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Tool Conditions Monitoring Using Fuzzy Decision Support System

Marek Balazinski[1] , Krzysztof Jemielniak[2]
[1]École Polytechnique de Montréal, [2]Warsaw University of Technology

Abstract This paper describes the application of the Fuzzy Decision Support System, (FDSS „Fuzzy-Flou”) for the tool wear estimation during a turning operation. The estimation is based on the measurement of cutting force components. The fuzzy logic based decision support system uses expert rules of the type if-then to process the information. Database of the Fuzzy Decision Support System developed for this project contains three premises, two conclusions, and eighteen rules. The results demonstrate that the precision of the tool wear assessment is sufficient for on-line tool wear monitoring.

Keywords: tool monitoring, cutting force, fuzzy logic

1. INTRODUCTION

Since tool wear has a direct effect on the quality of machined pieces, on-line tool wear monitoring is one of the most important challenges in manufacturing. Tool wear influences a variety of phenomena. Number of monitoring systems utilise the fact that tool wear causes an increase in the cutting force and force related quantities, AE and vibration amplitude and others [2,3,7]. All above-mentioned phenomena however, depend not only on the tool wear, but also on a variety of other parameters such as, tool geometry, cutting conditions, cutting material and work material. Moreover tool wear - signal magnitude relationship is very complex and has rather statistical than strict, predictable nature. Sometimes signals from the sensor are not exactly equivalent to the measured feature, but disturbed by other phenomena [5]. Values of parameters used in process models are somewhat uncertain, eg. material properties can vary considerably from one batch to the next. Therefore it is now widely acknowledged, that reliable tool wear monitoring based on one feature is impossible. The combination of different features today is ever increasing to overcome drawbacks of single sensor approach. Feature integration lessens the diagnosis uncertainty due to randomness in sensor signal reduction. Weighting of features provides a more reliable information than a single sensor. Moreover feature synthesis can provide greater resolution in parameter estimates. Information extracted from one or several sensors' signals have to be combined into one tool or process condition estimate. It can be achieved by various means like statistical methods, auto-regressive modelling, pattern recognition, expert system and others [2, 3]. Artificial neural networks and neuro-fuzzy techniques have recently been the most intensively studied and the most frequently chosen methods of artificial intelligence for feature fusion (eg [4,6,8,9]).

Cutting force measurement is one of the most commonly employed methods for on-line tool wear monitoring, especially in turning, because cutting force values are more sensitive to tool wear than eg. vibration or acoustic emission [2,3]. Cutting force components however, are also sensitive to uncut chip cross section area. This area is a product of feed and depth of cut, of which the latter not always is known. A simple tool wear estimation method using only information from force components and the feed would be very useful in machine shop practice. The aim of this paper is to present the use of a fuzzy decision support system (FDSS) for the estimation of the depth of cut and the flank wear during the turning process. This assessment is based on the feed and two cutting force components (cutting force and feed force) values.

2. SELECTED ASPECTS OF DECISION MAKING IN A FUZZY ENVIRONMENT

Fuzzy logic is a major development of fuzzy set theory. This is a multi-valued logic that allows intermediate values to be defined between conventional evaluations like yes/no, black/white, etc. Notions like „rather cold” or „pretty warm” can be formulated mathematically and processed by computers. Fuzzy logic was designed to represent and reason with knowledge in linguistic or verbal form. In traditional set theory and computing, sets of elements are „crisp” and an element is either a member of a set, or it is not. In fuzzy set theory, an element could be a member of several sets with varying degrees of membership. For example, an average feed force of 400 N can be a member of both fuzzy sets defining forces (around ~300 N) and (around ~600 N) at the same time. Evidently the degrees of membership could be different for each fuzzy set and depend on the relative proximity between the observation (400 N) and the defined fuzzy set. Because 400 N is closer to ~300 N than ~600 N, the membership of this observation in the fuzzy set, ~300 N is higher than that in the fuzzy set ~600 N. This characteristic, that is a corner stone of fuzzy set theory, is completely ignored by classical set theory.

