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CUTTING TOOL GEOMETRY SUGGESTIONS BASED ON A FUZZY LOGIC MODEL

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Abstract. *This work is about a fuzzy logic model in order to suggest an initial cutting tool geometry for each work-tool material combination. The Takagi-Sugeno-Kang model was used to design the fuzzy system that was trained with suggested empirical cutting tool geometry values. The system inputs are the specific cutting energy of the work material and the ratio of the quadratic bending strength over modulus of elasticity of the cutting tool material. The outputs are: the normal rake angle (γ_n), the normal clearance angle (α_n) and the cutting edge inclination angle (λ_s). The outputs evaluation is based on a macro-level optimization of cutting tool geometry proposed in the literature; in this methodology the tool geometry is characterized by a geometric entity number that is calculated in terms of the cutting tool angles and its optimal value depends of the work-tool paired materials.*

Keywords*: Machining, Cutting tool geometry, Fuzzy logic.*

1. INTRODUCTION

Fuzzy logic systems and other soft computing techniques have been proposed in the machining processes domain for process planning and control in order to reduce manufacturing costs and assure quality requirements. Chen *et al.* (1995) introduced a fuzzy expert system for the design of machining operations. With this system can be selected commercial cutters and near-optimal cutting conditions, even with partial or imprecise information about shop floor requirements. The system had a learning mechanism to tune some of the fuzzy membership functions, giving it a self-improvement capability.

El Baradie (1997) proposed a fuzzy logic model to calculate the cutting speed recommended for the hardness range of work material. In this model, there was a fuzzy logic module for each combination of cutting tool material (high speed steel, uncoated brazed carbide, uncoated indexable carbide or coated carbide) with depth of cut (prefixed 1, 4, 8 or 16 mm). The fuzzy model input is the hardness of the work material and the output is the cutting speed. The results agreed with the Metcut Research Associates (1980) handbook data used as knowledge source. Wong *et al.* (1999) extended the work of El Baradie (1997) and implemented the fuzzy model to calculate the cutting speed for carbon steel machining. They also include a fuzzy logic model for feed rate recommendations with the depth of cut as unique input. The authors also proposed a methodology to extract the fuzzy model for any type of tool from the basic model of any other, obtaining therefore a generalized model for all kinds of tools. Wong and Hamouda (2002) created an internet version of this fuzzy system in order to permit the online consultation of the cutting speed and feed rate recommendations for a given tool type, work material hardness and depth of cut in turning operations. For non-overlapping recommended cutting speed data, Hashmi *et al.* (2003) applied the same fuzzy logic model in order to select the cutting speed. They used a superimposition scheme that produced the best matching between predicted and actual Metcut Research Associates (1980) handbook data for turning operations.

Shehab and Abdalla (2001) applied the fuzzy logic principles to create a model for cutting time estimation in drilling operations with hole depth, hole diameter and surface finish as input variables. This fuzzy model was a subpart of a greater model to calculate the manufacturing costs in product development.

D'Errico (2001) presented a review of the fuzzy systems that have been proposed for monitoring and control of machining processes; those include among others: tool condition monitoring in turning operations, tool wear length estimation in finishing milling and feed rate control to avoid tool breakage by regulating the cutting force in end-milling and turning operations.

The present work is about the determination of a priori near-optimal cutting tool tip geometry by using a fuzzy logic model trained with empirical data. The proposed model was inspired on the Kaldor and Venuvinod (1997) methodology for macro-level optimization of cutting tool geometry. A using example is included.

2. CUTTING TOOL GEOMETRY EVALUATION

Cutting tool life is influenced by work material, tool material, cutting parameters, cutting geometry, cutting operation and machine tool, as consequence, in order to attain the maximum tool life, the specific operation conditions should be considered and processed in numerical or analytic models that have a predefined criterion for tool life terminating (flank wear, crater wear, edge fracture etc.). Nevertheless for process planning, the tool material and tool geometry should be selected a priori without precise knowledge of all other inputs (Lo *et al*., 1998).
The tool edge geometries recommended in machining handbooks and other sources are supposed to assure a near-maximum tool life for general operation conditions within the practical range. Concepts like tip strength and heat dissipation are invoked in explaining empirical optimum tool geometry. Figure 1 shows the geometric specification of single point tools.

