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Full Length Research Paper

Fuzzing modelling of a single point lathe cutting tool

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A few modern industrial materials are of serious concern to the home model engineer turning with a light lathe machine. Virtually all turning is done using either carbon steel, high speed steel or tungsten carbide tipped tooling. This is mainly due to the fact that the newer and more exotic materials such as ceramic and diamond require high speed and rigid industrial machinery to operate correctly. The benefits of the new materials are more associated with optimising production and extending tool life than improving the surface finish. In this paper, a new intelligent based methodology employing fuzzy soft computing technique is proposed for improving the surface of a product during machining operation with a light lathe. Data was extracted experimentally from the existing turning tools and an improved geometry of the turning tool was modelled from this data. The studies have shown that intelligent based approaches can provide efficient and cost effective ways of optimising the performance of a lathe cutting tool with respect to the surface finish.

Key words: Modelling, simulation estimation, fuzzy control, depth of cut, feed rate.

INTRODUCTION

Machining is widely used for metal removal and it involves turning, milling, boring and cutting. The realisation of surface finish is a diagnostic tool that is needed to guarantee product functionality. Choice of optimized cutting parameters is very important to control the required surface quality. In fact, the difference between the real and theoretical surface roughness can be attributed to the influence of physical and dynamic phenomena such as: built-up edge, friction of cut surface against tool point and vibrations. The focus of this study is the collection and analysis of surface roughness and tool vibration data generated by lathe dry turning of mild carbon steel samples at different levels of speed, feed, depth of cut, tool nose radius, tool length and work piece length. A full factorial experimental design that allows considering the three-level interactions between the independent variables has been conducted. Vibration analysis has revealed that the dynamic force, related to the chip-thickness variation acting on the tool, is related to the amplitude of tool vibration at resonance and to the variation of the tool's natural frequency while cutting (Thomas et al., 2000). The quality of a surface plays an important role in the functionality of a machined product. Methods must be developed to control tool parameters during machining operation, so that a good surface finish can be obtained. Those methods also enable machine operators to adjust cutting machine parameters easily and within a shorter time. With these methods both material and time cost could save. A trial and error soft control method for improving the surface finish of a machined product is investigated with three controllers, namely: standard fuzzy PD type controller, a fuzzy PID-type controller and a fuzzy PID-type with a parallel added integral part. The soft control is based on the knowledge and experience of human operators, who are trained to control a lathe machine using linguistic rule of classical IF (cause) THEN (effect) ELSE form.

The control technique considered in this work is a special case of adaptive dynamic fuzzy that contains delays that account for the machining process past history. A standard fuzzy logic (N-FLC) can be slow to react to a sudden change but will always come to a solution, while a PID controller can find a target quickly and very accurately but may fluctuate first before settling. It is this fluctuation that may affect the rate of feed, which may result in a poor finish of cut, tool breakage and possible harm to the operator. Due to this fact, the

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methodology of fuzzy logic seems to be the best option to conventional modelling approach. The lathe tool can be characterised by optimizing one of its three properties, namely: material, geometry and force. In this article, the geometry parameters (tool clearance angle, rake angle, wedge angle) are considered. For improving the surface finish of turning process with light lathe a dynamic fuzzing soft computing technique is used. The optimization of lathe is performed by use of properties: material, geometry and force to obtain the proper cutting speed and feed for turning process. The experiment is applied at cutting of aluminum and mild steel with diameter of 30 mm by used tungsten carbide tool and HSS tool. The goal of this study is recording and analysis of workpice's surface roughness and tool vibration data generated by dry turning of mild carbon steel and aluminum samples, at various values of speed, feed, deep of cut and other geometric parameters of tool. The active control of machining process with lathe can be made with controllers, such as fuzzy PD, fuzzy PID and fuzzy PID with a parallel added integrate part than presents a better performance. One important step in analysis of tool behavior is the investigation of heat generation during turning process that is performed with an infrared camera for lathe tools of tungsten carbide and HSS, realized by altering the RPM, feed depth of cut and separately at aluminum and mild carbon steel workpieces. The variation of temperature due to these parameters has a direct influence about surface finish of workpiece which recommend introducing them in algorithm control of turning process.

A tool lathe model is performed by a fuzzy lathe system to model the controller, and the network is trained by using linguistic rules. These rules were supported by Matlab program and fuzzy methodology with Sugeno-Mandani interference method, which involves a fuzzy interference engine, based on various membership functions to development a predicted model and analysis the correlation function tests. The experiment involves using Matlab program for loading in data that contains the inputs and outputs of system. Prediction of fuzzy logic controller is used to predict the future state control of lathe tool under desire depth of cut and feed rate at varying tangential forces. The fuzzy network used for modeling lathe tool parameters by implementing of FLC Lathe system (Mandami) that has two inputs (DE ERROR-feed rate and ER ERROR-depth of cut) one input (roughness surface or surface finish) and 14 rules, which has the ability to automatically adjustment of fuzzy controller to the changing data. This modeling of fuzzy system represents an alternative for improving the conventional technique but can't substitute a supervision and control the stability turning system, being necessary other installation to resolve that. This work represents an alternative for improving the quality of workpice's finished surface by cutting with a traditional lathe, and the future authors' research with extinction at CNC lathe can be more efficiently to actual demand of machining market.

Related work

The turning operation is a combination of linear (tool) and rotational (workpiece) machine movements. The rate in IPR (inches/revolution) that the tool travels along or across the workpiece is referred to as the machine feed or the feed speed. The SFPM (surface feet/minute) or speed at which the part surface rotates is known as the cutting or surface speed. These two important criteria are selected to either maximize tool life and productivity or to balance them.

Selecting the proper cutting speed

Cutting speed is determined primarily by the machinability of the material and the hardness of the cutting tool. Machinability describes the ease or difficulty with which a metal can be cut. The machinability of a material has a direct correlation with the material's hardness, or its ability to resist penetration or deformation. There are a number of tests that measure materials hardness, but the most common test for machinability and hardness is Brinnel. Brinnel or BHN is stated as a number: the higher the BHN number the harder the material. Different material structures pose different problems for the machinist. With the cutting tool type being equal, look at what happens to the cutting speed as the materials Brinnel hardness increases. Advanced cutting mechanics involves the art of metrology that is the art/science of measurements consisting of the following three main areas:

i) Dimensional metrology (length, area and position).
ii) Surface metrology (roughness, straightness and flatness).
iii) Physical metrology (hardness, sub-surface finish and chemical composition).

In manufacturing engineering, the realisation of surface finish is a diagnostic tool in a batch of processes that are needed to guarantee product functionality. Therefore, surface finish can be used as a control parameter to guide engineers as shown in Figure 1. The overall fuzzy model can result in a virtual prototyping environment for design optimization (Martin and Ebrahimi, 1999). The turning process has been investigated by many researchers (Dan and Mathew, 1990; El-Baradie, 1991; Balkrishna and Shin, 1999). A model of the dynamic cutting force process for three-dimensional oblique turning operations has been reported in Weng-Hong et al. (2001). In using the conventional approach, the first step is to understand the physical system and its control requirements. Based on this understanding, the second

