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Monitoring and control of manufacturing process to assist the surface workpiece quality when drilling

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Abstract

There is a variety of reasons for the installation of a monitoring system in a manufacturing process. Hole-making mainly drilling is one of the most common operation used and usually is carried out as one of the last steps in the production process. Holes in rotating turbine and compressor disks are among the most highly-stressed geometric features of jet-engines. For manufacturers of jet-engine components it is important to assess the quality of these at an early stage in the manufacturing of the product. The use of commercially available monitoring systems in hole-making has been successful in individual cases so far. Major reasons for this lack of effectiveness are the large material variations within one production batch, the overall difficult machinability of the materials applied, the small lot size which makes "teach-in" operations ineffective. The paper describes a design of adaptive control system for drilling process of aerospace critical components. The proposed system is directed towards the real time control of selected surface roughness parameter. Proposed model for monitoring and control consists of two subsystems: surface roughness prediction subsystem and decision making subsystem. The artificial neural network was employed to calculate surface roughness parameters throughout process monitoring indices such as torque M_z, force F_z, power P and cutting conditions feed f, cutting speed v_c. Due to ability to predict nonlinear behaviour and quickly calculate future values, artificial neural networks are ideal for both predictive and adaptive controllers. Test samples were nickel based super alloy Udimet 720 used in discs for gas turbine engines. The experimental results show that predicted values of surface roughness are very close to the values measured experimentally. Advantages of the proposed subsystem for surface roughness prediction are simplicity, computational power and speed, capacity and ability to learn from system changes as they become.

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Keywords: Adaptive control; Monitoring; Drilling; Surface quality; Neural networks

Nomenclature

f	feed rate [mm]
v_c	cutting speed [m/min]
Fz	cutting force [N]
Mz	torque [Nm]
P	power consumption [W]
Ra	surface roughness parameter [µm]
Ra_{lim}	limitation of the roughness parameter [µm]
Ra_{pred}	...predicted roughness parameter [µm]
VB	tool flank wear [µm]
CC	cutting conditions
PM	process monitoring
SI	surface integrity

1. Introduction

There is a variety of reasons for the installation of a monitoring system in a manufacturing process. Hole-making mainly drilling is one of the most common operation used and usually is carried out as one of the last steps in the production process in highly stressed aero engine components. Holes in rotating turbine and compressor discs belong to the most highly stressed geometric features of aero engines. Udimet 720 is well-known as a difficult to cut material used in aerospace industry in applications such as turbine discs.

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Consequently, it is important for engine manufacturers to assess the quality of these holes in an early stage of the manufacturing chain and not as late as in final inspection [1-3]. Surface quality is an important performance to evaluate the productivity of machine tools as well as machined components [4]. Many researchers have studied surface roughness parameters during machining processes with different approaches in recent years [5-7]. Due to ability to predict nonlinear behaviour and quickly calculate future values, neural networks are ideal for both predictive and adaptive controllers [8]. Pontes et. al. [9] employed Radial Basis Function (RBF) neural network for predicting of surface roughness in hard turning. The authors concluded that RBF networks can be an effective, efficient and affordable alternative for surface roughness in hard turning. Asilturk [10] et. al. used multiple regression model and Artificial Neural Network (ANN) for modelling and prediction of surface roughness when turning AISI 1040 steel. They developed prediction model for surface roughness in a term of cutting speed, feed rate and depth of cut using back-propagation training algorithms. Upadhyay and Mehta [11] proposed multiple regression and ANN models for in-process prediction of surface roughness in turning titanium alloy Ti-6Al-4V using feed rate, depth of cut, radial and tangential vibrations signals. Developed models can predict the surface roughness within reasonable accuracy making them suitable for in process prediction.

Objective of this study is to present the purpose of Adaptive Control System (ACS) for drilling process of nickel based super alloy Udimet 720 that will recognize the surface roughness of workpiece during machining and be able to adapt the operation to obtain surface with required values of Ra. The general requirement on surface roughness finished bolt holes in turbine discs is given Ra < 1,6 μm [3].

