Implementation of Adaptive Control for Cutting Tool Vibration Minimization

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Abstract **Present work is the implementation of adaptive control for machining process. It is another step towards the automation, in which the decision-making elements are added. When a component is being manufactured, the important variables are measured and then if needed be, the certain variables are altered with programmed limits, to get as accurately finished part as possible. The constraint of the adaptive control in present study is tool vibration. Adaptive Control Constraint (ACC) is used to constraint the tool vibration and finding the affected parameter. The outcomes of the regression analysis are validated with respect to the experimental observations. This study can further be used for the optimization of the affected parameter and can be fed in to the system for reconsideration**:

Keywords - Adaptive control, Regression, Machine tool, Vibrations, Automation, Experimentation

I. INTRODUCTION

Control system, implies by which a variable amount or set of variable amounts is made to adjust to a recommended standard [1]. It either holds the upsides of the controlled amounts steady or makes them shift in an endorsed way [2]. A control framework might be worked by power, by mechanical methods, by liquid pressing factor (fluid or gas), or by a mix of means [3]. At the point when a computer is engaged with the control circuit, it is normally more advantageous to work the entirety of the control frameworks electrically, in spite of the fact that intermixtures are genuinely normal [4].

There are several studies conducted on the application of optimization techniques and adaptive control mechanism along with several other methodologies by a number of researchers [5]. Adaptive control is a step towards automation, where in decision making elements are added [6]. When component is being manufactured, the important variables are measured and then if needed be, certain variables are altered with programmed limits, to get as accurate finished part as possible [7].

Adaptive control is the ability of the framework to alter its own activity to accomplish the most ideal method of activity [8]. An overall meaning of versatile control suggests that a versatile framework should be fit for playing out the accompanying capacities: giving nonstop data about the current situation with the framework or recognizing the cycle; contrasting present framework execution with the ideal or ideal exhibition and settling on a choice to change the framework to accomplish the characterized ideal presentation; and starting an appropriate adjustment to drive the control framework to the ideal [9].

In statistical modeling, regression analysis is a bunch of measurable cycles for assessing the connections between a reliant variable (frequently called the 'result variable') and at least one free factors (regularly called 'indicators', 'covariates', or 'features') [10]. The most widely recognized type of relapse investigation is direct relapse, in which one discovers the line (or a more intricate straight mix) that most intently fits the information as per a particular numerical measure [11]. For instance, the strategy for customary least squares figures the extraordinary line (or hyperplane) that limits the amount of squared contrasts between the genuine information and that line (or hyperplane) [12]. For explicit numerical reasons (see direct relapse), this permits the scientist to appraise the restrictive assumption (or populace normal worth) of the reliant variable when the free factors take on a given arrangement of qualities [13]. More uncommon types of relapse utilize somewhat various systems to gauge elective area boundaries (e.g., quantile relapse or Necessary Condition Analysis) or gauge the restrictive assumption across a more extensive assortment of non-straight models (e.g., nonparametric regression).

With the aim of implementing adaptive control methods to the machine tool vibration problem, present study has been conducted.

II. METHODOLOGY

. Adaptive control constraint (ACC) is one of the machining cycle control types [6]. The significant ACC of

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the frameworks can be contemplated dependent on the criticism control, boundary adaptive control/self-tuning control, model reference adaptive control, variable construction control/sliding mode control, neural network control, and fluffy control [14]. ACC is one of the effective methods of solving the above problems of cutting tool vibration [15]. ACC controls the machining parameters to maintain the maximum working conditions during the time-varying machining process [16]. The early versions of parameter adaptive control based ACC systems were developed using a simple on-line estimator for the process gain and an integral strategy to adjust the gain of an integral controller. The defects of this strategy are that the dynamics of the cutting process were neglected and no theoretical adaptive design technique was used. The adaptive controller consists of two functions: (a) On-line estimation of the parameters of the cutting process and (b) Real-time control.