Decisions in fuzzy systems are based on inputs in the form of linguistic variables. The variables trigger, or „fire", a certain number of IF-THEN rules, which produce one or more responses (conclusions) depending on which rules are fired. The conclusion of each rule is weighted according to the degree of membership of its inputs. Usually, the centre of gravity of the responses is calculated to obtain an appropriate crisp output.

The major advantages of the fuzzy logic approach are: i) a mathematical model is not necessary, ii) the knowledge base is formed by a set of practical rules using linguistic variables, and iii) this method is very efficient under uncertain conditions, which are common in everyday situations.

In this section we shall present a rule-based approach to decision making using fuzzy logic techniques. This approach has been introduced in 1965 by Lotfi A. Zadeh of the University of California at Berkeley as a mathematical way to represent vagueness in everyday life [10].

The representation of knowledge by means of fuzzy linguistic variables makes it possible to carry out quantitative processing as part of the inference procedure. This procedure, often called approximate or fuzzy reasoning, is based on the compositional rule of inference. Such knowledge can be collected and delivered by a human expert. It is expressed by a finite number (k=1,2,..,K) of heuristic fuzzy rules of the MIMO type (multiple input multiple output) , and may be written in the form:

$$R^{(k)}_{MIMO}\text{: if } x_1 \text{ is } X^{(k)}_1 \text{ and } x_2 \text{ is } X^{(k)}_2 \text{ and.....and } x_N \text{ is } X^{(k)}_N \text{ then } y_1 \text{ is } Y^{(k)}_2,...,y_M \text{ is } Y^{(k)}_M \quad (1)$$

where: $X_1^{(k)}$, $X_2^{(k)}$,..., $X_N^{(k)}$ denote values of linguistic variables $x_1,x_2,...,x_N$ of the antecedent defined in the following universes of discourse: $\mathbf{X_1}$, $\mathbf{X_2}$, ..., $\mathbf{X_N}$ and $Y_1^{(k)}$, $Y_2^{(k)}$,..., $Y_M^{(k)}$ stand for values of independent linguistic variables $y_1,y_2,...,y_M$ of the consequent in universes of discourse $\mathbf{Y_1}$, $\mathbf{Y_2}$, ..., $\mathbf{Y_M}$, respectively. (where N is the number of premises and M is the number of conclusions).

For example, in layman's terms, equation (1) can be read as: „**If** the average cutting force **is** *~850* **and** the average feed force **is** *~320* **and…and** the nth force **is** *X*, **then** the tool **is** *sharp* **and** the depth of cut is ~1.5".

Generally, in the case of a knowledge base of MIMO system, the compositional rule of inference can be written symbolically as:

$$\left(Y_1^{'},\ Y_2^{'},...,Y_M^{'}\right)=\left(X_1^{'},\ X_2^{'},...,X_M^{'}\right)\circ R \quad (2)$$

where R represents a global relation aggregating all rules, (X_1', X_2',... , X_N') denote inputs (observations) and (Y_1', Y_2',... , Y_M') stand for outputs (conclusions). Symbol "$\circ$" stands for the compositional rule of inference operators (e.g. **supremum-minimum (sup-$\wedge$)**, **supremum-product (sup-*)**).

Both inputs and outputs are respective fuzzy sets. Equation (2) can also be read as: „The value of fuzzy conclusions ($Y'_{1,2...M}$) depends on fuzzy observations ($X'_{1,2...M}$), the fuzzy rule base R, and can be calculated from the rule base using operators of the compositional rule of inference.".

For example taking into account **suppremum-minimum** or (**supremum-product**) operations as compositional operators, **minimum** or (**product**) for fuzzy relation, **minimum** or (**product**) for sentence connective 'and' and **maximum ($\vee$)** or **sum ($\sum$)** for sentence connective 'also', we obtain respective inference results.

Different combinations of the operations constitute several different variants of the compositional rule of inference (CRI) and is the basis of the inference mechanism used in the Fuzzy Decision Support System (FDSS) called FUZZY-FLOU. This system was developed at École Polytechnique, de Montréal (Canada), and at the Technical University of Silesia in Gliwice (Poland) [1].