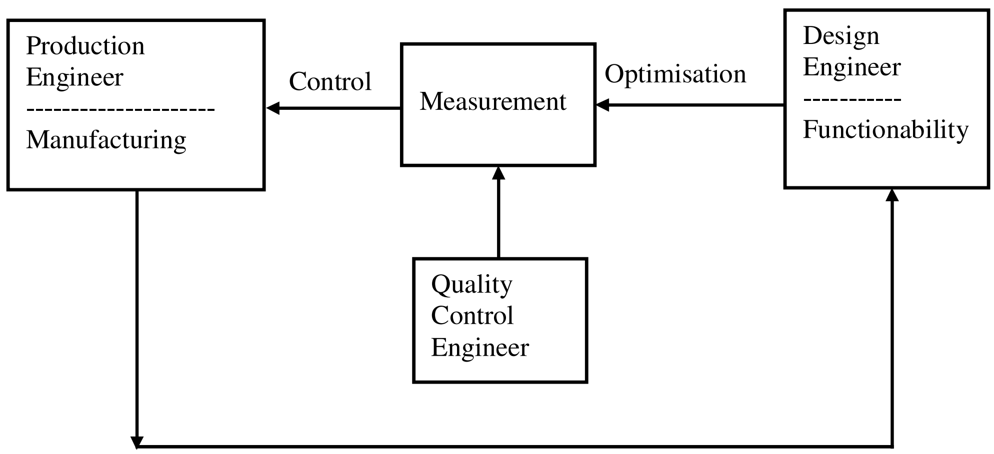

Figure 1. Surface finish control process.

step is to develop a model which includes the plant, sensors and actuators. The third step is to use linear or linearised system's control theory in order to determine a simplified version of the controller, such as the parameters of a PID controller. The fourth step is to develop an algorithm for the simplified controller. The last step is to simulate the design, including the effects of non-linearity, noise and parameter variations. If the performance is not satisfactory it is necessary to modify the system modelling, re-design the controller, re-write the algorithm (procedure) and re-try.

In the age of globalization manufacturers are constantly facing the challenges of quality, cost and lead time in order to survive in the cut-throat competitive market. The quality of machined components is evaluated in respect of how closely they adhere to set product specifications for length, width, diameter, surface finish, and reflective properties. Dimensional accuracy, tool wear and quality of surface finish are three factors that manufacturers must be able to control at the machining operations to ensure better performance and service life of engineering component. In the leading edge of manufacturing, manufacturers are facing the challenges of higher productivity, quality and overall economy in the field of manufacturing by machining. To meet the aforementioned challenges in a global environment, there is an increasing demand for high material removal rate (MRR) and also longer life and stability of the cutting tool But high production machining with high cutting speed, feed and depth of cut generates large amount of heat and temperature at the chip-tool interface which ultimately reduces dimensional accuracy, tool life and surface integrity of the machined component. This temperature needs to be controlled at an optimum level to achieve better surface finish and ensure overall machining economy. Drilling is one of the most important final operations in the construction of aeronautical components. In aeronautical applications parts are often drilled during final assembly. Stacks comprising different metal and non-metal materials, such as fibre-reinforced plastics (FRP) are frequently drilled, where the burrs that appeared at the interface between layers often result in parts being disassembled for subsequent deburring processes. Monitoring thrust force and torque in drilling enables drill wear to be estimated. Moreover, knowing the thrust force and cutting torque in advance may be of great help in estimating the effect of that force on the workpiece during the process. Various analytical, semi-empirical and numerical methods have been proposed to determine force and cutting torque levels before the drilling process begins.

The earliest studies of drilling were conducted by Armego et al. (1972 and 1984). Most of their work centred on studying conical-tip drill bits. More recent work on drilling includes the paper of Chandrasekharan et al. (1995), who developed a mechanistic model for any drill bit geometry, using a vectorial, abstract approach from which they arrived at a generalization for different types of drill bit that enables different behaviours to be studied. Altintas (2000) based his development for drilling on the introduction of the effects of shear and friction in a way similar to that used for milling models. Paul et al. (2005) studied the effect of the chisel edge taking into account geometrical parameters relative to the grinding operation that gives rise to that chisel edge. Most of the models proposed consider a static system, and take no account of the dynamic effect caused by the flexing of the tool or possible grinding errors in the production of edges. These points are considered in some studies that link initial drilling statuses with the shape and quality of the hole obtained, such as the papers by Gupta et al. (2003) and Gong et al. (2005). Some models, such as that of Strenkowski et al. (2004) combine an analytical, numerical approach based on the finite element method (FEM) to obtain the thrust force and torque in any drill geometry. Other papers (Lauderbaugh, 2003) seek to model the size of the burrs produced at the drill exit through a 2D numerical model. A more elaborate model is that of Guo and Dornfeld (2000), who present a 3D FEM model for simulating burr formation in the drilling of 304 stainless steel. Such a drill has not been used in many models published to date, excepting that by Zhao and Ehmann (2003), for spade drills for wood drilling. In the developed model, the contribution of the chisel edge to the torque has been rejected as proposed in Altintas (2000); because the cutting speed is low at this edge, this author finds that the chisel edge does not cut but only spreads the material sideways by an indentation mechanism. The effect of the chisel edge on the thrust force has been modelized as this author proposes in the same research reference. With respect to the specific coefficients of this model, two different approaches have been followed and compared, specific coefficients are depending either on the Z coordinate of edge points (Altintas, 2000) or on cutting speed and inclination angle (Chandrasekharan et al., 1998).

The main characteristics of the model are presented in the following studies, along with the obtaining of coefficients and a discussion of results. Fuzzy logic has great capability in capturing human commonsense and reasoning, decision making and other aspects of human cognition. Stein (2002) showed that it overcomes the limitations of classic logical systems, which impose inherent restrictions on representation of imprecise concept. The coefficients and constraints may be naturally modelled by fuzzy logic. Modelling by fuzzy logic opens up a new way to optimize cutting conditions and also tool selection. With fuzzy logic the first step is to understand and characterize the system behaviour by using our knowledge and experience. The second step is to directly design the control algorithm using fuzzy rules, which describe the principles of the controller's regulation in terms of the relationship between its inputs and outputs. The last step is to simulate and debug the design. If the performance is not satisfactory we only need to modify some fuzzy rules and re-try. The ideal surface roughness is a function of only tool feed and geometry. It represents the best possible finish which can be obtained for a given tool shape and corner radius (turning cutting tools are usually provided with the roundness corner) by the following theoretical expression:

$$R_a = \frac{0.0321 f^2}{r} \tag{1}$$

Where: R_a represents the height of the profile; f the feed and r the radius of round corner of cutting tool.

It is also known that such R_a can be achieved only if built-up-edge, chatter inaccuracies in the machine tool movements and other factors are eliminated completely. The most popular surface roughness parameter is R_a or average roughness parameter. It is the arithmetic average deviation from the mean line:

$$R_{\max} = \frac{l}{L}\int_0^l \left|y(x)\right| dx \tag{2}$$

Where L represents a sampling length; y the ordinate of the profile curve.

$$R_q = \sqrt{\frac{l}{L}\int_0^l \left(y(x)\right)^2 dx} \tag{3}$$

Both R_a and R_q are surface profile parameters. It is already known that roughness profile parameters can not give satisfactory results. Hence, it must be possible to introduce more profile parameters because of the 3-D metrology measuring instruments.

ANALYSIS OF GENERATED TEMPARATURES

The experiment was carried out to investigate tool behaviour when loaded without lubricant during contact between the tool and the material. The data collected was expected to guide in the selection of the right tool, considering heat generated by friction and the ability to cut at red-hot temperature.

Instrument

The instrument used is FLIR Therma Cam P60, Infra-Red Camera.

Positioning camera

The camera was positioned approximately 1 m away from the point of a tool in order to protect the lens from been hit by hot sparks from a flying swarf.

Lathe turning tool used

i) Tungsten carbide tool.
ii) High speed steel tool.

Aluminium and mild steel of both 30 mm diameter were used for the experiment. After each run of a cut, the tool was cooled to room temperature before a different depth of cut was set. The rotational speed of the machine was also altered, as well as the feed rate. Note: the work piece was not cooled until the last run was reached in order to examine the heat transfer. Figure 2 indicates

Figure 2. A representation of heat generation during the machining process.

