FUZZY MODELING OF TOOL WEAR IN DRILLING

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Abstract. *Machining operations confronted by a shortage of technical manpower and pricing competition, not only need to implement automated and operator-free technology, but also to meet the demands for much higher performance of products, higher reliability, longer life and miniaturization. Tool wear has a large influence on the economics of the machining operations. Hence, tool wear sensing should be one of the primary objectives in order to produce the required end products in an automated industry, so that, a new tool may be introduced at the instant at which the existing tool has worn out. Thus preventing any hazards occurring to the machine or deterioration of the surface finish. Often, tool wear affects the surface texture seriously and changes the tool geometry. This paper discusses a specific approach of surface modeling and approximation of tool wear in drilling based on cutting force analysis by fuzzy system.*

Keywords*: tool wear, fuzzy system, fuzzy modeling, drilling*

1. Introduction

The progress toward the development of automated manufacturing systems has been hindered by the lack of dependable machine tool diagnostic schemes. In particular, the problem of reliably measuring the tool wear has been a significant obstacle to the realization of effective automated machining system. Often, tool wear affects the surface texture seriously. Hitomi.K., Nakamura, N., Inoue, S., (1979), Merchant, M.E., (1944), and Mauch, C.A., Lauderbaugh, L.K., (1990), found that prediction of tool wear and tool life by the conventional methods of empirical approach using optimization techniques namely design of experiments (DOE) and response surface methodology (RSM), which usually requires a large number of experimental tests and hence it is cost-intensive and time-consuming. Sivarao, P.S., Lee, T.S., Chin, C.W., (2004), also found that the statistical and mathematical analyses are the same as above mentioned. The aim of this tool wear modeling by fuzzy system is to predict most accurate and reliable out-put to consider tool wear limits as the criteria for tool replacement. Mamdani's fuzzy inference method has been used in this fuzzy modeling, where the input parameters used were the experimentally recorded data. Based on experience and machining conditions, few rules were fed into the system in generating the membership-function to obtain the singleton output, which is the ultimate goal of the research.

2. Experimental procedure

It is a metal drilling manufacturing operation. The machine is a single tool drill, repetitively carrying out a single identical task on parts as they arrive. The task involves the drilling of a single hole in each part. When a part is completed, another part is immediately available for drilling. As holes are drilled, the tool wears and is susceptible to breakage. It is assumed that there is a limit to the wear beyond which the tool is unacceptable as it directly affects the internal surface roughness of the drilled hole. Unmonitored tool wear may lead to tool breakage or bad surface roughness and may cause the almost finished product to be reworked or rejected. This will incur the manufacturing cost and machine down time, where, the evolution of tool wear necessitates the occasional replacement of the tool. Replacement of the tool involves some costs for both time and material. The spindle speed and the feed rate of the drill are fixed. The experimentation basic in obtaining the cutting force has been indicated by Chandrasekharan, V., Vijayan, G., (1995), Galloway, D.F., (1957), and Iwata, K., Murotsu, Y., (1972).

Eight identical experiments were carried out with 10 mm drill tool on a radial drilling machine in dry cutting condition to test the stability of the tool in producing required surface roughness to maintain the quality of holes in unmanned drilling operation. For the purpose of experimentation, a mechanical type drill dynamometer with individual digital output of thrust force and torque were used. The work piece was clamped on the dynamometer with the help of chuck jaw. The observed values of thrust force and torque are the average readings taken during the drilling process.

The values of tool wear (flank wear) has been measured with tool maker microscope with 80X magnification upon drilling of each hole. The measurements were done by four average values with two at each site of the flank. The cutting conditions and tool specifications are as shown in table 1 and the worked samples are as shown in figure 1.

Table 1. Machining conditions and tool specification

Cutting Condition		Tool Specification	
Cutting speed	12.69 m/min	Material / Dia.	HSS 10
Feed	0.285 mm/rev	Point angle	118^o
Number of holes	30	Helix angle	32^o
W/ piece material	Mild steel (EN31)	Clearance angle	10^o
W/piece thickness	25 mm	Hardness (3P Avrg.)	57 Rc
W/piece dimension	160X160X25 mm	Flute length	86 mm
Cutting fluid	No	Overall length	136 mm

Figure 1. The worked samples

3. Fuzzy system

Fuzzy modeling and approximation are the most interesting fields where fuzzy theory can be effectively applied. As far as modeling and approximation is concerned, one can say that the main interest is towards its applications. According to Hung, T., Nguyen, Nadipuram, R., (2000) and Segaran Nair, Nadipuram, R., Prasad, (2003), if one intends to apply fuzzy modeling and approximation to an industrial process, one of the key problems to be solved is to find fuzzy rules. Few ways to find fuzzy rules are; the operator's experience, the production engineer's knowledge, fuzzy modeling and approximation of operator's action, fuzzy modeling of the process. The rules fed to the fuzzy system for the purpose of modeling and approximations of this work are as shown in figure 2.

