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Evaluation and Development of Advance Control Strategies Which Uses Pattern Recognition Technique for Nonlinear System

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***Abstract*—A general controller evaluation method is introduced, based on robustness criteria of well-known PID Controller formulate for process of non-linear systems using experimental of coefficients for flank wear of dynamic models obtained are calibrated with the actual conditions. These developed models will be used for the simulation of flank wear and using control variable such as cutting speed; the flank wear will be controlled. For model validation, the flank wear is estimated using a non-linear model. In the present work, an attempt has been made to control the flank wear during turning of on-line cutting process using the Fuzzy Logic Controller and Neural network based on self-tuning of PID controller approaches. Those approaches are treat the material as dynamic system and involve developing state space models from available material behavior model. The evaluation of performance criteria can be compared for those approaches of PI controller with Neural network and Fuzzy PID controller based on self-tuning of PID controller. Simulation studies are carried-out for the non-linear system using MATLAB software.**

***Index Terms*—Tool wear estimation, Flank wear, Dynamic system models, turning of PID-Controller, Neural network based on self-tuning of PID controller, Fuzzy Logic Controller.**

I. Introduction

Within the control community a huge no of results have been presented, where new or modified control strategies have been compared with different experimental flank wear models. Too often such comparisons are not objective since, only some of performance and robustness issues are considered. Typically Productivity and quality in the finish turning of hardened steels can be improved by utilizing predicted performance of tools. There are many parameters such as cutting speed, feed rate and tool nose radius that are known to have a large impact on surface quality. Tool wear is an important factor directly affecting the surface quality of machined parts. The direct measurement of tool wear in real time during cutting operation is an impossible task. There are already considerable research efforts affected in modeling the correlation between the measurable variables such as cutting force, temperature and tool wear. The results show that the cutting force provides significant information about the state of machining process and tool wear.

There are four important types of wear to be considered. They are crater wear, major flank wear, minor flank wear and nose wear. All of them are important but the amount of flank wear is often used in determining the tool life. The present work includes development of mathematical model and comparison with experimental results. Some important factors like the index of diffusion, wear co-efficient, the rate of increase of normal load with respect to flank wear and the hardness of tool influencing the flank wear were used as input parameters to develop the mathematical model. The developed mathematical model is used to relate the wear to the input parameters for a turning operation. The model is then used to predict the tool wear [7].

II. Objective Of The Present Study

The aim of present work is to develop a model to predict flank wear and compare it with the experimental results. Consider the SISO system in figure1, where first step is assumption of empirical models for flank wear in terms of cutting parameters and cutting forces. Next step is experimentation. Flank wear is obtained as a function of cutting speed, feed, depth of cut and cutting forces. The proposed dynamic model contains certain constants. Evaluation of constants for the proposed dynamic model has been done. The simulation and control of flank wear and comparison of the approaches of controllers have been performed.

III. Problem Description

The control of flank wear in metal working processes is needed for better quality. A methodology for computations of optimal control parameters during turning process for flank wear control is proposed. This approach is based on design and implementation of conventional PI controller with Fuzzy Logic Controller and Neural network based on self-tuning of PID controller through simulation. It involves developing state space models from available material behavior model. The non-linear flank wear model contains many of the important variables such as cutting force, flank wear, cutting temperature, feed, depth of cut and the cutting speed. In this model, flank wear is separated into two components: One caused by abrasion (W_{f1}) and the other by the diffusion (W_{f2}).

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These two components are used as state variables. The input to the process is cutting speed V_c. The model is given by the following equations.

$$\overset{*}{W}_{f1} = \frac{-V_c}{l_o} W_{f1} + \frac{V_c}{l_o} K_F \frac{F_c}{fa}\cos(\alpha r) \quad (1)$$

$$\overset{*}{W}_{f2} = K_D \sqrt{V_c}\exp\left[\frac{-A_e}{273+\theta_f}\right] \quad (2)$$

$$F_c = F_o + aC_w W_f \quad (3)$$

$$F_o = \left(K_4 f^{n1}(1-K_5\alpha r) - K_6 - K_7 V_c\right)a \quad (4)$$

The tool wear W_f is the sum of two components of the flank wear W_{f1} and W_{f2}.In the above equation αr is an effective rake angle; C_w,l_o,K_F,K_D,K_4,K_5 K_6,K_7,n_1 and are the model parameters, depending on the cutting conditions and tool work piece combinations. F_o is the vertical component of the initial cutting force for the sharp tool. θ_f is the tool-work piece temperature on the flank side of the tool. An alternative way to obtain the tool-work temperature is to calculate it using an empirical relation.