The typical adaptive control constraints (ACC) are: tool vibration, tool force, chip load, spindle power and chip tool interface temperature. The constraint used for the present study is tool vibration. The strategies implemented in the analysis are: (a) root mean square (RMS) Component Calculation by regression equation. (b) Compare the RMS Value with Constraints value. (c) Find the responsible parameters for Tool Vibration. (d) Generate signal for altering the responsible parameter.

The ACC maximizes the feed rate under the condition that several measured or estimated variables of the cutting process are kept below or at respective constraint limit values are rather simpler to construct the systems than the rest. Adaptive control constraint has only been applied for practical systems [15]. The adaptive control program generates the desired feed rate according to the change of the cutting process.

First, the experimentation was performed and the corresponding regression equations were formulated for four dependent and three independent parameters using three different types of polynomials. Later on, concept of the adaptive control parameters was applied and the corresponding corrective action process was performed. The experimental observations are compared to the regression findings for the validation purpose.

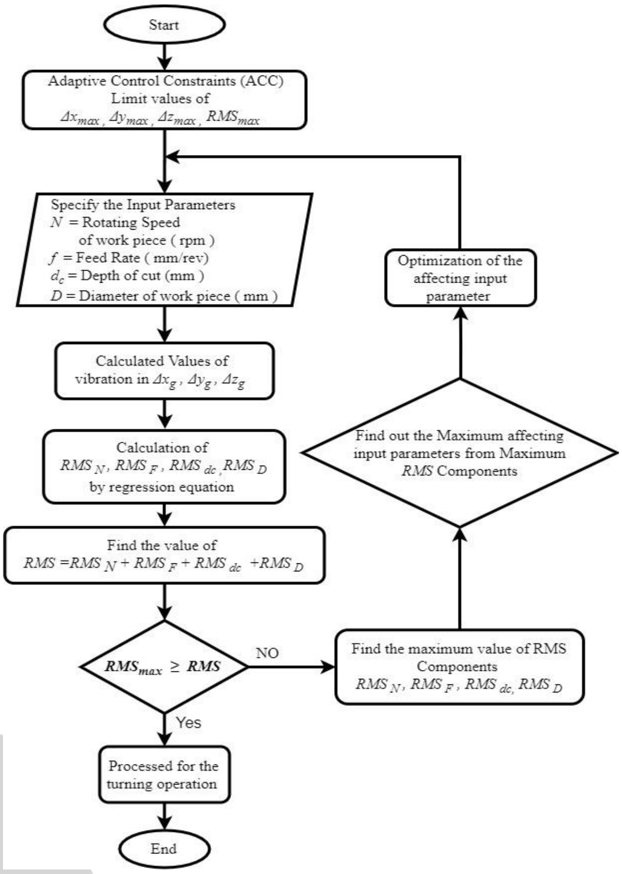

Fig. 1. Flowchart of ACC methodology

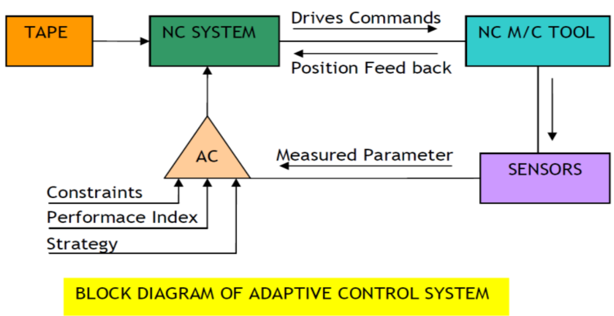

Fig. 2. Block diagram of adaptive control system

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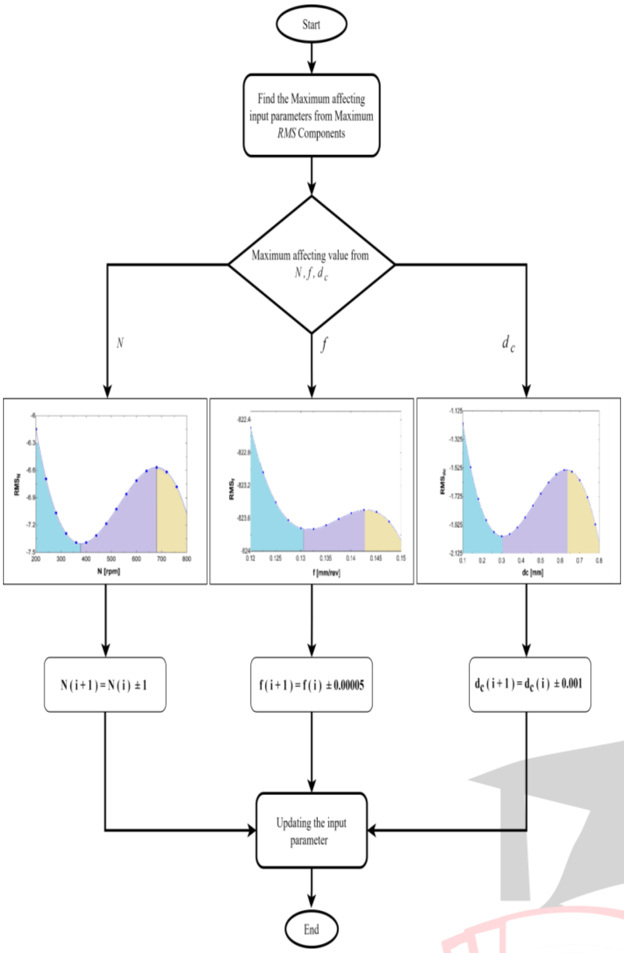

Fig. 3. Flowchart of ACC corrective action

III. REGRESSION ANALYSIS