2. Concept of closed loop adaptive control system for drilling process Accent – ACC

The Accent – ACC scheme illustrated in Fig. 1 represents Adaptive Control Constrain System (ACCS). This system enables to adjust cutting conditions (feed and/or speed) to maintain the measured variables below their constraint limit values. ACC controls the machining parameters to maintain the maximum working conditions during the time – varying machining process. The artificial neural network (ANN) was employed to calculate surface roughness parameters (SI) throughout process monitoring (PM) indices and cutting conditions (CC).

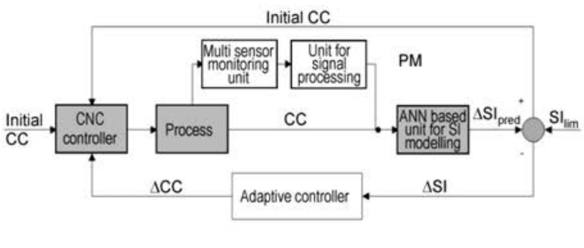

Fig. 1. Concept of closed loop ACCENT - ACC system.

3. Experimental work and data acquisition system

Results from experimental measurements performed at the Laboratoire Génie de Production – ENIT Tarbes - France [12] were chosen as input parameters for training and testing of neural networks, which were used as an alternative way to estimate the surface roughness in real time when machining. Forged nickel alloy Udimet 720 with diameter of 80 mm was used as testing material. This type of material is mostly used in the manufacture of aircraft turbine discs. Tested samples have undergone the same heat treatment used as a real disc. Employed cutting tool was coated (TiAlN) carbide tool with removable cutting head of diameter 15.5 mm. Length of drilled holes was 37 mm and were pre-bored with drill of 13 mm. The experiments were conducted on 3-axis vertical milling machine tool with NC Siemens 840D controller. Analog data was collected for the different cutting parameters by using sensors. Spindle power sensor Watt–Pilote was used to measure the power consumption for each setting of machining operations. Force measurements were realized by using Kistler piezo–dynamometer for 4 component measurement (Fx, Fy, Fz, Mz) type 9272. Variable cutting conditions have been selected according to aerospace components producers' recommendations and are listed in Table 1.

3.1 Artificial Neural Network for surface roughness (Ra) prediction subsystem

Constructive learning method has been used for design the proper structure of ANN. Learning process starts from the simplest to more complex on trial and error basis. The multi – layered feed forward ANN shown in Fig. 2 with back propagation Levenberg-Marquardt (LM) training algorithm was employed for prediction of surface roughness in drilling nickel based super alloy Udimet 720.

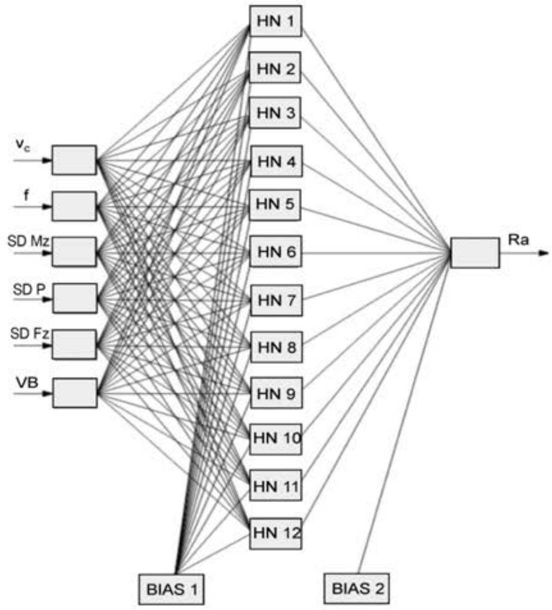

Fig. 2. Developed structure of ANN prediction model.

