Design and Implementation of an Effective Control Strategy for Metal Cutting Process

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Abstract

In this paper, a mathematical model of cutting tool flank wear for the metal cutting process is used to evaluate a control approach for a nonlinear system. The dynamic cutting force and machining parameters work together to produce the flank wear model. When the flank wear model is calibrated to actual conditions, the nonlinear dynamic model is created. Many working conditions, such as softening and brittle fracture, cause tool failure during cutting and shorten the tool's lifespan. PID, PID based MPC, KALMAN and Extended KALMAN, Artificial Neural Networks, and Fuzzy Logic Controllers have been used in the paper work to manage the flank wear during the cutting process. The controller will be forced to limit the amount of tool ware, extending the life of the cutting tool.

Keywords: *Nonlinear dynamic model, Flank wear, MPC, KALMAN Filter, Fuzzy Logic Controller, Artificial Neural Networks*

Introduction

For example, a cutting tool may fail due to softening or brittle fracture, mechanical stresses or wear on the working component. Brittle fractures cause the cutting tool to be under a lot of pressure and severe loads. These failures cause the cutting operation to quickly freeze, and the tool to cut under chatter circumstances. The following failures can be avoided by carefully selecting cutting parameters such as feed, wedge angle, depth of cut, and so on.

Two distinct parts of the cutting tool are subjected to wear during the cutting process. Known as flankwear, it is the wear that occurs below the cutting edge of a tool, and it extends parallel to that edge. Carter wear, on the other hand, is wear that arises on the tool's face and forms a cavity away from the cutting edge. Due to its wear, a cutting tool has a limited lifespan. A direct correlation exists between productivity and cutting-tool wear.

Mechanical abrasion and thermal erosion are the two primary causes of tool wear. Despite the fact that both processes are taking place at the same time, the way they behave will vary depending on the cutting conditions. Mechanical wear is more prominent when low cutting speeds are used or when the work piece has a high machinability. Thermal wear occurs when high cutting rates are utilized on work components that are difficult to machine. The quick relative motion of produced chips on the surface causes friction. The cutting tool's phase is now subjected to friction at or over the recommended level. The result of scrubbing the work item is also received. As a result, this friction also affects the vehicle's flanks.

Methodology

The goal of this project is to create a model that can predict the wear on the flanks and then assess the findings. Models based on observations like cutting powers and parameters are first assumed. The next step is to conduct experiments, which follows feed, cutting pressures, cutting speed, and depth of cut all factor into the calculation of flank wear.

The proposed dynamic model's constants will be evaluated. There will be a simulation and control of flank wear, as well as a study of controllers' approaches.

An actuating signal (m) is generated by comparing the measured output to the set point. This allows the desired value to be obtained. The controller receives an error signal, which is just the difference between the set point and the measured output. There are various types of controllers based on the relationship between the error signal and the output value. (PID), (PI) and Proportional controllers are the three most common types of controllers.
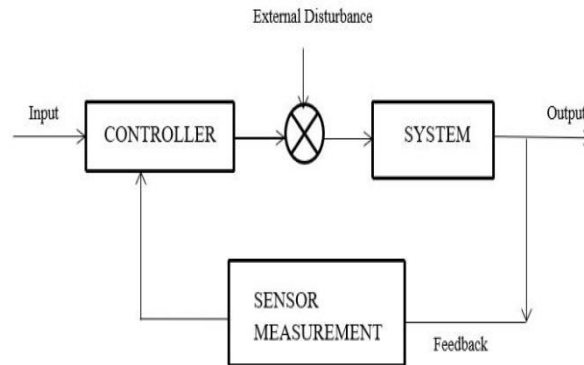

Fig 1: Flow Diagram

Results and Discussion

PID Controller: PID is derivation for proportional integral and derivative. Proportional is to multiply by a constant, if the proportionality gain is high it repeatedly produces the oscillations means overshoots the set point. Integral provides the addition of error over a certain interval of time. The error can become large if the error adds up. Sometimes the error may become small if the positive error is added to negative error. As the integral time decreases the integral functionality becomes more precise. The rate of change during certain interval is defined by derivative. The effect of the derivative is to alter the overshoot caused by the P and I.