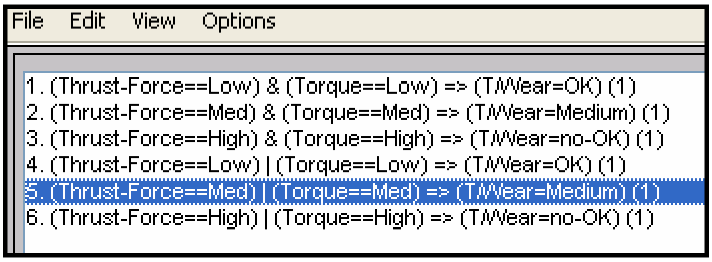

Figure 2. The rules used in the study

Through scientific practice, articulation of problems in fuzzy logic terms becomes more familiar and quite natural. It is then recognized as valuable tool in the expression and solution of cases where uncertainty, vagueness or ambiguity exists and where approximations are norm. Therefore, John Harris, (2000) and Kuo, R. J., (1998) clearly indicates that basically, there are four types of different fuzzy systems. They are used at different conditions and rules as they have their own advantageous in the vast applications of fuzzy system. They are Mamdani, Larsen, Tsukamoto and Takagi-Sugeno-Kang (TSK). The one practiced in this paper is a special case of the Mamdani type in which the rules always have crisp consequence.

3.1. Fuzzy algorithm

Fuzzy logic has vast applications in the real world. Basically the system will accept the input or some inputs and then pass the inputs to a process called fuzzification. In fuzzification process, the input data (can be digital, precise/imprecise) will undergo some translation into linguistic quantity such as low, medium, high of physical properties. The translated data will be sent to an inference mechanism that will apply the predefined rules. The inference mechanism will generate the output in linguistic form. The linguistic output will go through defuzzification process to be in numerical form (the normal data form). Defuzzification is defined as the conversion of a fuzzy quantity represented by a membership function to precise or crisp quantity. This is clearly stated by James, J., Buckley, Esfandiar Eslami, (2002), in his publication.

3.2. Components in fuzzy system

There are three basic components for a typical fuzzy system. They are input fuzzification, inference mechanism (rules application) and output defuzzification. The entire fuzzy components of the system are as shown in figure 3.

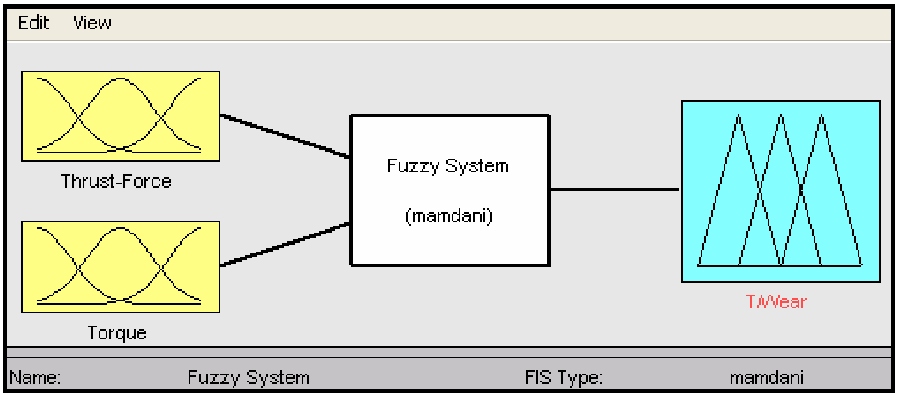

Figure 3. Basic fuzzy system of designed model

3.2.1 Input fuzzification

Input fuzzification ‘translates’ the system-input variables into universe of input memberships. Some refer to universe of input membership as degree of membership. The translating processes involve various sets of input membership. A series of fuzzy set is needed to be defined with analogue to the input range.

3.2.2 Fuzzy inference systems

Marco Russo, Lakhmi, Jain, C., (2001), states that the fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all of the pieces, which called membership functions, fuzzy logic operators, and if-then rules. There are two types of fuzzy inference systems that can be implemented in the fuzzy logic; Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined.