In order to develop an empirical relation among the independent and dependent parameters the regression analysis has been performed using different polynomial orders as elaborated below.

Regression equations for assuming Polynomial relation of order 2 can be given as following:

$$\Delta Xg = 1.455 + 20.49f + 18.75f^2 - 98.12d_c + 2.10d_c^2 + 0.006D \quad (1)$$

$$\Delta Y_g = 88.92 - 0.01N - 93.52f + 3281.25f^2 - 7.696d_c + 8.297d_c - 0.926D + 0.014D^2 \quad (2)$$

$$\Delta Z_g = 71.65 - 0.006N - 809.2f + 2837.5f^2 - 3.215d_c + 3.531d_c^2 - 0.611D + 0.008D^2 \quad (3)$$

$$RMS = 60.31 - 0.006N + 642.5f - 2233.7f^2 - 4.883d_c + 5.544d_c^2 - 0.587D + 0.007D^2 \quad (4)$$

$$RMS_N = -0.006N \quad (5)$$

$$RMS_f = 642.5f - 2233.7f^2 \quad (6)$$

$$RMS_{dc} = -4.883d_c + 5.544d_c^2 \quad (7)$$

$$RMS_D = -0.587D + 0.007D^2 \quad (8)$$

Regression equations for assuming Polynomial relation of order 3 can be given as following.

$$\Delta Xg = 733.5 - 0.01N - 1724.6f + 128.1f^2 - 31635f^3 - 7.304d_c + 21.17d_c^2 - 15.88d_c^3 + 3.299D - 0.008D^2 \quad (9)$$

$$\Delta Y_g = 629.9 - 0.006N - 11625f + 82762f^2 - 196250f^3 - 19.7d_c + 44.48d_c^2 - 30.16d_c^3 - 5.496D + 0.135D^2 - 0.001D^3 \quad (10)$$

$$\Delta Z_g = 751.7 - 0.0523N - 16650f + 120625f^2 - 233890f^3 - 12.63d_c + 31.91d_c^2 - 23.65d_c^3 + 2.194D - 0.068D^2 \quad (11)$$

$$RMS = 844.8 + 4.794N - 18054f + 13169f^2 - 319666f^3 - 15.65d_c + 37.99d_c^2 - 27.04d_c^3 - 0.632D + 0.009D^2 \quad (12)$$

$$RMS_N = 4.794N \quad (13)$$

$$RMS_f = -18054f + 13169f^2 - 319666f^3 \quad (14)$$

$$RMS_{dc} = -15.65d_c + 37.99d_c^2 - 27.04d_c^3 \quad (15)$$

$$RMS_D = -0.632D + 0.009D^2 \quad (16)$$

Regression equations for assuming Polynomial relation of order 2 including cross-terms can be given as following.