For a sake of generality and simplicity we use the membership function representation of the CRI variants in the formula written below :

$$Y'(y)=\begin{pmatrix}\bigvee_k\\ \sum_k\end{pmatrix}\sup_{\substack{x_1\in X_1\\ x_2\in X_2\\ \dots\dots\\ x_N\in X_N}} *_t\left[*_t\left(X_N^{'}(x_N)\right),....,\left(X_2^{'}(x_2)\right),\left(X_1^{'}(x_1)\right),R_F^{(k)}\left(X_1^{(k)}(x_1),X_2^{(k)}(x_2),...,X_N^{(k)}(x_N),Y^{(k)}(y)\right)\right] \quad (3)$$

where $R_F^{(k)}$ denotes a fuzzy relation between ($X_1^{(k)}$ (x_1), $X_2^{(k)}$ (x_2), ..., $X_N^{(k)}$ (x_N)) and $Y^{(k)}$ (y) and "$*_t$"stands for any t-norm.

A list of all operators used in FUZZY-FLOU is shown in Table 1.

Table 1. Options of FUZZY-FLOU inference mechanism

No.	Sequence of operations	Conn. **also**	Comp. Operations	Connective **And**	Fuzzy relation	Abbreviation

1	MAX-SUPMIN-MIN-MIN	MAX	SUPMIN	MIN	MIN	MA-SMI-MI
2	MAX-SUPPROD-PROD PROD	MAX	SUPPROD	PROD	PROD	MA-SPR-PR
3	SUM-SUPMIN-MIN-MIN	SUM	SUPMIN	MIN	MIN	SU-SMI-MI
4	SUM-SUPPROD-PROD-PROD	SUM	SUPPROD	PROD	PROD	SU-SPR-PR

To obtain the discrete value of the final membership function Y'(y), various methods of defuzzification can be applied. Three frequently used defuzzification methods are applied in FDSS FUZZY- FLOU. These are: centre of gravity (COG), mean of maxima (MOM), height method (HM).

For example when MAX-SUPMIN-MIN-MIN sequence of operations is used, formula (3) becomes:

$$Y'(y) = \max_{k} \sup_{\substack{x_1 \in X_1 \\ x_2 \in X_2 \\ \dots\dots \\ x_N \in X_N}} \min\left[\min\left(X'_N(x_N)\right), \dots, \left(X'_2(x_2)\right), \left(X'_1(x_1)\right), \min\left(X_1^{(k)}(x_1), X_2^{(k)}(x_2), \dots, X_N^{(k)}(x_N), Y^{(k)}(y)\right)\right] \tag{4}$$

Figure 1 is shows a diagrammatic representation of fuzzy reasoning according to this sequence of operations. The example describes a situation with two premises X_1 and X_2 and one conclusion Y(y). The input is a crisp observation. For the sake of simplicity, only three rules type **if** X_1 **and** X_2 **then** Y(y) are considered. Each of premises 1 and 2 contain three fuzzy sets, $X^{(1)}$, $X^{(2)}$, and $X^{(3)}$. The conclusion, Y, also contains three fuzzy sets $Y^{(1)}$, $Y^{(2)}$, $Y^{(3)}$. These fuzzy sets could represent linguistic variables such as: low, high, around 300, around 500, etc. The crisp observations are x_{10} and x_{20}. We can see that the first rule is not „fired" because there is no intersection between the premise fuzzy sets and the observations. Rules 2 and 3 are fired and two partial conclusions are obtained using operators from the first line of table 1. The final fuzzy conclusion is obtained by aggregating conclusions $Y^{(2)}$ and $Y^{(3)}$ using a MAX operator. To obtain a crisp conclusion, the centre of gravity of the final conclusion Y' must be calculated (defuzzification process). Figure 2 presents the same reasoning for the case of a fuzzy input.