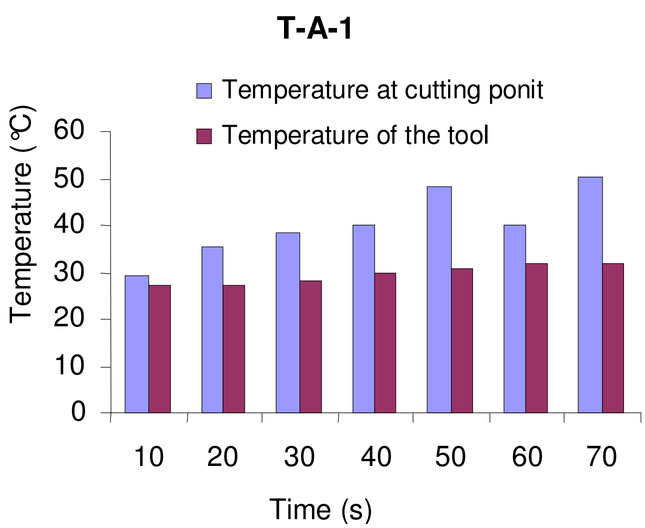

Figure 3. Heat generation cutting aluminium with tungsten carbide at 1 mm depth of cut.

how temperature varies during machining process and is a representation of all the machining experiments. The lower temperature at the dark point represents a temperature through tool tip. The upper temperature at the brighter area represents a temperature at a tool cutting point. The cutting process began from the right hand side to the left.

ANALYSIS OF RESULTS

Figures 3 and 5 show how temperature varies with time when aluminium is cut with tungsten carbide and high speed steel. Figure 3 indicates that when aluminium is cut with tungsten carbide tool the temperature of aluminium slightly and gradually increased from 30 to 50℃ over 70 s. The temperature of the tool also increased gradually and slightly. But for Figure 5, both the material and tool almost remained at a constant temperature of 30 and 45℃, respectively. Figures 4 and 6 show how temperature varies with time when mild steel is cut with tungsten carbide tool. In Figure 4, the temperature of mild steel increased gradually, but slightly over time, from 50 to 60℃. The temperature of tungsten carbide also increased slightly, from 40 to 50℃. In Figure 6, the temperature of mild steel increased steeply over time from 46℃ to a maximum of 120℃. The drop in temperature could have been caused by air flow from the chuck. The temperature of high speed steel almost remained constant at 40℃. Differences in temperature especially for the materials, (mild steel) can be observed when cutting mild steel with different cutting tools: that is tungsten carbide and high speed steel. The difference is also partly the basis for choosing a correct tool for the machining operation and for controlling the surface finish of the product. Figures 7 and 8 show graphs of temperature against time when using tungsten carbide to cut aluminum at various feed rates and rotational speeds. The machining process was performed without a coolant.

It could be observed that as feed rate increased from 0.5 to 2 mm, the graphs shifted upwards, indicating the increase in temperature. A comparison between Figures 7 and 8 show that as the speed of rotation increase, the temperature generated between the tool and the work piece increased. Generally, high temperature makes it necessary for the coolant to be considered, due to the fact that as temperatures increases the surface finish of the product deteriorates. The other reason is that the performance characteristics of the product deteriorate. A comparison between tungsten carbide and HSS tool Figures 7 to 10 show that, generally, tungsten carbide tool produces slightly higher temperatures. This is clearly shown by a comparison between Figures 7 and 9, when looking at graphs of 0.5 and 1 mm feed rate. Similar observations as earlier stated can be made when comparing Figures 9 and 10, where temperature increased as speed of rotation was increased. The highest temperature were recorded when feed rate was 2 mm. A comparison between Figures 9, 10, 11, 12 and 13 show that HSS tool caused high temperatures when machining mild steel. This was due to the fact that mild steel is harder than aluminum and its hardness approaches that of HSS. At 625 rev/min HSS tool burnt when cutting mild steel at 2 mm feed rate. This could be minimized by using coolant, so that high temperatures are reduced. Peaks of temperatures were observed during the cutting process. This might indicate different structures of crystals of materials which normally caused by error during material processing leaving material ingots with soft and hard portions or due to change

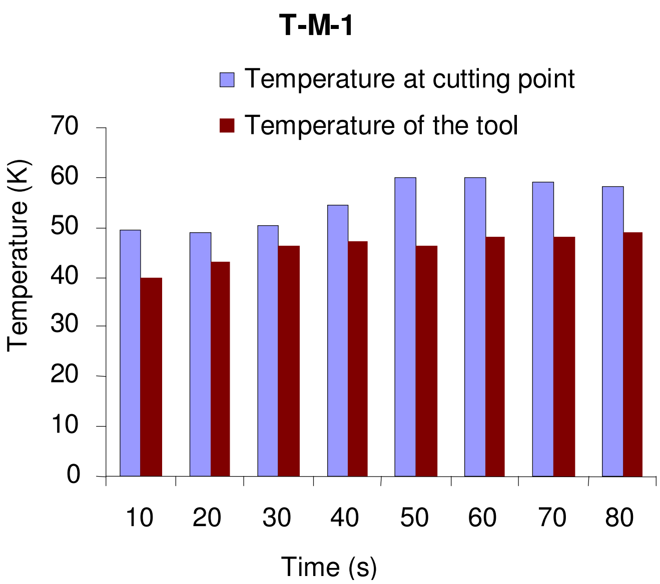

Figure 4. Heat generation cutting mild steel with tungstne carbide at 1 mm depth of cut.

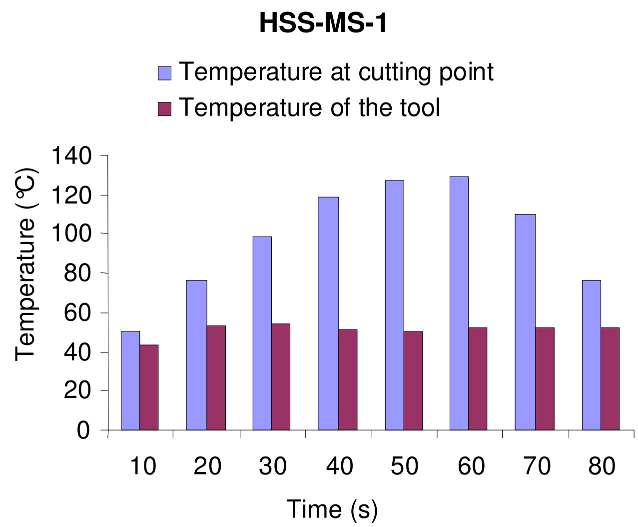

Figure 6. Heat generation mild steel with high speed steel at 1 mm depth of cut.

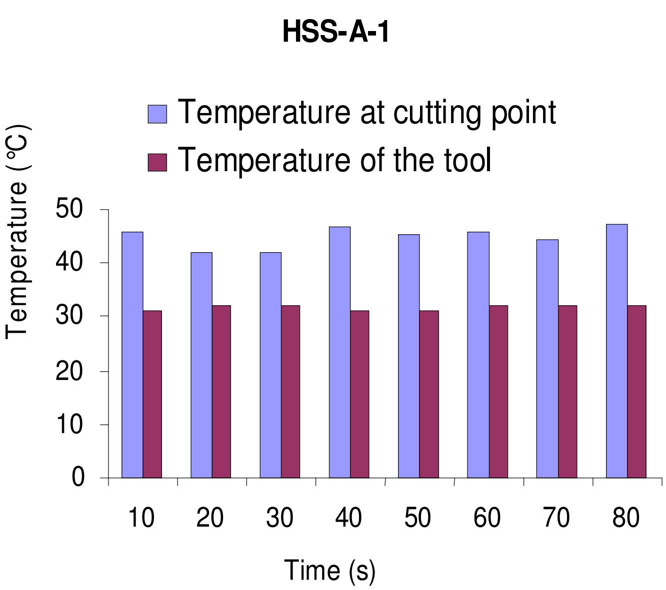

Figure 5. Heat generation cutting aluminium with high speed steel at 1 mm depth of cut.