$$\Delta Xg = 1.09 + 0.037N + 144.9f - 173.6f^2 + 8.193d_c + 1.987d_c^2 - 0.244D + 0.002D^2 - 0.089Nf - 0.001Nd_c - 58.50fd_c + 0.196fD + 0.038d_cD \quad (17)$$

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$$\Delta Y_g = 38.79 - 0.0423N - 287.4f + 1176.2f^2 - 57.54d_c + 11.48d_c^2 + 0.144D + 0.003D^2 + 0.138Nf + 0.001Nd_c + 207.7fd_c - 5.101fD + 0.421d_cD \quad (18)$$

$$\Delta Z_g = 29.51 - 0.014N - 23.08f + 1321.6f^2 - 25.65d_c + 6.021d_c^2 - 0.172D - 0.005D^2 - 0.007Nf + 0.003Nd_c + 56.76fd_c - 3.98fD + 0.303d_cD \quad (19)$$

$$RMS = 21.01 - 0.007N - 124.2f + 789.6f^2 - 30.1d_c + 7.593d_c^2 - 0.109D + 0.003D^2 - 0.08Nf + 89.75fd_c - 3.28fD + 0.288d_cD \quad (20)$$

$$RMS_N = -0.007N - 0.08Nf \quad (21)$$

$$RMS_f = -124.2f - 0.08Nf + 89.75fd_c - 3.28fD \quad (22)$$

$$RMS_{dc} = -30.1d_c + 7.593d_c^2 + 89.75fd_c + 0.288d_cD \quad (23)$$

$$RMS_D = -0.109D + 0.003D^2 - 3.28fD + 0.288d_cD \quad (24)$$

R-squared is an integrity of-fit measure for direct relapse models. R-squared measures the strength of the connection between your model and the reliant variable on an advantageous 0-100% scale. The R-Square values for each of the three dependent variables for all three considered polynomial types are presented in Table 1; and the 2nd order polynomial with cross-terms has been identified to be the most reliable one with the highest R-Square values of 86.47, 91.79 and 91.43 for three dependent parameters.

Table 1. R-Square values for the considered three regression fits

Polynomial Order	Direction	R-Square (%)
2	X	46.71
	Y	70.95
	Z	66.12
3	X	84.86
	Y	79.65
	Z	82.02
2 (Cross Term)	X	86.47
	Y	91.79
	Z	91.43

IV. VALIDATION OF REGRESSION RESULTS WITH EXPERIMENTAL OBSERVATIONS

The experimental observation for the input parameters: rotational speed (N) of the spindle i.e. work-piece, feed rate (*f*), depth of cut (DOC) (d_C) and the work-piece diameter (*D*) are presented in Table 2.

The regression equation using three different typed of polynomials, i.e. second order polynomial, third order polynomial and second order cross-term polynomial, as presented in the earlier section. Moreover, the expressions for the RMS value for all three types of polynomial equation and for all four independent variables (both combined and separate expressions of RMS) are formulated.

Based on the regression analysis, the vibration components are developed as tabulated in Table 3 and the percentage different between the respective vibrations components are presented in Table 4 along with the RMS values. Fig. 4, Fig. 5 and Fig. 6 depicts the impact of individual parameters namely for depth of cut, feed rate and rotation speed (rpm) respectively on RMS values.

Table 2. Experimental recordings

Sr. No.	N (rpm)	f (mm/rev)	d_C (mm)	D (mm)	ΔX_g Max	ΔY_g Max	ΔZ_g Max
1	225	0.12	0.2	32	0.72	2.49	2.3
2	225	0.13	0.4	37	0.48	0.42	0.42
3	225	0.14	0.6	42	1.31	0.61	0.76
4	350	0.12	0.2	32	0.61	1.43	1.31
5	350	0.13	0.4	37	0.37	0.89	0.41
6	350	0.14	0.6	42	1.17	0.6	0.19
7	500	0.12	0.2	32	0.81	1.74	1.92
8	500	0.13	0.4	37	0.5	0.62	0.03
9	500	0.14	0.6	42	1.28	0.28	0.24
10	800	0.12	0.2	32	0.79	1.92	1.85
11	800	0.13	0.4	37	0.42	0.45	0.11
12	800	0.14	0.6	42	1.06	0.14	0.35