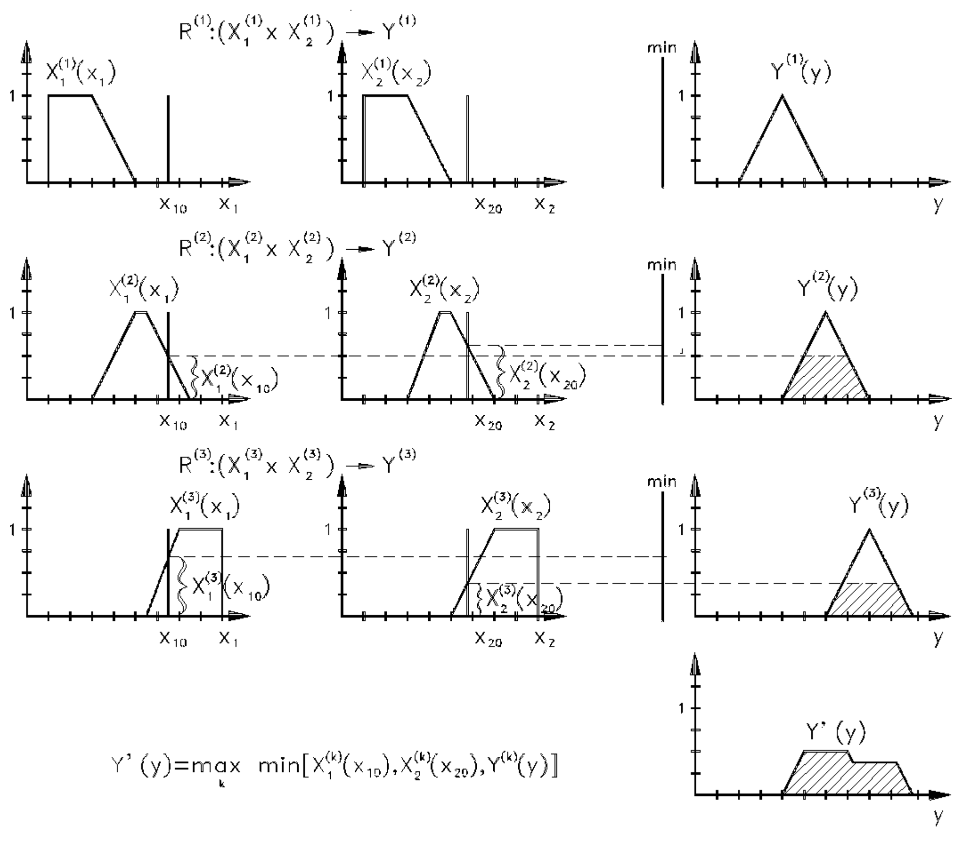

Fig. 1. Diagrammatic representation of fuzzy reasoning for crisp input according to MAX-SUPMIN-MIN-MIN operator.