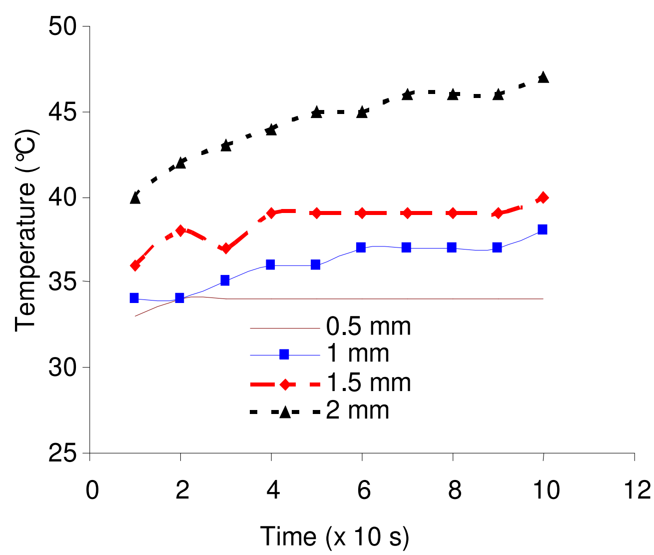

Figure 7. Temperature variations for tungsten carbide tool cutting aluminum at 470 rev/min.

of flow of air during experiment since cooling was left to natural air. The variation of temperature due to tool material, work-piece material, depth of cut and speed of rotations, shows that indeed the machining parameters can control the surface finish of a work-piece. That is due to fact that the aforementioned parameters have direct effect on temperature of the tool and the work-piece.

The parameters can be implemented in the control algorithm to control the surface finish as shown in the following study.

LATHE TOOL MODEL DEVELOPMENT

The modified mechatronic neuro-fuzzy lathe system is used to model the controller. The network is trained using linguistic rules. Figure 14 shows the general arrangement of the experimental rig. The controller has two inputs: the error between desired and actual force e_k and the change

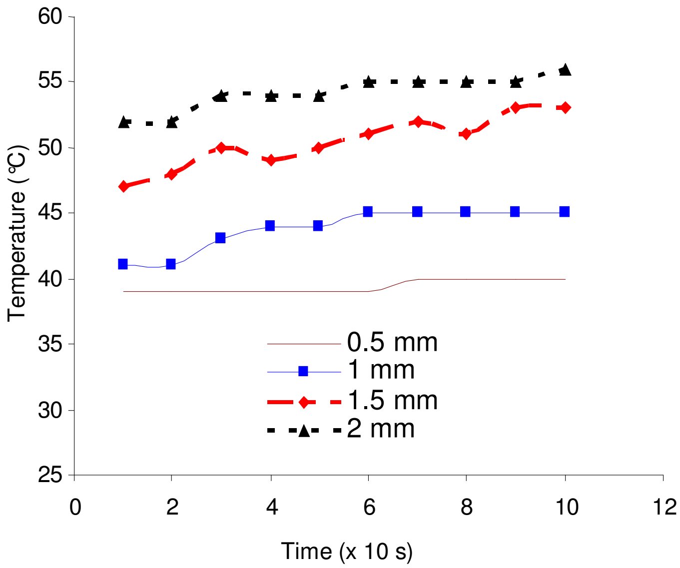

Figure 8. Temperature variations for tungsten carbide tool cutting aluminium at 625 rev/min.

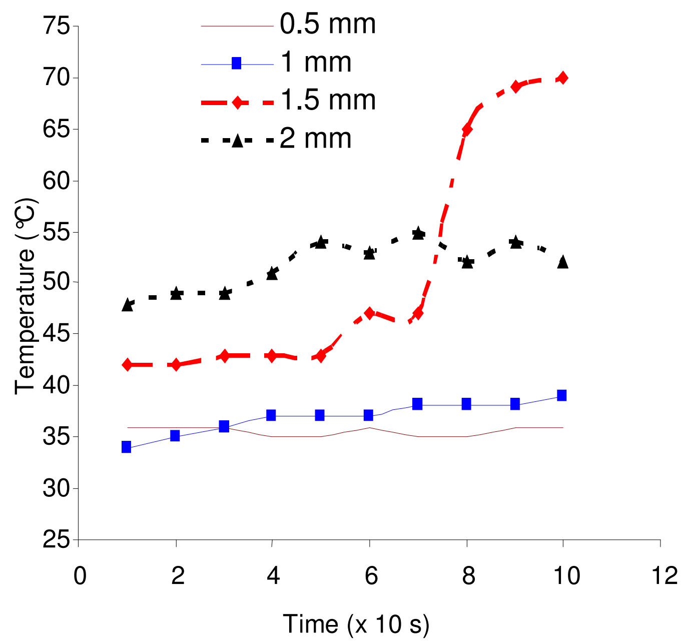

Figure 10. Temperature variations for HSS tool cutting aluminium at 625 rev/min.

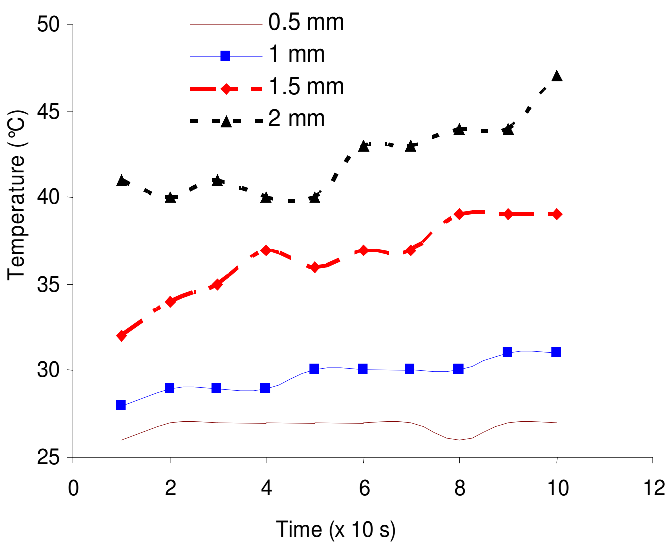

Figure 9. Temperature variations for HSS tool cutting aluminium at 470 rev/min.