All three of these are together combined to produce output, which is from measured errors from the system. With the combination of these three P, I and D factors any changes or disturbances are quickly eliminated.
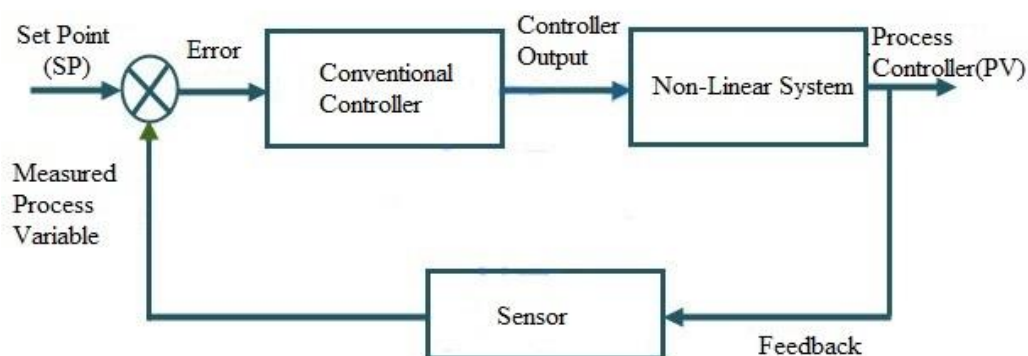

Fig 2: Conventional PID Control System
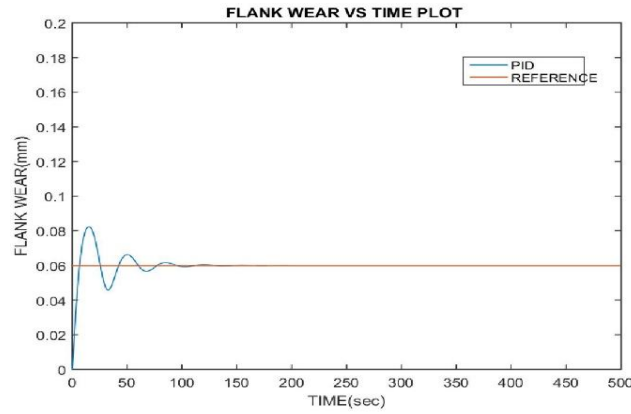
Simulation Results using PID Controller

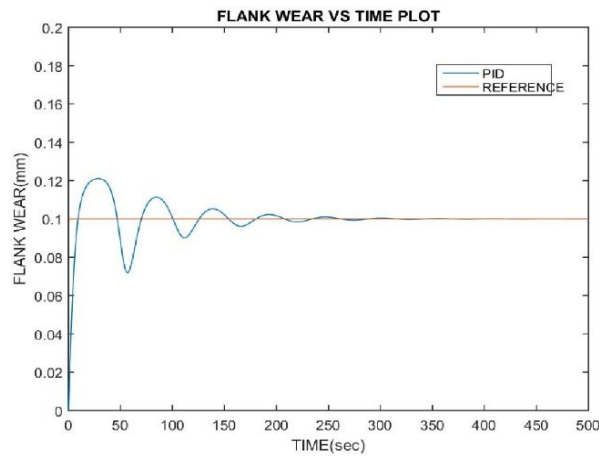
Fig 3a: PID response for 0.06 input

Fig 3b: PID response for 0.1 input

MPC Controller for Non-Linear Systems: Model predictive control is based on the prediction methodology, in which the future values of output are projected using the Model and current data. Multivariable control problems benefit greatly from this strategy. Calculating input variable changes is made easier with the use of predictions and measurements. The output variables are the control variables in MPC applications. Input variables are being adjusted at the same time. The PID controller lacks the ability to forecast future values, but the MPC can do so and apply the appropriate control measures. Two parameters are used in MPC prediction- Horizons of prediction and control. Predictive horizon is the time period in which the controller must analyze future control intervals. Control intervals will be optimal for the modified variables. It is the total number of variables that will be modified during the control interval.