Mamdani-type inference, as we have defined it for the fuzzy logic, expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It is possible and in many cases, much more efficient to use a single spike as the output membership function which is known as a singleton output membership function. It enhances the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which finds the centroid of a two-dimensional function.

Fuzzy sets and fuzzy operators are the subjects and verbs of fuzzy logic. These if-then rule statements are used to formulate the conditional statements that comprise fuzzy logic. A single fuzzy if-then rule assumes the form if X is A then Y is B where A and B are linguistic values defined by fuzzy sets on the ranges (universes of discourse) X and Y, respectively. The if-part of the rule "X is A" is called the antecedent or premise, while the then-part of the rule "Y is B" is called the consequent or conclusion, says Orlovski, S.A., (1978), in his paper.

3.2.3 Output defuzzification

Defuzz (X, mf, type) returns a defuzzified value out, of a membership function mf positioned at associated variable value X, using one of several defuzzification strategies, according to the argument, type. The variable type can be one of this: Centroid; centroid of area method, Bisector; bisector of area method, Mom; mean of maximum method, Som; smallest of maximum method, and Lom; largest of maximum method. If the type is not one of the above, it is assumed to be a user-defined function. The x and mf are passed to this function to generate the defuzzified output. In this work, weighted-centroid output method has been used to translate the linguistic-output into numerical form. Fuzzy membership function obtained is as shown in figure 4.

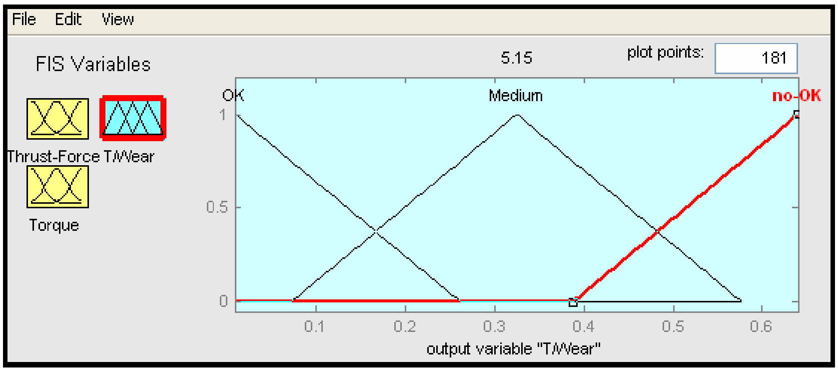

Figure 4. Membership function obtained by the fuzzy system

4. Result and discussion

The fuzzy modeling and approximation in this scientific research has been carried out successfully and the approximated values are very closely matching to the observed values of the experimental work carried out. The numerical output of the entire drill job for one of eight experiments carried out is shown in table 2. The results confirm that the use of fuzzy based modeling and approximating is effective for tool wear monitoring in order to maintain the quality of the drilled holes. The deviation of observed and fuzzy output for all the holes is within strongly acceptable region.

Table 2. Fuzzy system numerical output as compared to the observed values

Hole Number	**Thrust Force (N)**	**Torque (Nm)**	**Observed TW (mm)**	**Fuzzy Predicted TW (mm)**
2	1371.16	5.19	0.02	**0.021**
4	1385.10	5.36	0.07	**0.075**
6	1405.21	5.49	0.09	**0.095**
8	1426.37	5.63	0.10	**0.108**
10	1439.19	5.69	0.12	**0.125**
12	1451.29	5.79	0.16	**0.170**
14	1462.18	6.00	0.21	**0.210**
16	1472.16	6.19	0.26	**0.265**
18	1484.19	6.42	0.33	**0.325**
20	1500.00	6.84	0.38	**0.378**
22	1541.26	7.00	0.42	**0.409**
24	1584.39	7.24	0.47	**0.462**
26	1629.44	7.46	0.52	**0.511**
28	1681.46	7.86	0.59	**0.584**
30	1739.15	8.17	0.64	**0.636**

Figure 5 shows the rule viewer of the inference fuzzy system applied. It is clearly indicating how the input variables (yellow columns) of thrust force and torque is used in the rules to produce the predictive tool wear (TW) for each tool. The red/thick vertical line in the box on the right bottom corner provides a defuzzified value and its plot shows how the output of each rule is combined to make an aggregate output and then defuzzified.