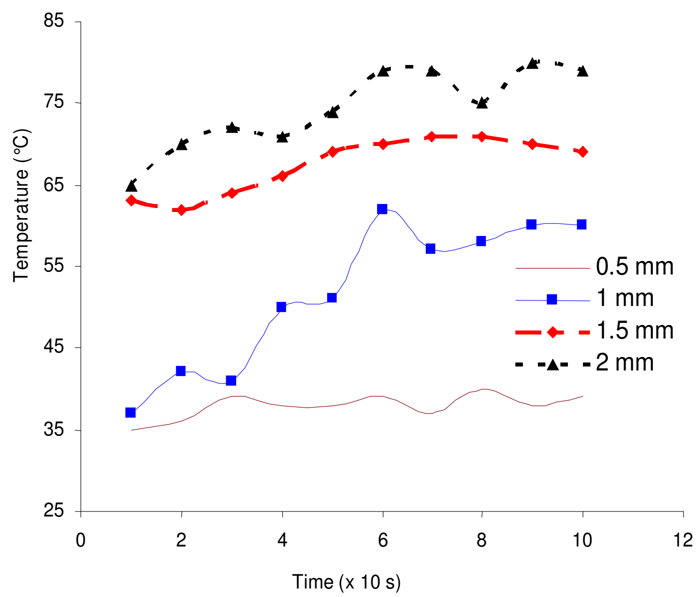

Figure 11. Temperature variations for tungsten carbide tool cutting mild steel at 470 rev/min.

in error $De_k = e_k - e_{k-1}$. The incremental output of the network is $Du_k = F\left(g_p e_k, g_k De_k\right)$ while the output of the neuro-fuzzy controller is simply:

$$u_k = u_{k-1} + Du_k = u_{k-1} + F\left(g_p e_k, g_k De_k\right).$$

Finally, the output of the controller is weighted before being applied to the plant as:

$$c_k = g_c u_k \tag{4}$$

The parameters g_i, g_p and g_c are the normalizing gains of the controller, necessary to convert the inputs to the controller into range (-1,1). The value $g_c = \left(c_k / u_k\right)_{\max}$,

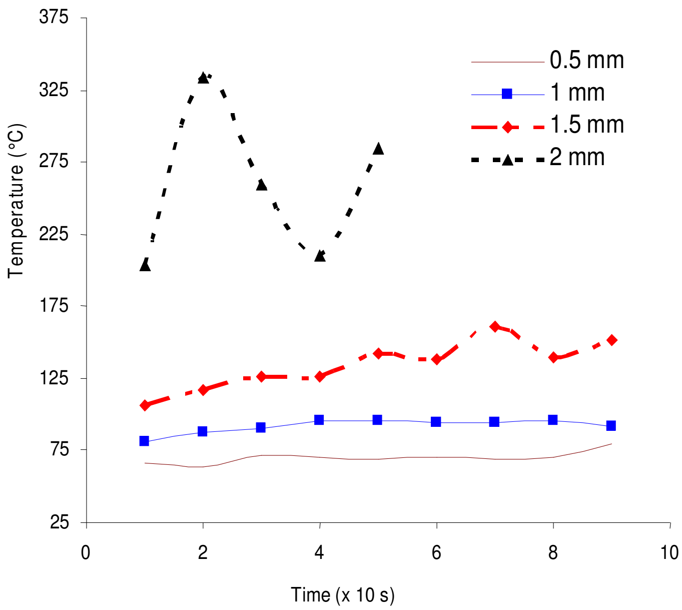

Figure 12. Temperature *variations* for tungsten carbide tool cutting mild steel at 625 rev/min.

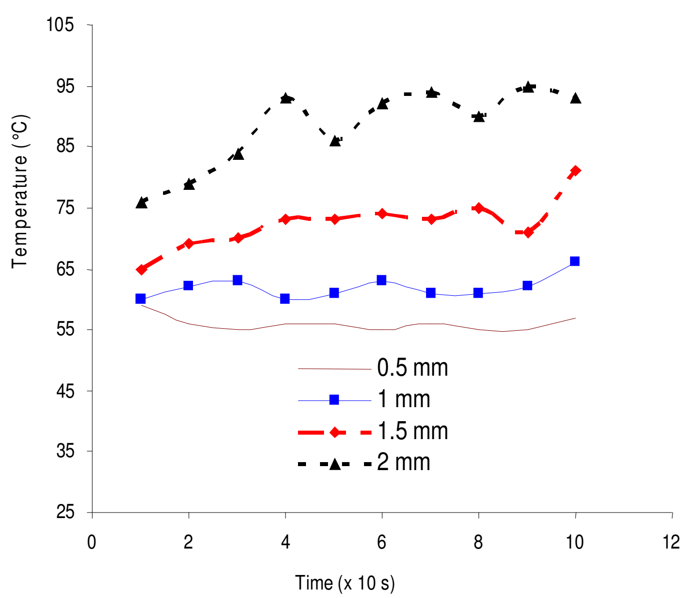

Figure 13. Temperature variations for HSS tool cutting mild steel at 470 rev/min.

while the pair of controller parameters (g_i, g_p) are tuned on-line or obtained in an identical manner to the Ziegler-Nichols method. The design objective is a controller, which results in a rise time of less or equal to the specified value T_{rise}, an overshoot, which does not exceed $p\%$ of the steady state value and a settling

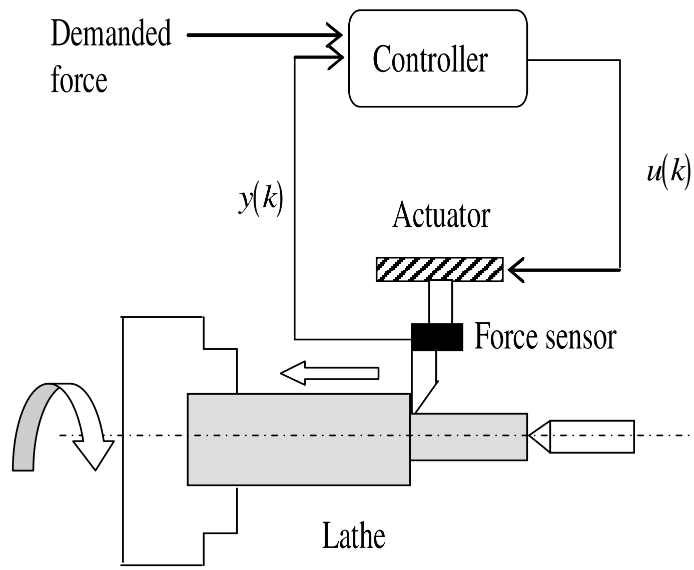

Figure 14. Force cutting lathe.

time T_{set} less than some specified value. The objectives can be achieved by the proper choice of the control rule base, which is the inference mechanism and the optimization of the free parameters of the controller. High speed steel cutting tools confer to retain its hardness up to temperature of 600°C. Tungsten carbide tools retain its hardness up to 2500°C (Stein, 2002). High speed steel material is an alloy of high carbon steel and tungsten, whilst Tungsten carbide consists of tungsten and lamp black (carbon). Since no lubricant was used, a friction between a cutting point/edge and a chip caused a significant temperature increases, more especially cutting mild steel, compared to aluminum.

Erik et al. (1996, 1997) found that temperature influences cutting action in several ways, such as altering properties of the machined surface, decreasing dimensional accuracy and affecting the strength, hardness and wear resistance of the cutting tool. During the experiment of metal cutting (mild steel and aluminum) the Infra–red Camera showed the difference of temperature at a cutting point and through the tip. This relate to the theory of heat that flows through a cross section of a bar divided by time and area is proportional to the temperature gradient; change of temperature *dT* at change of length *dx*, during cutting. Figure 15 shows the effects of heat on a tool bit. The cutting point wears out due to friction between a chip and cutting edge. The small curve (crater) is also developed when chips pass along the tool surface, hence causing wear. Table 1 contains of data for speed, feed rate and depth of cut for medium to high speed steel taken from machine handbook by Jang et al. (1997). Most of the look-up tables give minimum and maximum roughness of the work piece but here it is not necessary because it is the controlled parameter and the roughness

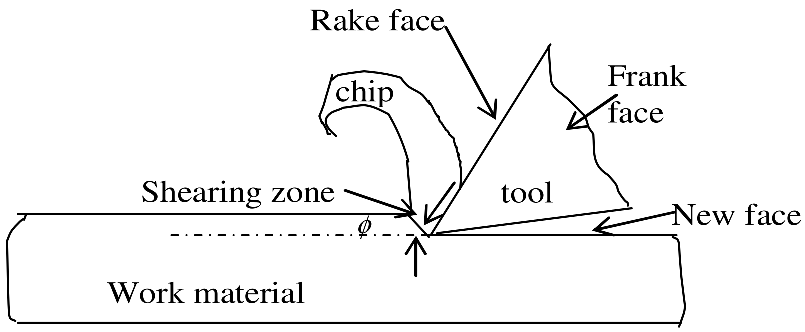

Figure 15. Diagram of tool action.