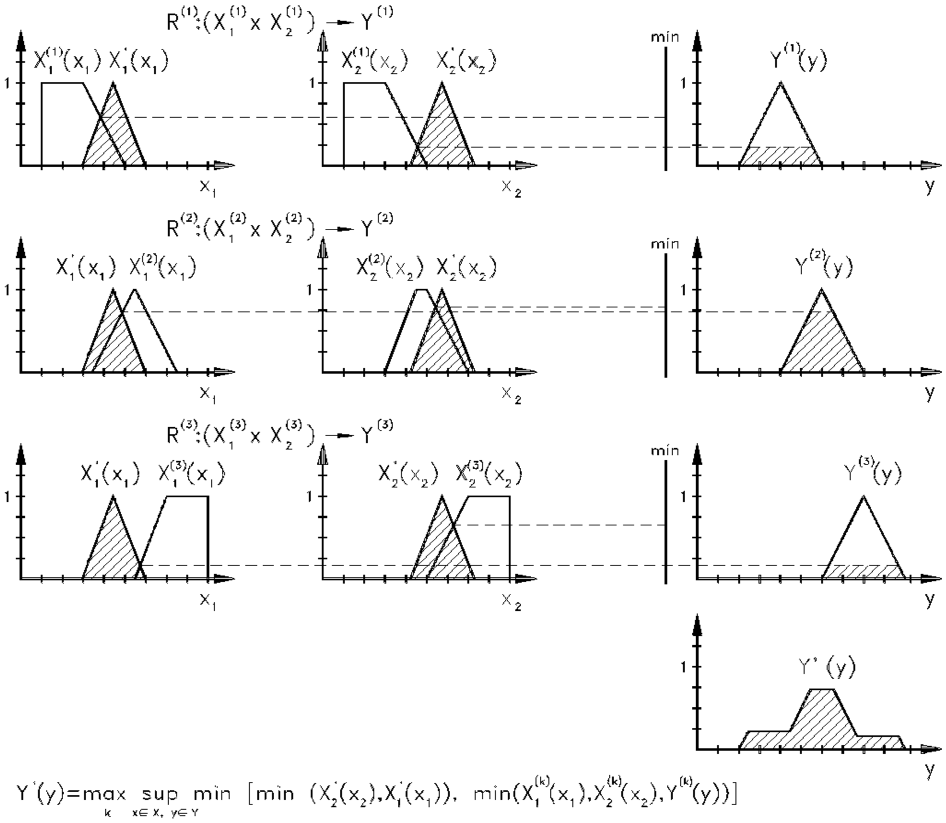

Fig. 2. Diagrammatic representation of fuzzy reasoning for fuzzy input according to MAX-SUPMIN-MIN-MIN operator

The architecture of FDSS FUZZY-FLOU consists of three main parts: a knowledge base, an inference engine and a user interface. The knowledge base consists of two components: the linguistic term base and the fuzzy production rule base. The linguistic term base is divided into two parts: fuzzy premises and fuzzy conclusions. It can contain more than one premise and conclusion. It should be emphasised that only the pseudo trapezoidal forms of membership functions are used as fuzzy premises and fuzzy conclusions. Knowledge is represented by a set of **if-then** rules which specify a relationship between observations (causes) and conclusions (effects). The knowledge base can be created directly from the monitor by using the tree view (described below) or can be written in a text editor and then charged into FUZZY-FLOU.

3. EXPERIMENTAL CONDITIONS AND RESULTS

The experiments have been conducted on conventional lathe TUD-50. The toolholder CSRPR 2525, equipped with TiN - AL_2O_3 - TiCN coated sintered carbide insert SNUN 120408 was used in the tests. Cutting forces were measured using Kistler 9263 dynamometer. To simulate conditions close to these in factory floor, six sets of cutting parameters were selected and applied in sequence, half a minute cutting time each. The parameters are presented in Table 2:

Table 2. Cutting parameters used in experiments

Set No	feed (mm/rev)	depth of cut (mm)	cutting speed (m/min)
1	0.24	1.5	351
2	0.17	1.5	417
3	0.47	1.5	251
4	0.47	3.0	251
5	0.33	1.5	300
6	0.33	3.0	300

Since inserts applied in experiments had soft, cobalt-enriched layer of the substrate under the coating, their tool life had tendency to end suddenly after wear out of the coating. To establish the tool life criterion, test were carried out until a tool failure occurred. Two such tests were conducted. In the first one ten cycles were performed, until sudden rise of the flank wear VB_B happened, reaching some 0.5 mm. In the second test, wear out of the coating resulted in chipping of the cutting edge at the end of 9-th cycle when the flank wear was some 0.35 mm. Thus the tool life criterion for these inserts was established as VB_B = 0.3 mm.

In Figure 3 presents the cutting force components - main F_c and feed F_f versus the tool wear obtained in both tests. Worth noticing and characteristic is week dependence of main cutting force on the tool wear. On the other hand, the feed force almost does not depend on tool feed, being effected only by depth of cut and the tool wear. This gives an interesting opportunity to estimate the tool wear without information about the depth of cut.