$$\theta_f = K_T V_c X f^y a^z F_c \quad (5)$$

Another relation is given by

$$\theta_f = K_9 V_c^{n2} f^{n3} + K_{10} W_f^{n4} \quad (6)$$

where K_T,X,y,z,K_9,K_{10},n_2,n_3 and n_4 are the model parameters, depending on the cutting conditions and tool work piece combination. The model in state variable equations are given by

$$\overset{*}{X}_1 = aK_2C_w(X_1 + X_2 + X_3) + K_2F_o \quad (7)$$

$$\overset{*}{X}_2 = \frac{1}{\tau}\left(K_oF_o - X_2\right) \quad (8)$$

$$\overset{*}{X}_3 = aK_1C_w\left(X_1 + X_2 + X_3\right) \quad (9)$$

$$F_C = F_o + aC_wW_f \quad (10)$$

Where X_1,X_2 and X_3 are the variables.

$$W_{f1} = X_2 + X_3 \quad (11)$$

$$W_{f2} = X_1 \quad (12)$$

$$W_f = W_{f1} + W_{f2} = X_1 + X_2 + X_3 \quad (13)$$

Where K_o, K1, K2, Cw and τ are model parameters [1].

The integrator provides the conversion from wear-rate to wear. The mechanically activated mechanism is represented by a first order lag with a time constant, which varies inversely with the cutting speed. The total wear W_f at any time is the sum of the wear due to the thermally activated mechanism W_{f1} and the wear due to the mechanically activated mechanism, W_{f2}. A step change in cutting speed is given and the open loop response for tool wear is given in Figure 1.

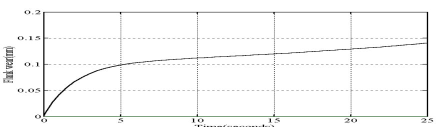

Figure 1: Open Loop Response to Estimate Controller Parameters

The transfer function for the above model is given by

$$G(s)=\frac{K}{\tau s+1} \quad (14)$$

Where τ =63.2% of maximum value corresponding to time axis value, K =. $\frac{change(in)output}{change(in)input}$

Therefore the transfer function for the tool wear model is given by

$$G(s)=\frac{0.0040}{4.84S+1} \quad (15)$$

IV. Conventional Control System

The function of a controller is to receive the measured process variable (pv) and to compare it with the set point (sp) so as to produce the actuating signal (m) that drives the process variable to the desired value. Thus the input to the controller is the error (sp-pv). Depending of the relation between the error and the controller output signal, controllers are classified as Proportional, Proportional + Integral (PI), Proportional +Integral + Derivative (PID) controllers [3].

V. Design Of Pi Controller For Non-Linear System (Tool Wear)

Determination of the controller parameters to provide the desired response is known as controller tuning. Controller tuning can be done by using synthesis method. Design of controller by synthesis method is one of the recommended methods in process control. However the synthesis method is applicable only for open loop stable process in order to get a stable controller. Hence, the unstable process must be stabilized using a proportional controller [4].

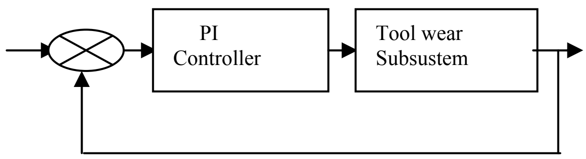

Figure 2: Block diagram of conventional PI Control System

The synthesis controller is the combination of two parts. The first part compensates for the process transfer function and the other is used to obtain a specified closed loop response of the controlled variable to the set point. When the process transfer function does not have dead time, the closed loop transfer function becomes

$$\frac{Y(s)}{X(s)} = \frac{K_p}{\tau_c s+1} \quad (16)$$

The closed loop time constant τ_c can be adjusted to shape the response of the loop, the smaller the τ_c the faster controller response. Thus τ_c provides a convenient parameter to reach a compromise between fast approach to set point and acceptable variations in the controller output.

The PI controller parameters are

$$K_c=\tau/k_p\tau_c \quad (17)$$

$$T_i=\tau \quad (18)$$

From the transfer function model

K_c= 250.985 and T_i=51.856 secs

VI. Simulation Results Using PI Controller

The simulation results of PI controller for different tool wear set points changes are shown in Figures 3& 4.