Table 1. Data chart for medium to high speed tools.

Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)
250-500	0.0500	0.1300
250-500	0.0800	0.2500
250-500	0.1000	0.4100
250-500	0.1300	0.7900
250-500	0.1500	1.1900
250-500	0.1800	1.5700
250-500	0.2000	1.9800
250-500	0.2300	2.3900
250-500	0.2500	2.5400
100-200	0.2800	3.1800
100-200	0.3000	3.8100
100-200	0.3300	4.7800
100-200	0.3600	5.0800
100-200	0.3800	6.3500
100-200	0.4100	7.9200
95-170	0.4600	9.5300
95-170	0.5100	11.1300
95-170	0.5600	12.7000
95-170	0.6400	15.8800
95-170	0.7100	17.4800
95-170	0.7600	19.0500
95-170	0.8100	20.6200
95-170	0.8900	23.8300
95-170	1.0200	25.4000

of the finished product is measured by the close match between the actual and the predicted model output. Fuzzy logic is frequently described as computing with words rather than mathematical descriptions. Thus, instead of describing the control strategy in terms of differential equations, control is expressed as a set of linguistic rules. The control system works by taking readings from lathe tool data model and passing these to the N-FLC, which will then determine whether the set feed rate is sufficient to keep the tool at steady and at the desired depth of cut. The outcome of the N-FLC is fed back into the lathe tool model completing the loop.

Modelling of cutting tool forces with speeds and feeds

The acquired data were analysed in the time domain for cutting tool wear correlation. The method employed was geared towards developing an understanding of the spectra energy content of the dynamic cutting force signals and how it could be used as an input sensor signal in the development of a tool wear monitoring system. Analysis of the data indicated that the spectra energy content correlated well with the measured tool wear at certain tool temperatures (Jang and Sun, 1993).

Encoding linguistic rules

Matlab was used as support for easy implementation of the set of rules. The fuzzy methodology applied was the Sugeno-Mandani inference method (Zadeh, 1973). Two set of rule based on acquired knowledge on the process and handling of the regulation of the input depth of cut in dependence on the feed rate and the error were set up. The training of a neural network (part of the neuro-model) is normally performed with a numerical training set. As control rules involving linguistic variables cannot used directly for network training, it is therefore necessary to encode the linguistic rules into numerical form prior to using them in existing network training packages. The choice of membership functions is based on past experience and function found in the literature (Jang and Sun, 1993). The problem then reduces to one of finding suitable mapping that maps the linguistic (that is, qualitative) rule set $R(L)$ into a corresponding numerical (that is, quantitative) training set $R(Q)$:

$$\mathrm{T} = R(L) \rightarrow R(Q) \qquad (5)$$

Typical definition of variable could be:

$NL = Negative\_Large$, $NSM = Negative\_Small$,
$NZ = Normal$, $PSM = positive\_Small$,
$PL = Positive\_Large$

Then one to one transformation of linguistic variables into numerical equivalents defined in normalised range $[-1,1]$ could be as follows:

$$\left[|NL||NSM||NZ||PSM||PL|\right] \rightarrow [-1.0/-0.5/0/0.5/1.0]$$

Thus a rule with three input variables:

$INPUT\_1$, $INPUT\_2$ and $INPUT\_3$

and output variable:

$CONTROL\_VARIABLE$

IF
INPUT_1 is Negative_Small
AND INPUT_2 is Positive_Small
AND INPUT_3 is Zero

THEN
CONTROL_VARIABLEmust be Positive_Large

Will appear as the training string:

$$[-0.5, 0.5, 0] \rightarrow [1]$$

The training of rule-based neural controllers of specified topology is performed off-line. The results of this training are the optimum values of the synoptic weights and biases of the neural network that yield the control surface. The weights are subsequently downloaded to the real-time version of the controller. Should it prove it necessary to modify or add any rule then the network must be re-trained off-line. Fortunately, small changes require very short training times since the network parameters will be initialised with its previous known values rather than entirely random values as in the case of a new controller. The training set is used to train the neural network hundreds or even thousands of times in random order until the synaptic weights converge. The initial estimates of the unknown synaptic weights are taken randomly. At every epoch (that is iteration of the training algorithm), the synaptic weights are updated in accordance with the training algorithm used. The back-propagation algorithm (BP) is by far the most popular training algorithm, though it converges slowly, particularly when the network contains many neurons and layers.

Fortunately, in the majority of control applications neural controllers normally contain very few neurons and training is fast. Learning is considered completed when some measure of the error between the desired and actual outputs of the networks reaches some acceptable limit, or the numbers of epochs reach some upper limit.

Parametric modelling and control of a single point lathe tool

According to Zadeh (1973) fuzzy logic involves a fuzzy inference engine and a fuzzification-defuzzification module. Fuzzification expresses the input variables in the form of fuzzy membership value based on various membership functions. Governing rules in linguistic form, such as if cutting force is high and machining time is high, then tool wear is high, are formulated on the basis of experimental observations. Based on each rule, inference can be drawn on output grade and membership value. Inferences obtained from various rules are combined to arrive at a final decision. The membership values thus obtained are defuzzified using techniques to obtain true value such as flank wear. In this investigation, parametric identification of the lathe tool with simple least squares is considered. The experiments involve development of predicted model, and the analysis of correlation function tests. Linear least squares or simple least square is a conventional method, which finds the line minimizing the sum of the squared distance between the observed points and the fitted line. This method of fitting ensures that the estimates of the slope and the intercept

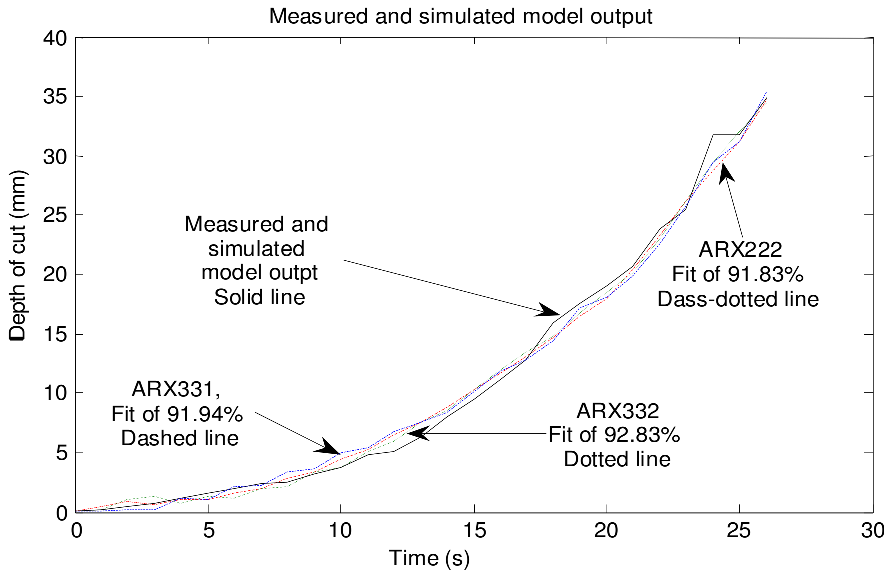

Figure 16. ARX 332, 331 and 222 outputs.