Table 1. Experimental conditions and results from drilling.

Trial number	Cutting conditions		Process monitoring signals			Measured variables	
	f [mm/rev]	v_c [m/min]	SD Mz	SD P	SD Fz	VB [mm]	Ra [μm]
1	19	0.1	0.06	2.73	111.60	60.00	0.57
2	19	0.25	0.14	8.02	327.80	198.30	2.81
3	25	0.2	0.14	5.03	270.40	181.30	1.41
4	25	0.15	0.08	3.02	162.30	104.20	1.27
5	25	0.1	0.05	2.49	133.90	79.00	0.95
6	30	0.1	0.13	1.83	118.30	80.00	0.92
7	30	0.15	0.53	2.39	154.10	123.20	0.92
8	30	0.2	0.28	4.68	302.00	154.10	0.88
9	30	0.05	0.12	1.82	117.50	83.50	1
10	15	0.25	0.14	5.38	173.50	132.20	0.97
11	15	0.2	0.08	2.76	89.10	84.70	1.99
12	15	0.15	0.08	3.06	98.60	65.90	0.94
13	15	0.1	0.09	2.88	92.80	74.20	0.49
14	19	0.1	0.10	3.09	126.17	66.63	0.4
15	22	0.125	0.13	2.95	139.60	100.10	1.4
16	22	0.175	0.10	3.86	182.40	124.70	1.46
17	19	0.2	0.10	2.85	116.68	114.44	0.92
18	25	0.1	0.17	2.08	111.86	132.73	0.76
19	22	0.2	0.10	4.51	213.40	133.20	1.08
20	22	0.15	0.11	3.18	150.40	118.30	1.13
21	22	0.1	0.54	3.28	155.20	59.10	0.56
22	19	0.2	0.09	2.43	99.50	81.50	0.89
23	19	0.2	0.09	3.88	158.40	117.80	1.24
24	25	0.1	0.13	3.00	161.00	94.20	0.98
25	19	0.1	0.13	1.37	55.93	81.02	0.43
26	19	0.2	0.15	7.44	303.90	179.40	1.24
27	22	0.15	0.12	3.84	181.91	163.00	1.13
28	19	0.1	0.04	2.76	112.58	77.80	0.39
29	15	0.2	0.11	5.69	183.68	123.73	1.5
30	22	0.15	0.21	4.43	209.75	169.80	1.09
31	15	0.2	0.14	4.98	160.72	103.92	1.19
32	19	0.1	0.07	1.70	69.40	95.90	0.59
33	19	0.1	0.09	1.56	63.82	81.28	0.39
34	19	0.1	0.12	1.90	77.48	76.90	0.37
35	22	0.1	0.11	1.99	94.10	64.90	1.17
36	22	0.1	0.11	1.53	72.49	86.48	0.71
37	22	0.1	0.12	1.91	90.37	81.73	0.59
38	22	0.15	0.06	2.77	130.90	113.00	1.09
39	22	0.15	0.09	2.97	140.67	122.77	0.98
40	22	0.15	0.14	2.93	138.67	126.06	0.93
41	15	0.1	0.07	1.98	63.70	51.60	0.6
42	15	0.1	0.11	1.26	40.59	66.20	0.37
43	15	0.1	0.12	1.34	43.08	66.70	0.38

The tangent of sigmoid function was used in the hidden layer whereas the output layer had pure linear neuron. Developed ANN consists of neurons divided into input layer, output layer and hidden layer. The neurons between the layers are connected by links having synaptic weights.

Designed ANN architecture consists of 6 input parameters (v_c, f, SD Fz, SD Mz, SD P, VB) and one output parameter (Ra).