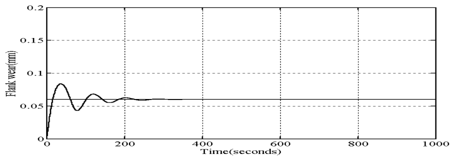

Figure 3(a) Response of Flank wear under PI controller for set point =0.06

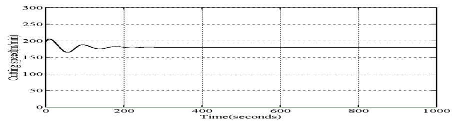

Figure 3(b) Output of PI controller for (input to the plant)

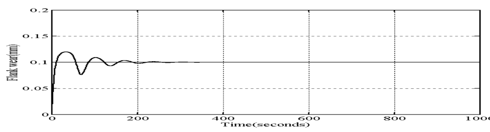

Figure 4(a) Response of Flank wear under PI controller for set point =0.1

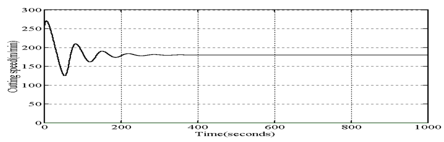

Figure 4(b) Output of PI controller (Input to the plant)

VII. Aritificial Neural Network

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons by compare with Artificial Neural Network (ANN) as shown the figure 5(a&b) [5].

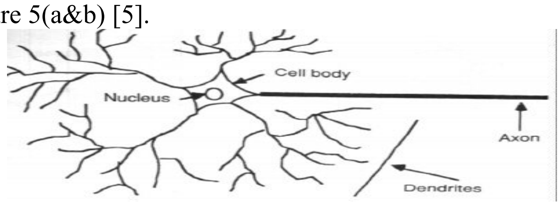

Figure 5(a): Biological Neural Network

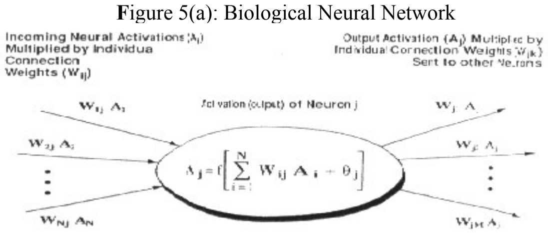

Figure 5(b): Artificial Neural Network

VIII. Development of Neural Network Based on Self-Tuning of PID Controller (Neuro PID Control)

Fine-tuned values of PID controller parameters are used as targets for development of Neural network based on self-tuning of PID controller to generate requisite control signal depending on error signal. The three-layered neural network constructed using Matlab/Sumlink tools, Back Propagation (BP) algorithm implemented to train the network for desired targets by assigning training parameter goal to $1e^{-13}$, which consists of an input layer, an output layer, and at least one hidden layer of non-linear model (flank wear model) processing elements (neurons). For simplicity, the three layered BP Neural network is explained briefly here. The input-output neurons relationship of BP Neural network at the m-th layer can be described as follow:

$$net_K^m = \sum w_{kj}^m \, out_j^{m-1} \tag{19}$$

$$out_j^m = f(net_j^m) \tag{20}$$

Where m is the number of layers, net_K is a total input of a neuron k, out is an output of a neuron j, W_{jk} is the weight between neurons j and k, and sigmoid function is normally used for f (.). In the BP algorithm, to minimize the cost function j which can be expressed as follows:

$$J = \frac{1}{2}\sum_k (r_k - out_k)^2 \tag{21}$$

Where r_K and out_K are respectively, a given reference value and an out of the output layer at k-th neuron. The weights are updated by

$$\Delta w_{kj}(n) = -\eta \frac{\partial j}{\partial w_{kj}} + \alpha \Delta w_{kj}(n-1) \tag{22}$$

Where $\eta > 0$ and $\alpha \geq 0$ are learning rate and momentum rate respectively.

The self-tuning control (STC) methods have been proposed to achieve effective, robust, and optimal method for adjusting the parameter values of some control systems. Learning method is to treat the Neural networks as pattern recognition system; this proposed learning method is based on neural network self-tuning control system as shown in figure 6. The basic idea is how to use the output error e(n)= r(n)-y(n) as a learning signal for the BP Neural network to adjust the parameters of PID controller where r(n) and y(n) are respectively, a reference value and a non-linear plant output at time(n). In the BP algorithm, the weights of the Neural network can be updated by back propagating the learning signal when the derivative can be expanded using the chain rule from equation (22), to minimize the cost function J.