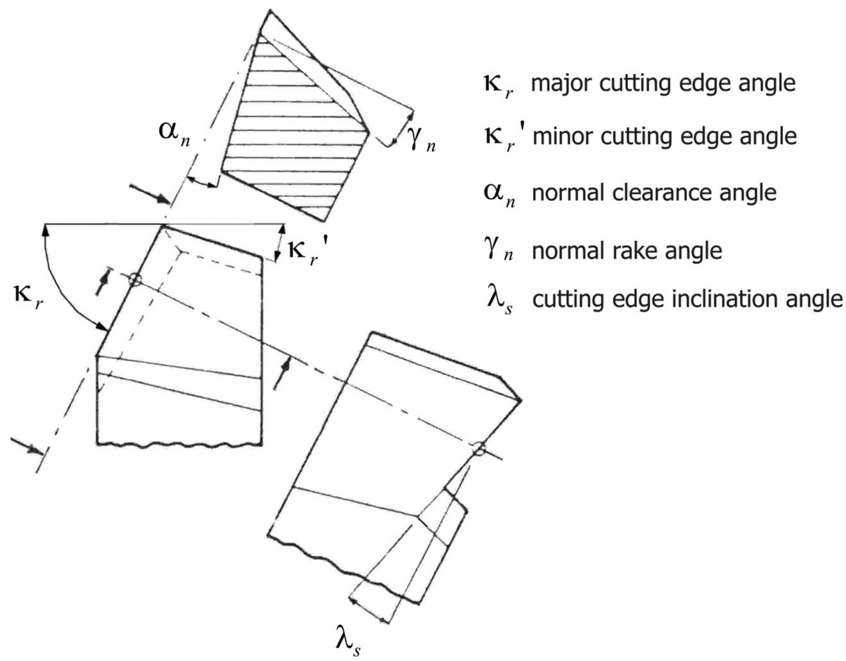

Figure 1. ISO 3002/1 geometric specification of single point tools (Boothroyd and Knight, 1989)

Kaldor and Venuvinod (1997) proposed a methodology to evaluate if a particular tool geometry is really optimized assuming a tool life termination criterion due to fracture or due to flank wear in the vicinity of the major cutting edge. They considered that the normal wedge angle β_n ($=\pi/2-\gamma_n-\alpha_n$) and/or the relative orientation ($=\alpha_n+\beta_n/2$) of the tool wedge with respect to the cutting tool direction have a evident influence on the tool's ability to resist fracture and proposed a geometric entity number $\overline{\sigma_r}$ calculated by Eq. (1), which is a measure of the radial stress field intensity that arises in the bulk of the two-dimensional cutting wedge associated with single-edge cutting when the cutting load is assumed to be concentrated at the major cutting edge.

$$\overline{\sigma_r} = \cos^2\lambda_s \frac{sen\left(\sigma_n + \frac{\beta_n}{2}\right) sen\left(\frac{\beta_n}{2}\right)\left(\frac{\beta_n}{2} + \frac{1}{2} sen\beta_n\right) - \cos\left(\sigma_n + \frac{\beta_n}{2}\right)\cos\left(\frac{\beta_n}{2}\right)\left(\frac{\beta_n}{2} - \frac{1}{2} sen\beta_n\right)}{\left(\frac{\beta_n}{2}\right)^2 - \left(\frac{1}{2} sen\beta_n\right)^2} \tag{1}$$

Kaldor and Venuvinod (1997) found an optimum $\overline{\sigma_r}$ value $(\overline{\sigma_r})_{opt}$, where the tool's susceptibility towards flank wear is in balance with that towards fracture, and this optimum value characterizes the condition for maximum tool life. They established that $(\overline{\sigma_r})_{opt}$ depends mainly on the tool-work material pair and is relatively insensitive to variations in cutting conditions. A $(\overline{\sigma_r})_{opt}$ empirical expression presented in Eq. (2) was deduced by them from the examination of 80 published sources.

$$(\overline{\sigma_r})_{opt} = \log_{10}\left(\frac{S_b^{\,2}}{Ep_s^{\,2}}\right) + 4.73 \pm 0.2 \tag{2}$$

Where S_b and E are the bending strength (GPa) and the modulus of elasticity (GPa) of the tool material, respectively, and p_s is the specific cutting energy (GPa) of the work material.