The structure of developed neural network in Fig. 2 is 6-12-1 (6 neurons in the input layer, 12 neurons in hidden

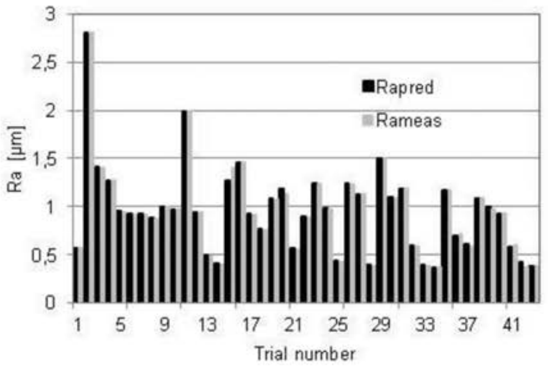

Fig. 3. The error profile of surface roughness parameter Ra for training, testing and validating patterns.

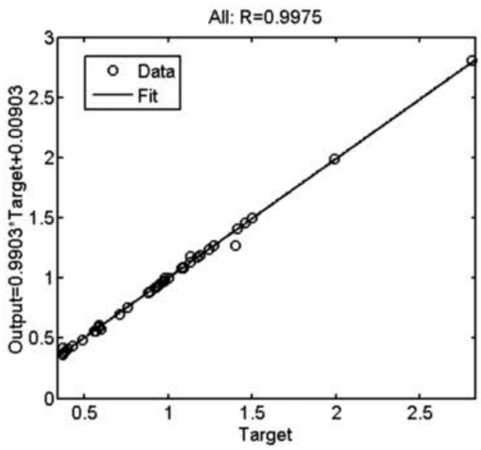

Fig. 4. Correlation of all dataset for surface roughness Ra.

layer and 1 neuron in the output layer) [13].Total number of experimental measured data (43) was divided into three data sets for training, testing and validation. Modeling, training and testing were realized by using Matlab Neural Network toolbox. The trained neural network model is validated and tested with regard to approximation property employing 4 random Ra values from experimental measurement trials (referred to as test and validation data set). The results predicted from ANN model are compared with experimental measurements as illustrated in Fig. 3. As shown in Fig. 4, there is very good correlation between ANN prediction and experimental measurements. Therefore it can be realized that the neural network presents a very good performance and predicted values of Ra are in accordance with those experimentally measured ones.

The correlation coefficient (R value) between the outputs and targets is a measure of model accuracy. For designed architecture of ANN for Ra prediction the value R for training, validation and testing datasets was equal to 1, and indicates excellent correlation. The R value for entire (all) dataset is 0.9975 and it represents high level of correlation.

It can be concluded that designed and trained ANN has high efficiency when predicting Ra by selected input parameters It can be seen from Fig. 3 that there is a strong relationship between the predictor variables (v_c, f, SD F_z, SD M_z, SD P, VB) and response variable (Ra). Comparing measured and predicted Ra values the highest percentage difference 9.47% occurred in pattern no. 15.