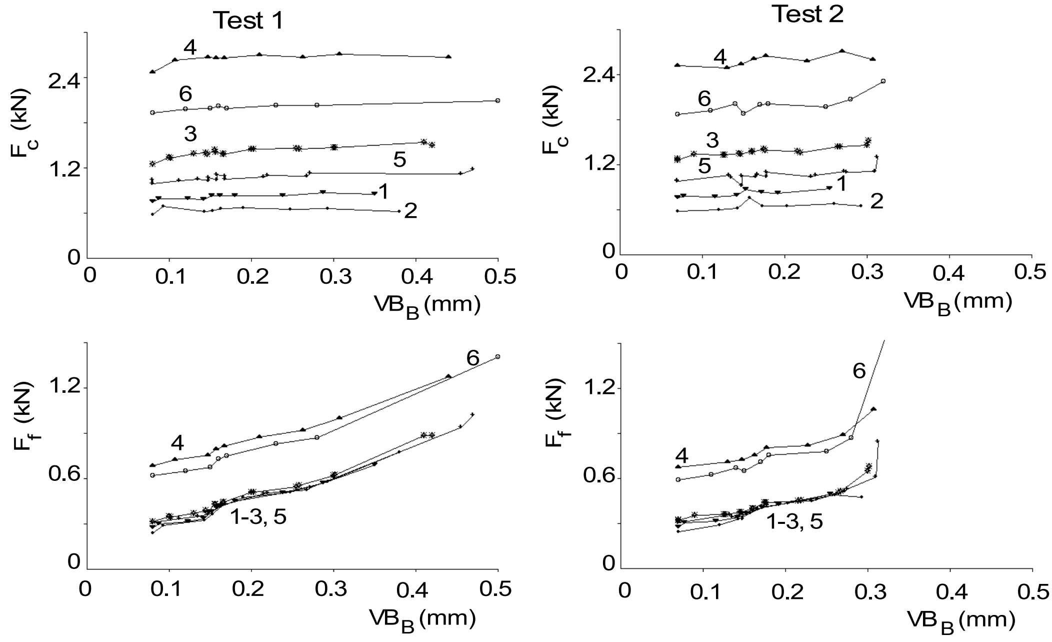

Fig. 3. Cutting force components vs. tool wear obtained in experiment.

4. PREPARATION OF THE KNOWLEDGE BASE FOR FDSS FUZZY-FLOU

The knowledge base for the decision support system was created directly from an analysis of the test 1 results presented in Fig. 3. It contains three premises (f, F_c and F_f) and two conclusion (a_p and VB_B). The first premise, the feed, is divided into four fuzzy sets according to the plan of the experiment (see Table 2). Six fuzzy sets for the second premise (F_c) are based on approximate values of the average cutting force in Figure 2, test 1 - one fuzzy set for each set of cutting parameters. As the cutting force barely depends of the tool wear, this premise, together with the feed, determines the first conclusion - the depth of cut.

The last, premise is the feed force F_f. Four fuzzy sets were determined for this key premise in relation to the tool wear and depth of cut - just form the results repeated for a sake of clarity in Figure 4. First, a conclusion concerning the tool wear were established. The conclusion is composed of three fuzzy sets shown above a diagram in Figure 4: **Sharp** for a new tool, **Worn** for VB_B~0.3 mm, and **Failed** for extensively worn tool (VB_B~0.5 mm). Here "worn" means the end of tool life - the insert should be replaced as soon as possible. "Failed" also means that tool life has expired, however this time there is a danger of catastrophic tool failure, so the insert should be replaced immediately.

Taking this into account and looking at the results presented in Figure 4, the fuzzy sets for the third premise were established (see right side of the Figure 4). The first set, **~320** covers cases when tool is **Sharp** and a_p=1.5, the second **~620** is for **Sharp** tool and a_p=3 mm, and for **Worn** tool and a_p=1.5, **~950 N** embraces **Failed** tool while cutting with a_p=1.5, and for **Worn** tool and a_p=3.0 and finally **~1400** refers to **Failed** tool and a_p=3.0.

The relationship between the premises and conclusions is assured by the set of rules. In the case of this analysis, a set of 18 rules was sufficient to define the relation between the inputs (premises) and output (conclusions). Fuzzy rules are coded as a matrix in which the first three columns refers to the premises, while 4-th and 5-th column embraces the conclusions. For example the third rule in the base is [3,3,1,1,1] and means:

RULE 3

If	the feed **is** around 0.33 mm/rev	(3-rd fuzzy set)
and	the average cutting force F_c **is** around 100 N	(3-rd fuzzy set)
and	the average feed force F_f **is** around 320 N	(1-st fuzzy set)
then	the depth of cut **is** around 1.5 mm	(1-st fuzzy set)
then	the tool **is** sharp	(1-st fuzzy set)

The term „around" is used because these linguistic variables are represented by fuzzy sets (triangles).