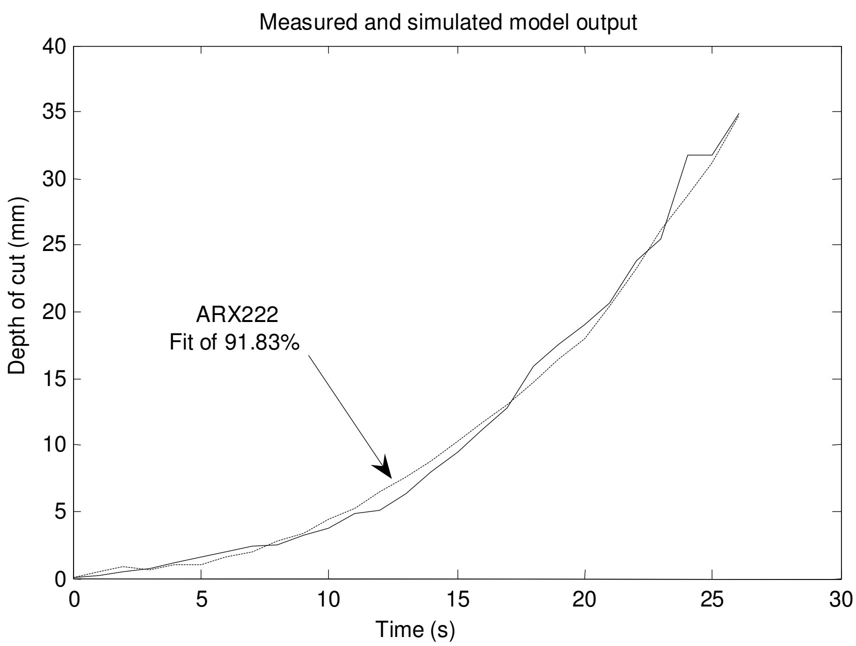

Figure 17. Actual and predicted output or ARX 222.

parameters of the model have some desirable statistical properties. The experiment involves using the Matlab program that loads in data that contains the inputs and outputs. Using this data, the system model can be estimated. The order of the system can be approximated to be 2, 3, 4, 5 or 6. Using this original data, the system can be estimated.

Experiment has been carried out for the following models: ARX 333, 331, 222, 221, 555 and 665. The models that showed the best fit and their correlation fell within the 95% confidence limit were parametric models that is, ARX models. Figure 16 shows the measured and simulated output which the whole modelling is based on. It has to predict a model which best traces it. In such a case the selected or recommended parametric model will be the ARX (222) shown in Figure 17, that is ARX model

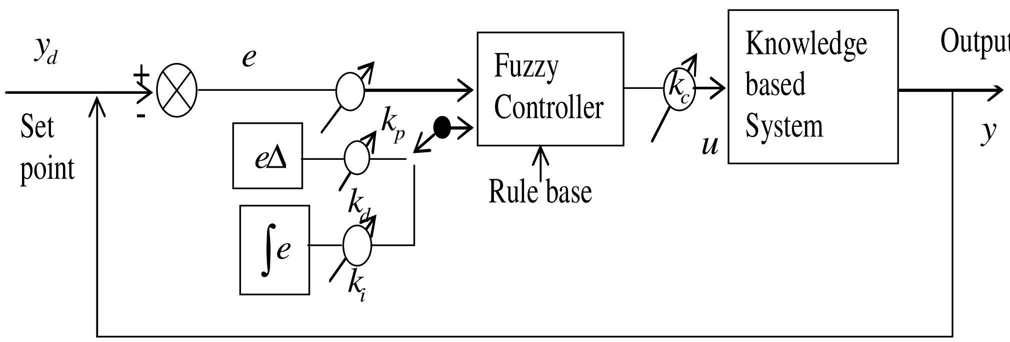

Figure 18. Block diagram of proposed PD-PI type N-FLC.

with *na* = 2, *nb* = 2 and *k* = 2. The reason being that results show that second-order models give results of good accuracy as that of third-order models and hence there is no need to high order equation when low order equations are good enough.

Non-parametric modelling and control of a single point lathe tool

The black box diagram of the switching PD-PI-type controller is shown in Figure 18. It is assumed that only two states of the lathe tool system, namely: the depth of cut and rate of feed are available for controller design. From the lathe geometry, further two states namely: change in feed rate and sum of error are derived. If one has made the choice of designing a P-, PD-, PI- or PID-like fuzzy logic controller, this already implies the choice of process state and control output variables, as well as the content of the rule antecedent and rule consequent for each of the rules. The process state variables representing the contents of the rule antecedent (if part of the rule) are selected as follows: error denoted by *e,* change of error denoted by *Δe* and sum of error denoted by *Σe.* The control output (process input) variables representing the content of the rule-consequent (then part of the rule) are selected as follows: control output, denoted by *u* and change of control output *Δu.* By analogy with the conventional controller they are defined as:

$$e(k) = y_d - y(k) \tag{6}$$

$$\Delta e(k) = e(k) - e(k-1) \tag{7}$$

$$\sum_{k=1}^{n} e(k) = e(k-1) + e(k) \tag{8}$$

$$\Delta u(k) = u(k) - u(k-1) \tag{9}$$

Where y_d represents the desired output or set point, *k* represents the process output, *n* represents the sampling time and is the maximum sample number. The Gaussian memberships are chosen for the input and output. To construct a rule base, depth of cut and feed rate are partitioned into 5 primary fuzzy sets labelled as (NB, NS, Z, PS, PB). PD-type and PI-type controllers are described by:

$$k_c * u = k_p * e + k_d * \Delta e \tag{10}$$

$$k_c * u = k_p * e + k_i * \sum e \tag{11}$$

Where k_p, k_d, k_i and k_c represent proportional, differential, integral and controller gain coefficients respectively. The PD-type and PI-type N-FLCs, accordingly constitute rules of the form:

$$\mathrm{R_n{:}IF(e\ is\ E_i)\ and\ (e\ is\ \Delta C_j)\ THEN(u\ is\ U_k)}$$
$$\mathrm{R_n{:}IF(e\ is\ E_i)\ and\ (\textstyle\sum e\ is\ S_j)\ THEN(u\ is\ U_k)}$$

IMPLEMENTATION OF RESULTS

Prediction of fuzzy state – a fuzzy logic controller is used to predict the future state of the control of the lathe tool under given depth of cut and feed rate at varying tangential forces. To implement control, the trend of tool profile needed to be determined. The predictive algorithm can be implemented by calculating the variation in current lathe tool set parameters and future change in set point. The quality of the finished work piece is critically dependent on the rate at which the metal is cut. It is important where a high quality finish is required that the depth of cut be controlled with great accuracy. In most existing cutting lathes this is achieved with conventional two term (PI) controllers. In Figure 19, a hybrid algorithm neuro-fuzzy was used to model the lathe tool geometry. As indicated in Table 1, a data set comprising three sets of 24 data points divided into two halves was used. The

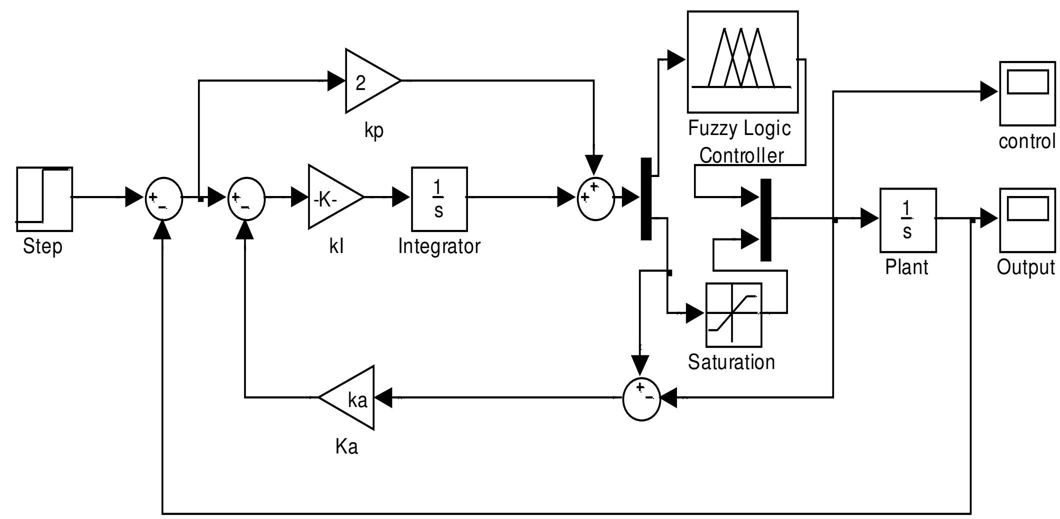

Figure 19. Non linear fuzzy control scheme.