Artificial Neural Network (ANN) improves the response obtained in the Ziegler-Nichols method. Self-tuning has considerable potential for control problems since it provides a systematic and flexible approach for dealing with uncertainties non-linearties, and time-varying parameters. Correspondingly, in recent years, the current interest has been focused on design of self-tuning controller by using

NNs. In this work, a method using a BP NN is proposed to realize the real time self-tuning of adaptive NN PID controller as shown in figure 6, through the computer simulations and some experiments to the linear and non-linear systems. Therefore, the proposed Neural network based on self-tuning of PID controller shows great advantages in real-time applications [6].

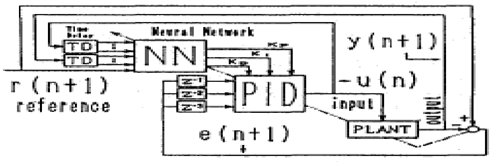

Figure 6: Self-tuning PID by neural network

IX. Simulation Results Using Neural Network Based On Self-Tuning Of PID Controller (Neuro PID Control)

The simulation results of flank wear for various set points under neural network based on self-tuning of PID controllers are shown in Figures 7& 8.

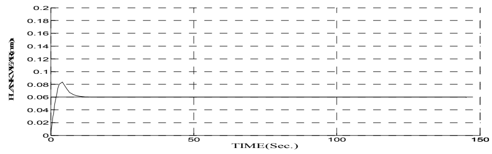

Figure 7(a) Response of NeroPID control (S.p=0.06)

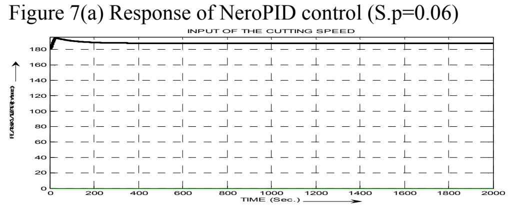

Figure 7(b) Output of Neuro PID (I/ P to the plant)

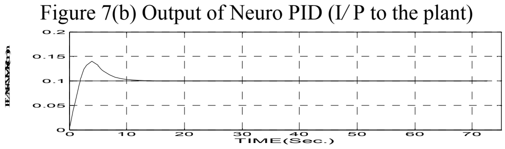

Figure 8(a) Response of NeroPID control **(S.p=0.1)**

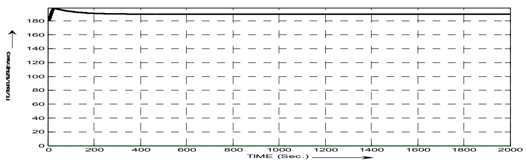

Figure 8(b) Output of Neuro PID (I/ P to the Plant)

X. Fuzzy Logic Controller

Fuzzy logic controller is excellent at developing human-made systems that can perform the same type of information processing that our brain performs. Fuzzy logic systems base their decisions on inputs in the form of linguistic variables derived from membership functions which are formulae used to determine the fuzzy set to which a value belongs and the degree of membership in that set. The variables are then matched with the preconditions of linguistic IF-THEN rules (fuzzy logic rules) and the response of each rule is obtained through fuzzy implication. To perform compositional rule of inference, the response of each rule is weighted according to the confidence or degree of membership of its inputs, and the centroide of the response is calculated to generate the appropriate output. At present, there is no systematic procedure for the design of fuzzy logic systems. The most straightforward approach is to define membership functions and rules subjectively by studying an existing controller and then testing the design fails the test. A simple fuzzy logic control system is shown in Figure 9. [8]&[9].

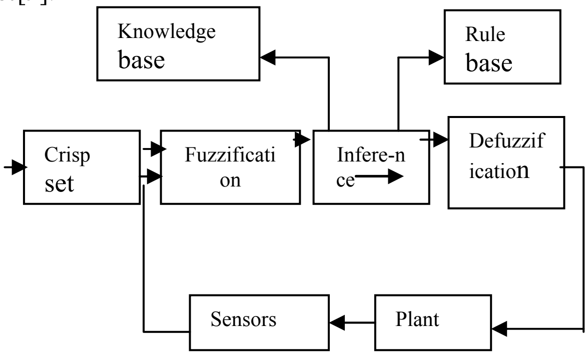

Figure 9 Block diagram of FLC System

XI. Simulation Results Using Fuzzy Logic Basis Function Of PID Controller

The simulation results of flank wear for various set points under Fuzzy Logic basis function of PID controller are shown in Figures 10& 11.