In agreement with the work of Kaldor and Venuvinod (1997), for a particular tool geometry, between closest is $\overline{\sigma_r}$ to $(\overline{\sigma_r})_{\text{opt}}$, more reliable is this geometry. The previous statement does not mean that any geometry defined arbitrarily with the geometric number equal or next to the optimal value is really an optimized one.

3. FUZZY LOGIC MODEL

The fuzzy logic model proposed uses the work material specific cutting energy (p_s) and the "destruction" specific energy of the tool material ($D=S_b^2/E$) as inputs. The outputs are α_n, γ_n y λ_s calculated through a fuzzy logic system (FLS) non linear function expressed by the equations (3), (4) and (5) for each one of the tool tip basic angles.

$$\alpha_n = f_{FLS}(p_s, D) \tag{3}$$
$$\gamma_n = f_{FLS}(p_s, D) \tag{4}$$
$$\lambda_s = f_{FLS}(p_s, D) \tag{5}$$

The UNFUZZY software (Duarte, 1997) was used to design the FLSs; with it, the designer chooses the type of fuzzy sets for the input and output universes and the system has a training module that permits to generate automatically the fuzzy logic rules. The fixed universes training mode was used for the trainings. The tool geometry training data (Tab. 1) was extracted by selecting the reliable ones in the Kaldor and Venuvinod (1997) compilation.

Table 1. Selected tool geometry data.

Tool material	Work material	σ_n [°]	γ_n [°]	λ_n [°]
Carbide M40, P40	Soft aluminum	8.13	17.90	10.70
H.S.S. M2	Soft aluminum	10.00	35.00	0.00
Carbide P30	Hard aluminum	7.90	15.60	2.30
Ceramic 690	Brass	12.60	0.00	0.00
Carbide P30	Copper	6.90	18.00	-1.30
Carbide M40, P40	Copper	10.60	19.40	7.50
H.S.S. M2	Copper	12.80	21.30	10.40
H.S.S. 17(+Co)	Copper	16.00	18.00	28.00
Ceramic 620	Mild steel (AISI 1045)	6.20	-16.00	-20.00
Carbide P30	Mild steel (AISI 1045)	18.00	-18.00	-16.00
Carbide M40, P40	Mild steel (AISI 1045)	11.00	0.00	7.00
H.S.S. M2	Mild steel (AISI 1045)	8.00	24.00	4.00
H.S.S. 17(+Co)	Mild steel (AISI 1045)	13.00	15.00	28.00
Ceramic 650	Hard steel (AISI 4340)	4.80	-25.30	2.00
Ceramic 690	Hard steel (AISI 4340)	4.80	-25.40	2.00
Carburo P30	Hard steel (AISI 4340)	4.80	-6.10	-3.50
Carbide M40, P40	Hard steel (AISI 4340)	7.24	7.75	13.40
H.S.S. M2	Hard steel (AISI 4340)	8.00	9.80	5.70
H.S.S. 17(+Co)	Hard steel (AISI 4340)	19.50	8.70	30.00
Carbide M40, P40	High strength steel (AISI 9250)	11.00	0.00	7.00
H.S.S. M2	High strength steel (AISI 9250)	5.80	15.50	4.10

The training data distribution is showed in Fig. 2. Because the lack of training data in the 13.4<D<58.3 region, were created a FLS for the 1.36<D<13.4 bottom region and one for the 58.3<D<68.76 upper one. A total of six zero-order Takagi-Sugeno-Kang (Sugeno, 1985) FLSs were designed, it is to say two FLSs for each tool tip angle, one for the upper region and one for the bottom one (Fig. 2). As example, Fig. 3 shows the universes for the inputs and the output of the FLS designed for γ_n calculus in the 1.36<D<13.4 bottom region. Figure 4 illustrates the respective function output graphic.