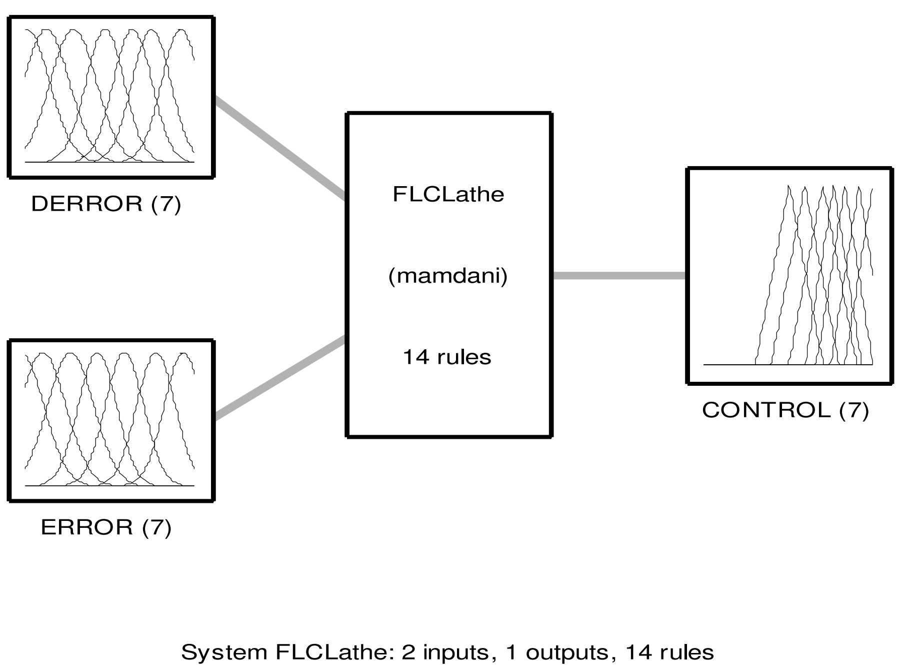

Figure 20. Neuro-fuzzy network used for modelling lathe tool parameters.

first half was used to train the network and model was validated using the second half that the neuro-fuzzy had never seen. To model the system, a first order Takaki, Sugeno and Kang (TSK/ Mamdani (1985) has been adopted. The model adopted to characterise the lathe tool model comprised of 10 input and output orders: ($n_u = n_y = 10$). At the identification of the lathe tool system and model validity, the fuzzifier posses two inputs as shown in Figure 20 (that is, DE ERROR, which represents federate and ERROR which represents depth of cut).

The approach utilises error and change in error for process state and application of the associated results to decide level of a single output that is, tool surface roughness or simply surface finish. Figure 21 demonstrates further analysis of lathe tool parameters data with high non-linearities. As noted in this figure, the error between the actual output and the reference signal is significant at depth of cuts greater than 15 mm. The

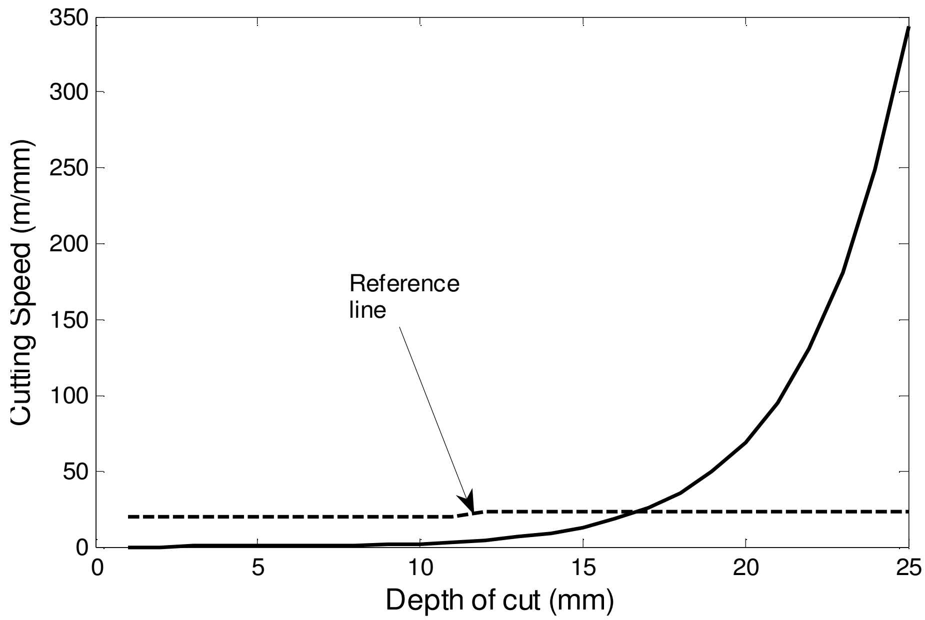

Figure 21. Error between actual and reference output.

fuzzy controller is still able to automatically adjust to the changing data.

DISCUSSION

This computer based design tool enables the user to carry out complete design of the neuro-fuzzy controller from a minimal number of inputs that has been implemented. However, it is worth noting that intelligent modelling techniques are an alternative to conventional techniques hence their application must be tried when there is a prove that conventional methods do not yield meaningful results. Fuzzy and neuro-fuzzy are meta-heuristic and applying these meta-heuristic to the knowledge based system can lead to instability. It is therefore recommended that stability of the system must be checked and verified which another branch of study that will be undertaken in the next phase of the research project. The experiment enables the researchers to appropriately select the cutting tools considering tool rigidity, friction resistant, volume of material removal and the quality of surface finish. The decrease in hardness wear resistance of the tool with increasing temperature is the major factor that controls useful tool life. The strength and thermal conductivity of the work piece, tool material, cutting speed and depth of cut all influence the temperature during machining. Thus mean cutting temperature is proportional to a value of cutting speed, feed and depth of cut. The experiment determined that between tungsten carbide and HSS cutting tool, the tungsten tool has the ability to remove the greatest amount of metal in the shortest time with a reasonable tool life.

The standard theory/conditions would be incorporated to prove the results of the experiments such as: determining forces acting on tool point, tangential, radial, axial and as well as finding the tool life cycle for a given speed of each tool.

FUTURE WORK

The experiment will be performed on an orthogonal lathe. A force measuring system and a temperature measuring systems will be set up on it. Both force and temperature measuring systems consisting of wireless transducers (flexi force sensors) will be attached to the CNC lathe with the transmitter attached to a computer USB port. The work will be carried out using neuro-fuzzy. Fuzzy logic will help with parameter partitioning, neural network will help to make dynamic model of systems and genetic algorithm will be used for model optimization. The whole control strategy will then be tested on the research specimen in the lab if successfully tested on components taken from the mines.

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