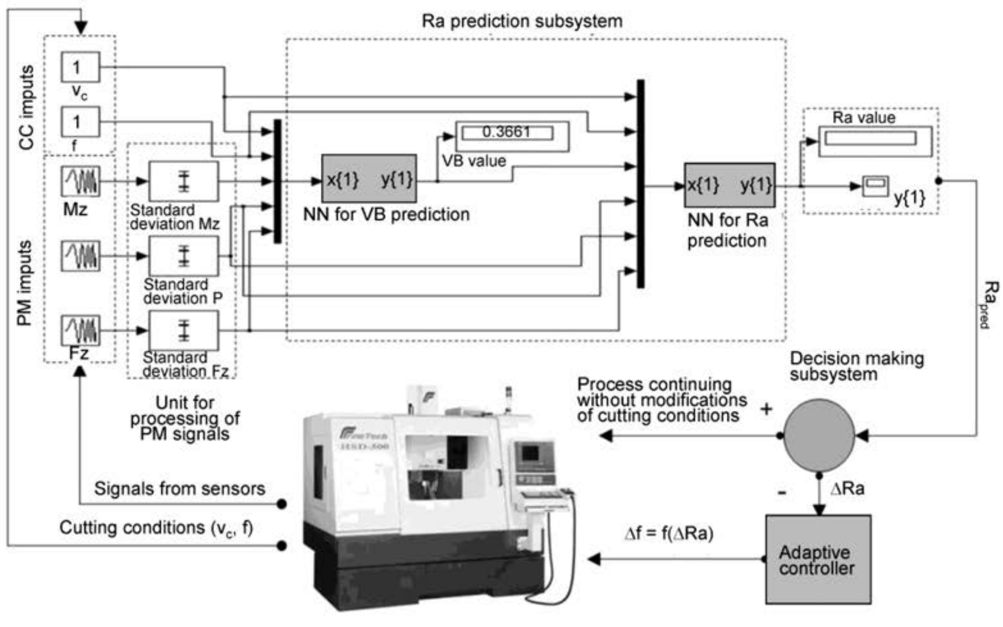

Fig. 5 Proposed model of ACCENT - ACC system for drilling process.

The correlation coefficient (R value) between the outputs and targets is a measure of model accuracy. For designed architecture of ANN for Ra prediction the value R for training, validation and testing datasets was equal to 1, and indicates excellent correlation. The R value for entire (all) dataset is 0.9975 and it represents high level of correlation. It can be concluded that designed and trained ANN has high efficiency when predicting Ra by selected input parameters. It can be seen from Fig. 3 that there is a strong relationship between the predictor variables (v_c, f, SDF_z, SD M_z, SD P, VB) and response variable (Ra). Comparing measured and predicted Ra values the highest percentage difference 9.47% occurred in pattern no. 15.

4. Design of adaptive control system for drilling process Accent – ACC

The proposed model of Accent – ACC system for drilling nickel based super alloy Udimet 720 is shown in Fig. 5. An ANN based in-process surface roughness prediction subsystem predicts surface roughness (Ra_{pred}) using process monitoring signals PM (force Fz, torque Mz, power P), cutting conditions CC (feed f, cutting speed v_c) and parameter of tool wear (flank wear VB). In the first stage of Ra prediction VB is determined by ANN model as a function of CC and PM due to stability and costs issues of the direct measurement methods. Output of VB calculation is subsequently sent to the ANN unit as an additional input to the ANN for Ra prediction. Then value of Ra_{pred} is sent to decision unit. In decision making subsystem the predicted surface roughness Ra_{pred} value is compared to the Ra_{lim} and thereafter ΔRa is determined according to Eq. 1.

$$\Delta Ra = Ra_{lim} - Ra_{pred} \tag{1}$$

A comparison between Ra_{lim} and Ra_{pred} determines whether variance of surface roughness is permitted or cutting conditions of drilling process are running out of the validated process window earlier defined by aerospace components producers. Based on deviation of surface roughness during machining (ΔRa) in adaptation system the feed rate is adjusted online to maintain surface roughness within acceptable limits. Maximum permissible value of surface roughness in drilling operation of highly stressed aero engine components is $Ra_{lim} < 1.6$ μm as was mentioned above.

Conclusions

In this study, ACC system for drilling process when machining nickel based super alloy Udimet 720 was proposed. Artificial neural network based subsystem for prediction of surface roughness parameter Ra by using sensor fusion was designed and tested to verify its prediction capability. The results show that predicted values of Ra are very close to the values measured experimentally. Advantages of the proposed subsystem for Ra prediction are simplicity, computational power and speed, capacity and ability to learn from system changes as they become. Future research is aimed at development of decision making subsystem and adaptive controller that will be able adaptively adjust feed rate to maintain surface roughness within acceptable limits. Results indicate possibility for further research in this area as well as applying adaptive control techniques to the manufacture. Benefits will be seen in term of elimination of costly part re-validation, reduced part manufacturing time, more consistent part quality and tool usage optimization.

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