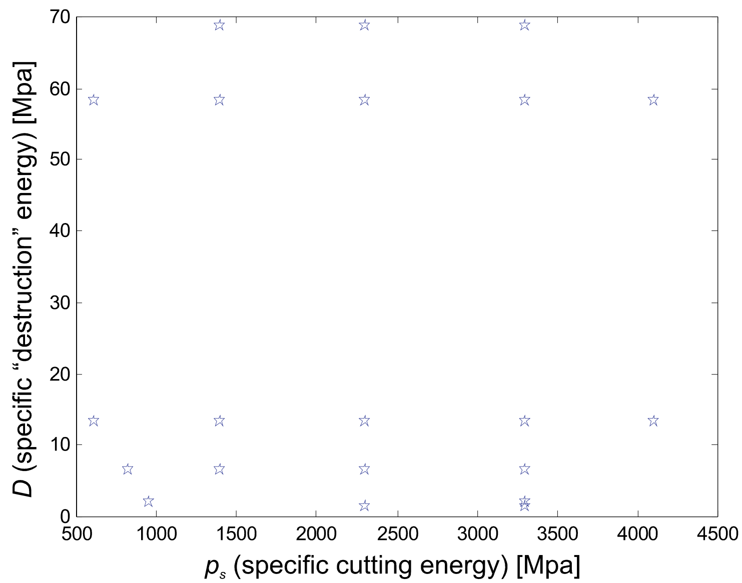

Figure 2. Available training data distribution for α_n, γ_n and λ_s

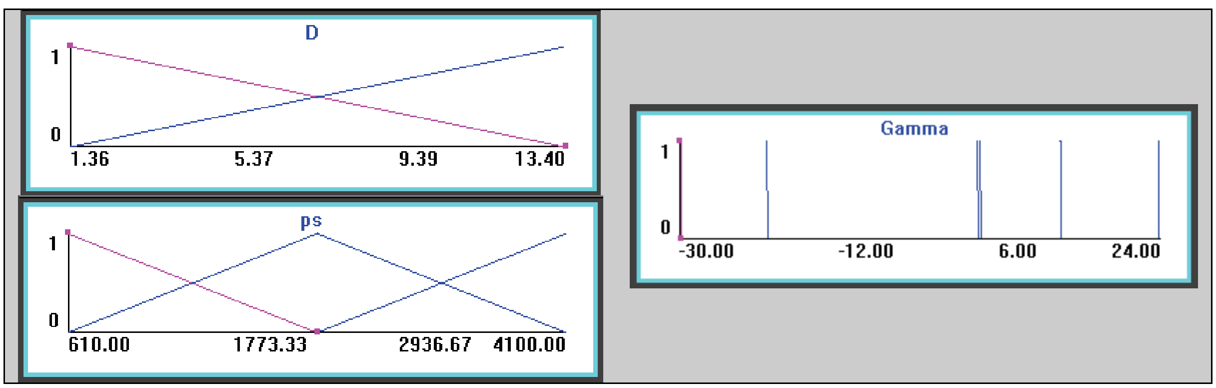

Figure 3. FLS inputs and output membership functions to calculate γ_n in the 1.36<D<13.4 bottom region.

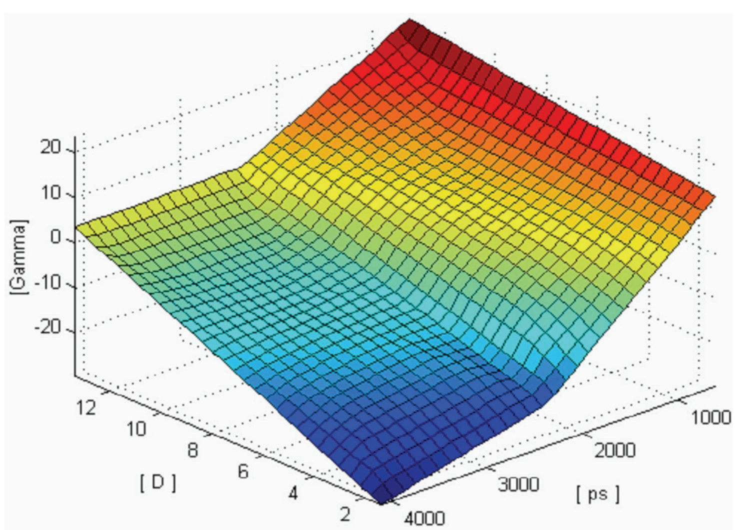

Figure 4. FLS transition function for γ_n calculus in the 1.36<D<13.4 bottom region.

