate no major problem during training the network as depicted in figure 5. Any significant variation between these curves is accounted for over fitting. Establishing the regression plots between network outputs and targets is next in the process of validating and perfect training culminates in exact relationship, but seldom occurs. Regression co-effient (R),R=1 represents exact and R=0 represents no relationship between outputs and targets. Some established observation from the Estimation by ANN study by considering 4 input parameters, 2 hidden layers and 12 hidden neurons were found to produce a regression coefficient closer to 1 and mean squared error closer to 0.Least Mean Squared Error (MSE) and best fit have been obtained when 70% of data is used in the training set. The least MSE value obtained during wear area estimation is 1.306e-^{10} at 504 epochs as depicted in figure5The results of experimental and theoretical analysis for Nimonic75 work material are presented in figure 6 to 7 through which a clear insight can be obtained about the various signals. Functional relationships between the obtained

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parameters have been shown to derive a basis for a more detailed analysis

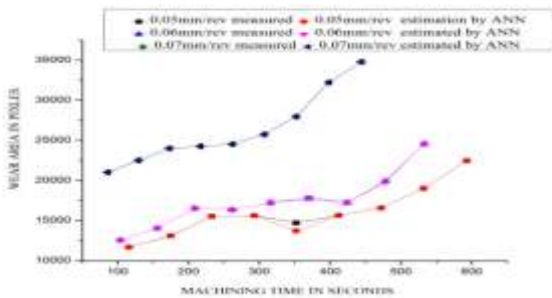

Fig.6.ANN Estimates of wear area at Spindle Speed450rpm and Depth of Cut of 0.2 mm

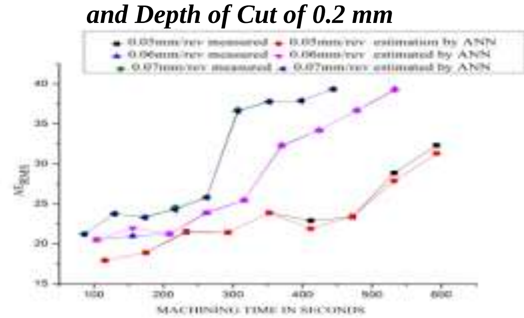

Fig.7.ANN Estimates of AE RMS at Spindle Speed450rpm and Depth of Cut of 0.2 mm

ANN estimates have ascertained the creation of trend of machine vision and AE parameters regardless of the cutting conditions. Even better correlations have been observed at high feeds, wherein large scale tool wear resulted in higher magnitude of vision and AE parameters. Further estimation of machining performances was carried out for Nimonic75 material using ANN

IV. CONCLUSIONS

The estimation of machine vision and AE parameters to assess the tool status of turning process while machining Nimonic75 using coated carbide insert was done using ANN. The relationship between input and outputs of process parameters has been carried out to theoretically estimate the tool status. The following observations were drawn

- The performance assessment of optimized network was done based on two parameters i.e. regression coefficient, R and MSE.
- The optimum topology obtained was 4-12-1.
- The tool status was assessed via wear area, perimeter, AE_{RMS} and AE_{COUNT} and these parameters were deemed as inputs to the ANN topology to estimate the respective parameters. The trend of wear area is created with the 4 inputs to respective ANN of 12 hidden neurons being machining time, AE_{RMS}, AE_{COUNTS} and perimeter.
- As observed from all the established trends have been found to exhibit higher and better correlation at higher cutting conditions

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