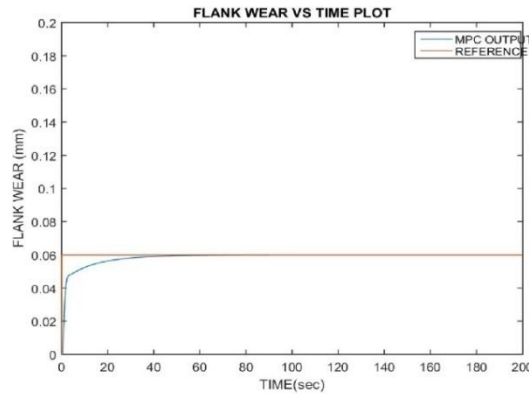## Simulation Results using MPC Controller
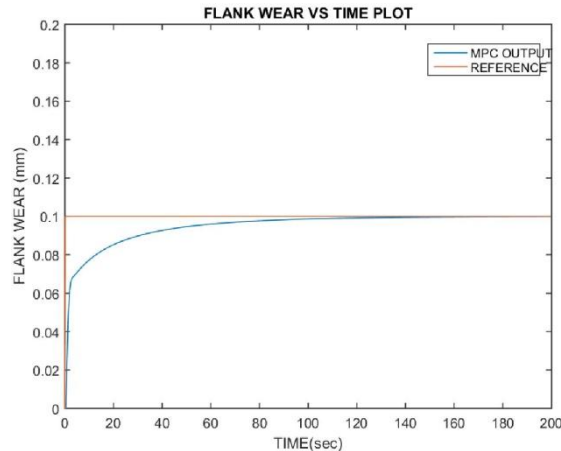

Fig 4a: MPC response for 0.06 input

Fig 4b: MPC response for 0.1 input

Kalman Filter for Non-Linear Systems: A straight Gaussian state space demonstration, known as the Kalman filter, is logically tractable. In honour of Kalman (1960), who proposed the use of the recursive connection to detect a flag of a known frame in the presence of irregular commotion inside the control hypothesis, it was given that name. It is an ideal estimator because it draws excitement parameters from off-the-charts and questionable impressions. A recursive approach is used to handle new estimators as they arrive. If the noise is Gaussian, the Kalman filter reduces the error in the evaluated parameters. That's why it's called the "optimal filtering method" (OFM). In addition, it extends the estimation to include the state's appraiser, making it more accurate. Indicator Corrector Sort Estimator is a collection of scientific conditions that provide an indicator corrector sort estimator that is optimal within its limitations. Kalman filters have received much investigation and application because to the clarity with which they are presented. This is especially true in the area of self-sufficient or assisted routes.
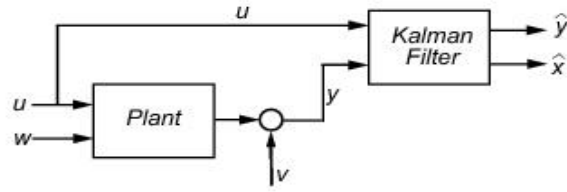
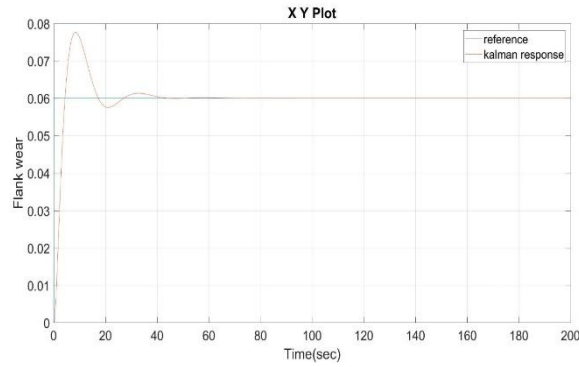**Fig 5: Kalman filter**

Simulation Results using Kalman Filter

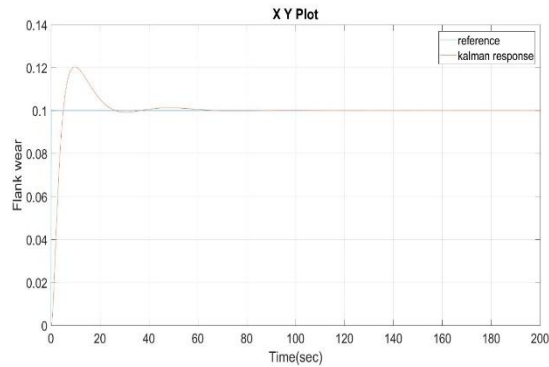**Fig 6a: Kalman response for 0.06 input**