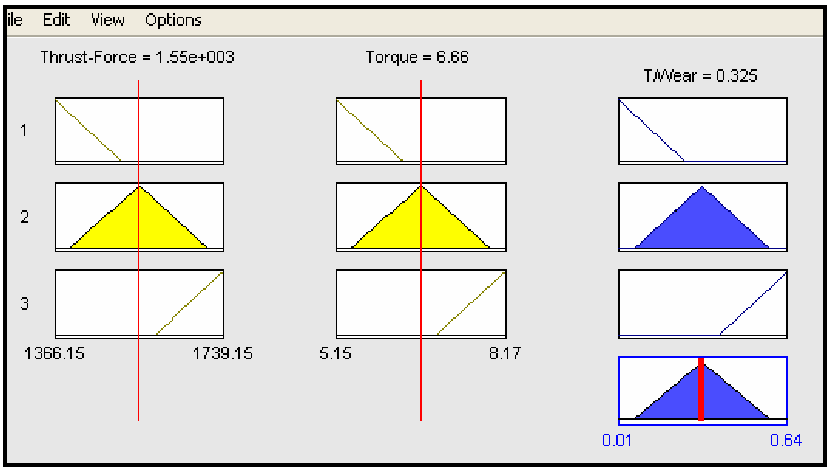

Figure 5. The rule viewer of the analysis carried out

The surface relationship of the input-output model is shown in figure 6, which clearly indicates the stages of the surface roughness based to the inference applied to the fuzzy system. The surface matches closely to the experimentally observed values.

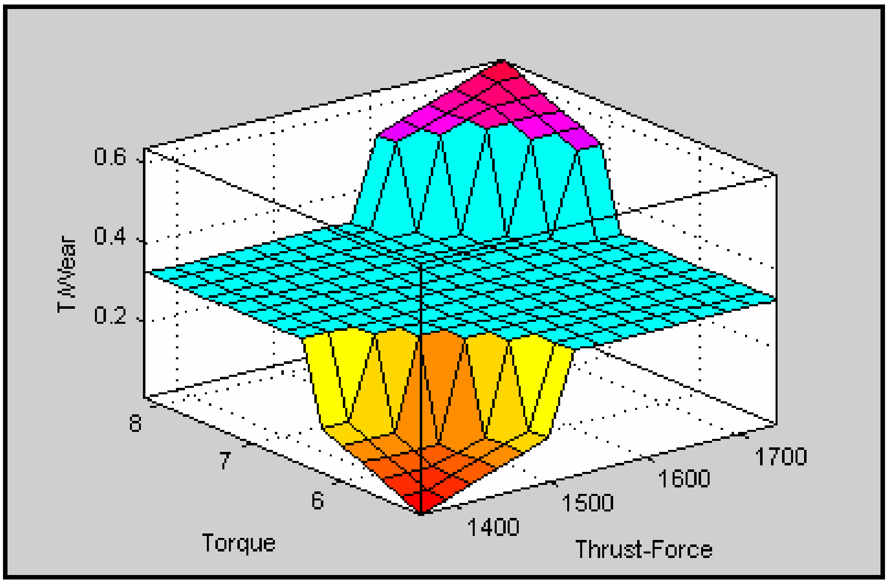

Figure 6. The input-output surface model

From the fuzzy model shown in figure 6, immediate tool wear occurs due to the 'running inn' of the tool during the initial machining operation. As the number of drilled holes increase, the wear increases gradually until the 'steady' stage of tool wear which falls between 2 mm to 4 mm. Towards few final holes of this drilling process, it is clearly presented that, the tool wear increases in rapid till it reaches the severe or 'no-OK' stage. At this region, the tool needs to be replaced or re-sharpen to prevent severe damage on the drilled surface on the work piece or tool breakage.

5. Conclusions

The conclusions of this scientific research can be summarized and drawn as follow;

A very general and direct approach of fuzzy system in this research is much efficient and accurate as compared to statistical and mathematical methods used by the author in his previous research.

The basic six (6) rules fed into the fuzzy system were exactly fitting the fuzzy inference, which generates the excellent output of tool wear studied within the range of experimental values.

The intuitions and experiences of a skilled machinist can be replaced by a set of fuzzy rules for drilling peripheral operation.

The relationship between the thrust force and torque with fixed speed and feed has shown an excellent output of fuzzy set as per the studies conducted by various researchers with other methods or response parameters.

The present work can be extended to obtain fuzzy model for surface roughness and also on decision making of response parameters which affect tool wear and surface roughness for the purpose of tool condition monitoring.

6. Acknowledgements

The author would like to thank Professor Dr. Mohd Razali bin Muhamad, Dean of Manufacturing Engineering Faculty for his kind support, professional & friendly personality. The authors are very much thankful to Ir. Vijayan.G, & Ir. Segaran Nair, the technical division engineers of K.P. Engineering for their sincere guide and contribution in making this publication possible.

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