Because of the few reliable empirical data, all of them were used for training the FLSs, without the conventional procedure of destining a data fraction for system reliability verification. In order to evaluate the outputs it is proposed the Kaldor and Venuvinod (1997) method. A "reliability" percentage comparing $\overline{\sigma_r}$ of the tool geometry output from the fuzzy logic system and $(\overline{\sigma_r})_{opt}$ is given by Eq. (6).

$$100 * \left[1 - \left| \frac{\sigma_r - (\sigma_r)_{opt}}{(\sigma_r)_{opt}} \right| \right] \% \tag{6}$$

4. USING EXAMPLE

Uncoated P30 carbide tools are intended to be used in finishing turning (depth of cut: 1 mm) of untreated AISI 9250 steel bars in a conventional machine tool. The estimated work material specific cutting energy is 3782 Mpa and the "destruction" specific energy of the P30 tool material is 6.47 Mpa. With these two inputs the FLS outputs (Fig. 5) are $\alpha_n = 5.9°$, $\gamma_n = -13.7°$ and $\lambda_s = 8.7°$. The "reliability" percentage calculated with Eq. (6) is 98%.

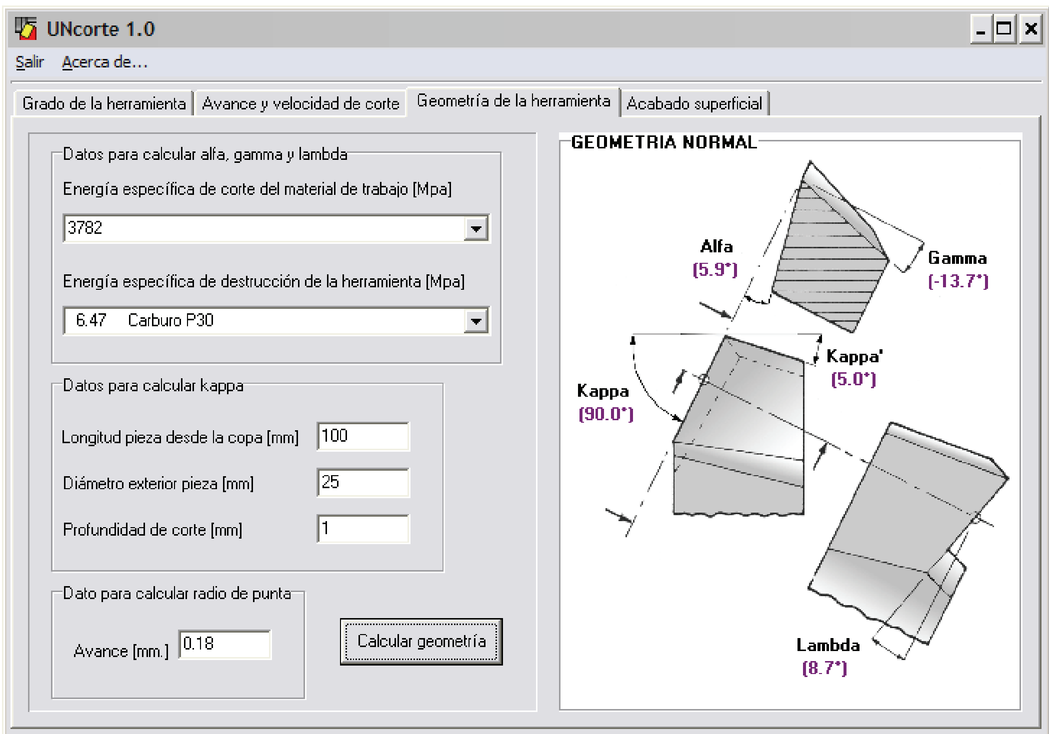

Figure 5. System output for AISI 9250 steel turning with P30 carbide tool.

5. CONCLUSIONS

In this work has been proposed a fuzzy logic method to suggest a reference tool geometry for different work-tool materials pairs by interpolating between empirically optimized tool geometries. With this method it is possible to suggest a tool geometry for not tested work-tool material pairs, diminishing the amount of experimental work necessary to optimize the tool tip geometry. The system can be improved by retraining it each time that the knowledge base of optimized tool geometries is increased or improved.

In order to model the empirical knowledge about recommended cutting tool geometry, the reliable available data to train the fuzzy logic system was very few compared with the space of the problem, therefore was not made the normal procedure of using a percentage of the data to verify the system. Alternatively it was used a method found in the literature for tool geometry reliability evaluation.

6. ACKNOWLEDGEMENTS

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