Fig 6b: Kalman response for 0.1 input

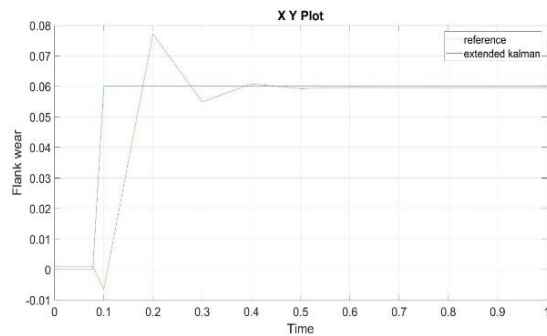## Simulation Results using Extended Kalman Filter

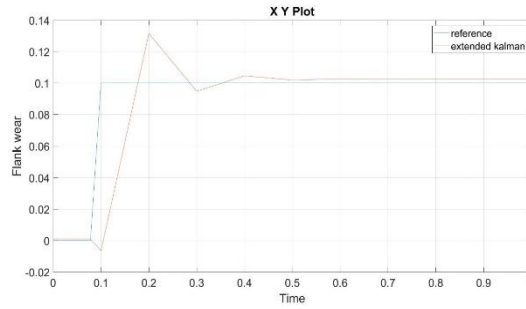**Fig 7a: Extended Kalman response for 0.06 input**

Fig 7b: Extended Kalman response for 0.1 input

Fuzzy Control: In order to achieve the desired performance, conventional controllers require a thorough understanding of the system and precise tuning. No precise scientific model of the system or sophisticated calculations is necessary for a Fuzzy logic controller. In a fuzzy logic controller, the control activity is addressed through the assessment of a set of fundamental semantic norms. However, a scientific model of the system isn't necessary for moving forward with the principles because all that's needed is an in-depth knowledge of the process to be regulated.

The fuzzy logic control system for the non-linear flank wear model is depicted in Fig.8, as shown.

The fuzzier, data base, rule base, decision-making, and defuzzifier are the five modules that make up the fuzzy logic controller. The inputs to the fuzzy controller are the error in output of surface roughness (e) and the change of error (ce) Several steps in the design of FLC for the non-linear flank wear model are outlined below:
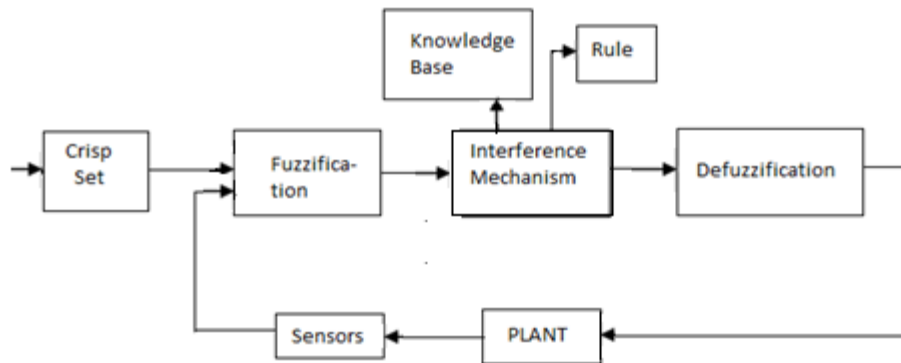

Fig 8: Functional Block diagram of Fuzzy Logic Controller System

Table 1: List of the parameters for design of the Fuzzy Logic Controller

Input parameters	Cutting Speed(m/min)
Number of Variables	07
Membership Function	Mamdani type of Triangular
Quantization levels	Error (e) and Change in error(ce)
Labels of Quantization levels	NB,NM,NS,ZE,PS,PM,PB
Defuzzification method	Centroid method
Decision making method	If then Else method
Number of Rules	49
Output of the plant	Cutting Force