Table 3. Regression findings

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Sr. No.	$\Delta X_{g\ Max}$	$\Delta Y_{g\ Max}$	$\Delta Z_{g\ Max}$
1	0.7531	2.665	2.26
2	0.4506	0.3829	0.448
3	1.182	0.6605	0.6952
4	0.6431	1.432	1.39
5	0.3406	0.8496	0.422
6	1.072	0.572	0.1748
7	0.8281	1.705	1.785
8	0.5256	0.5771	0.02705
9	1.257	0.2995	0.2202
10	0.7256	1.86	1.915
11	0.4231	0.4221	0.103
12	1.155	0.1445	0.3502

Table 4. Percentage difference between experimental and regression results

Sr. No.	$\Delta X_{g\ Max}$	$\Delta Y_{g\ Max}$	$\Delta Z_{g\ Max}$
1	-4.60	-7.03	1.74
2	6.13	8.83	-6.67
3	9.77	-8.28	8.53
4	-5.43	-0.14	-6.11
5	7.95	4.54	-2.93
6	8.38	4.67	8.00
7	-2.23	2.01	7.03
8	-5.12	6.92	9.83
9	1.80	-6.96	8.25
10	8.15	3.12	-3.51
11	-0.74	6.20	6.36
12	-8.96	-3.21	-0.06

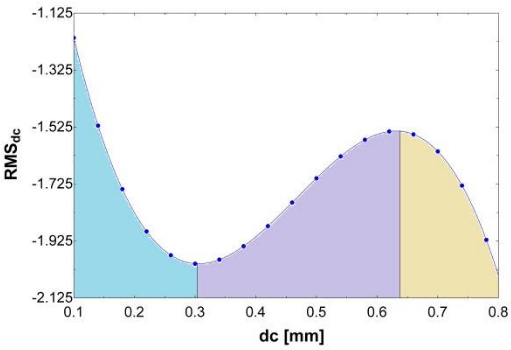

Fig. 4. RMS values for variable depth of cut

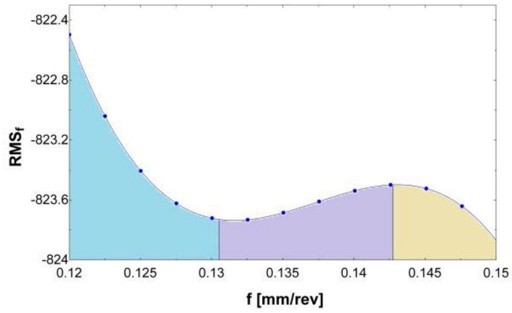

Fig. 5. RMS values for variable feed rate

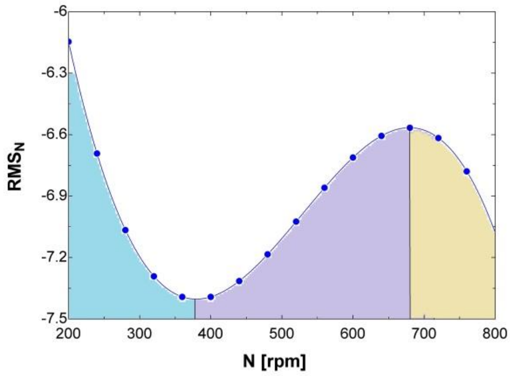

Fig. 6. RMS values for variable rotation speed

V. CONCLUSION

The aim of the present study was to perform the adaptive control methods to the machining tool application and validate the results with the regression formulations. The outcomes of the study indicates that the percentage different between the regression and experimental observations is found to be less than 10%. Hence, the proposed methodology is validated for the present application and can be used with decent reliability. The present study will benefit future researchers in defining the regression equations and using the same for different input conditions which will reduce the experimental cost requirements and will provide reliable predictions.

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