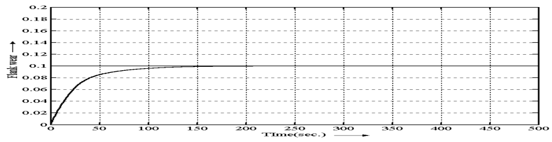

Figure 10(a) Response of FLC PID Controller (set point =0.06)

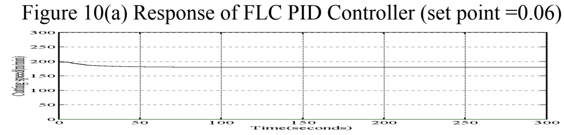

Figure 10(b) Output of FLC (input to the Plant)

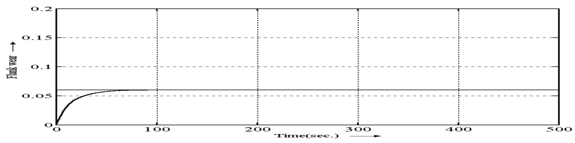

Figure 11(a) Response of FLC PID Controller (set point=0.1)

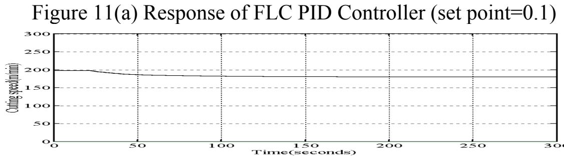

Figure 11(b) Output of FLC (input to the plant)

XII. Results And Discussion

The dynamic models developed are used for simulation. The optimization of process control parameters and process parameters are done. To optimize these parameters of PI Controller with Fuzzy Logic Controller and Neural network based on self-tuning of PID controller are used.

In the simulation of PI Controller with Fuzzy Logic Controller and Neural network based on self-tuning of PID controller, the cutting conditions are selected such that the flank wear become dominant. Such cutting conditions are obtained at high cutting speed. For a typical carbide tool and steel work piece combination, the cutting speed V_c is considered to be around 200m/min. The feed 'f' and depth of cut 'a' are chosen to be constant of 25mm/rev and 3mm respectively. In order to excite the system V_c is changed between 180m/min and 220m/min. The depth of cut 'a' is 3mm.

The simulation results of PI Controller for different flank wear set points are shown in Figures 3&4. The PI controller has large number of overshoots. Also the settling time is very large for different flank wear set points.

In Neural network based on self-tuning of PID controllers are defined for each controller input and output such that the three layered BP NN learning process is constant. The three layered BP NN with 4,12 and 1 neurons in the input, hidden and output layers, respectively, is used for the simulation results obtained by Neural network based on self-tuning of PID controllers are shown in Figures 7 & 8. Fuzzy Logic bais function of PID Controller (Fuzzy PID), 11 fuzzy sets are defined for each controller input and output such that the membership functions are triangular shaped and evenly distributed on the appropriate universe of discourse. The normalizing controller gains for error, change in the error, and controller output are $g_e = \frac{1}{2}, g_c = \frac{1}{2} \& g_u = 5$ respectively. The simulations results are obtained using Fuzzy PID are shown in figure10&11.Fuzzy PID and Neuro PID controller performances are better when compared to PI controller because there is an improvement in the simple criteria like, settling time use only isolated characteristics of the dynamic response criteria like ISE and IAE are based on entire response of the process. In the present work the performance criteria like ISE and IAE are calculated for flank wear control. The expressions are given by

$$ISE = \int_0^\infty E^2(t)dt \tag{23}$$

$$IAE = \int_0^\infty |E(t)|\,dt \tag{24}$$

where

$E(t) = y_{sp}(t) - y(t)$ is the deviation of the response from the desired set point.

The evaluation of performance of criteria for tool wears control as shown in table 1:1

TABLE1 1: SETTLING TIMES AND % OF OVERSHOOT FOR CONTROLLERS

Type of Controller	Setpoint for Flank wear	Settling Time (sec.)	% of over shoot	ISE	IAE
PI	0.06 0.10	350 400	50 45	0.036 0.128	2.106 5.780
Neuro PID	0.06 0.10	25 15	33 40	0.027 0.130	0.921 2.761
Fuzzy PID	0.06 0.10	60 170	-- --	0.003 0.0104	0.145 0.252

XIII. CONCLUSION

In this paper a general method for evaluation of controllers has been presented. The evaluation strategy involves three criteria expressing significant performance and robustness non-linear system properties based on comparing the responses of Neuro-PID controller with PI controller it is observed that there is an improvement in settling time and percentage of overshoot. As the cutting speed is increasing gradually the flank wear also increases. From the results, it is concluded that Neuro PID controller is the best suitable for tool wear control than PI control. Further improvement in this paper work can be compared Neuro PID and Fuzzy PID controller with the Neuro-Fuzzy PID controller for the non-linear system of tool wear control.

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