Fuzzy controller Results

The obtained simulation responses of flank wear for different set points under Fuzzy Logic basis function of PID controller are shown in Fig 10(a)-(d).
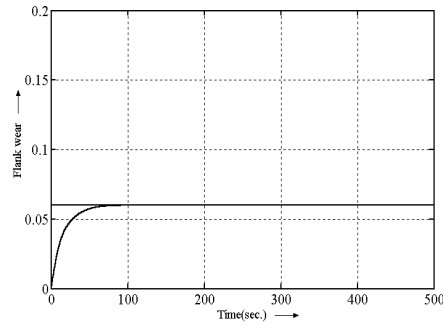

Fig 10a: Response of FLC {SP =0.06}

The Fig 10a shows the evaluation values settling time=100sec. and % of over shoot is nil, for the Fuzzy Logic basis function of PID controller of closed loop control system response based on input reference (Set point) is 0.06.
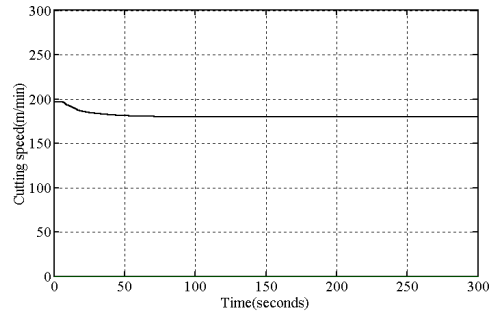

Fig 10b: Output of FLC

The Fig 10b shows that the cutting speed input varies from 180-220 (m/min), which is used as the input of the flank wear model of the plant in the closed loop controller system.
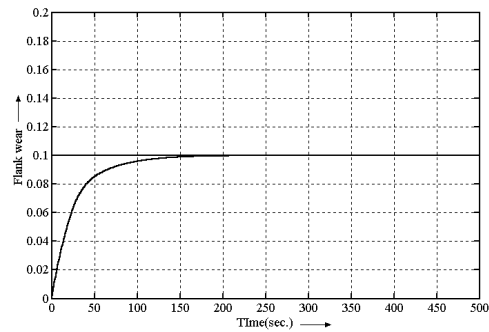

Fig 10c: Response of FLC {SP=0.1}

The Fig 10c shows the evaluation values settling time=170sec. and % of over shoot is nil, for the Fuzzy Logic basis function of PID controller of closed loop control system response based on input reference (Setpiont) is 0.1.
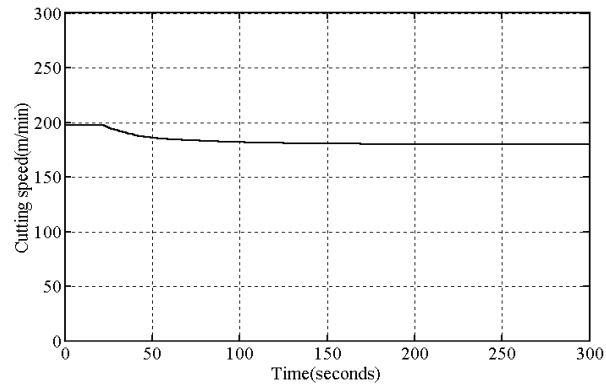
Fig 10d: Output of FLC

The Fig 10d shows the output of the cutting speed various between 180-220 (m/min), which is used to input of the flank wear model of the plant in the closed loop controller system.

ANN Based On Self-Tuning of PID Controller: The simulation results of flank wear for various set points under neural network based on self-tuning of PID controllers are shown in Figures 11a to 11d.
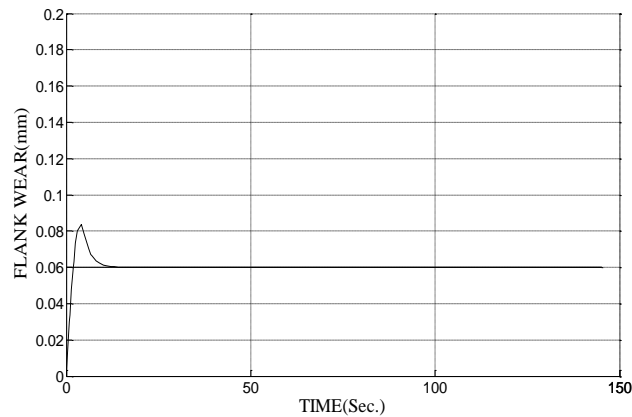

Fig 11a: Response of NeuroPID Control (SP =0.06)

The Fig 11a shows the evaluation values settling time=25sec. and % of over shoot =33%, for the tuning of PID controller using neural networks of closed loop control system response based on input reference(Set point) is 0.06.
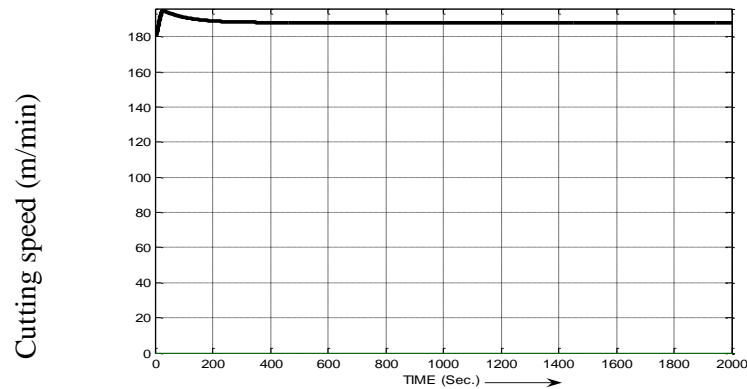

Fig 11b: Output of Neuro PID controller

The Fig 11b shows the input of the cutting speed various from 180-220 (m/min), which is used to input of the flank wear model of the plant in the closed loop controller system.
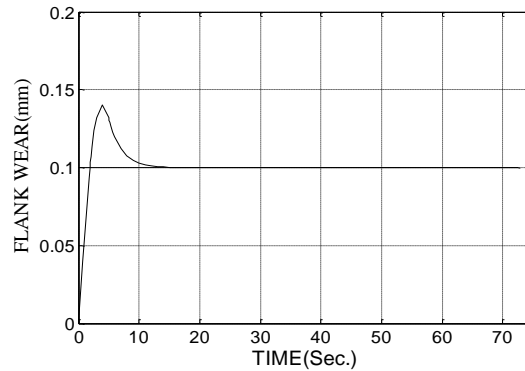

Fig 11c: Response of NeuroPID Control {SP=0.1}

The Fig 11c shows the evaluation values settling time=15sec. and % of over shoot =40%, for the tuning of PID controller using neural networks of closed loop control system response based on input reference (Set point) is 0.1.
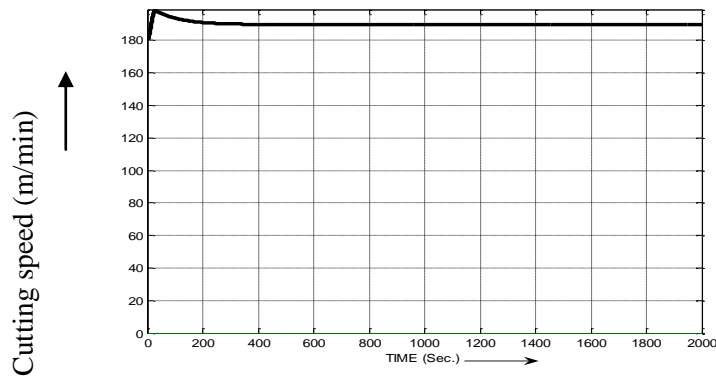

Fig 11d: Output of Neuro PID controllers

The Fig 11d shows the input of the cutting speed various between 180-220 (m/min), which is used to input of the flank wear model of the plant in the closed loop controller system.

Conclusion

The collected findings were evaluated, and it was discovered that the MPC performed significantly better than the PID, KALMAN, and Extended KALMAN filters in terms of characteristics such as settling time and % overshoot. Furthermore, when compared to the PID, KALMAN, and Extended KALMAN filters, the MPC controller produced fewer errors than the other three. As a result, it has been determined that MPC is the most appropriate strategy for this plant model.

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