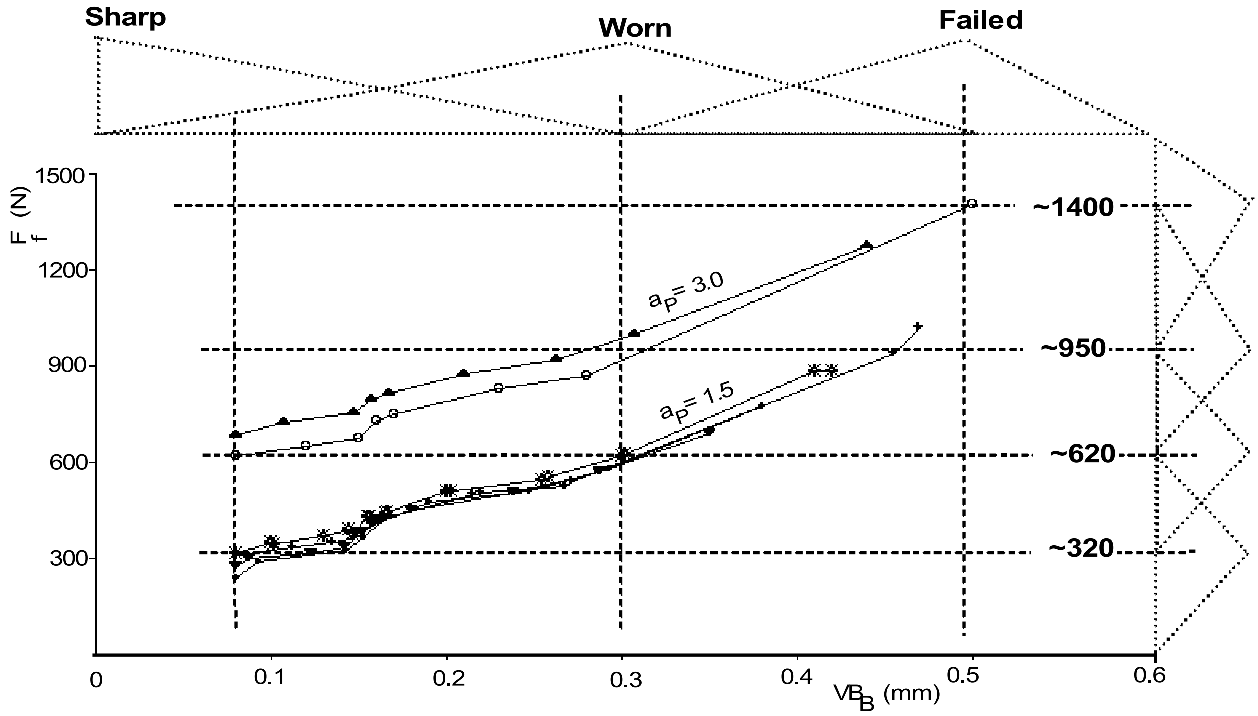

Fig. 4. Determination of fuzzy sets for conclusion VB_B and premise F_f.

5. RESULTS AND DISCUSSION

As mentioned above, the knowledge base for the decision support system was created from an analysis of the results of the first cutting test (Figure 3 and 4). Each set of data was tested using four inference engines. In each case the best result was obtained using the SUM-SUPPROD-PROD-PROD inference engine (see Table 1):

$$Y'(y) = \sum_k \sup_{\substack{x_1 \in X_1 \\ x_2 \in X_2 \\ \dots \\ x_N \in X_N}} \left[\left(X'_N(x_N)\right) \bullet \dots \bullet \left(X'_2(x_2)\right) \bullet \left(X'_1(x_1)\right) \bullet \left(X_1^{(k)}(x_1) \bullet X_2^{(k)}(x_2) \bullet \dots \bullet X_N^{(k)}(x_N) \bullet Y^{(k)}(y)\right) \right] \tag{5}$$

Figure 5 (left) shows the knowledge base structure of the software FUZZY FLOU with the premises, conclusions, and the rules. An example of the complete evaluation of the flank wear is presented on the right side of Figure 5. In this case, the feed was 0.24 mm/rev, average cutting force was 833 N and the average feed force was 403 N. The first three graphs in Figure 5 (right) show the premises. The two last graphs show the conclusions. The centre of gravity calculation for these conclusions resulted in crisp values of a_p=1.5 mm (accurate estimation) and VB_B=0.164 mm (the actual tool wear value in this case was 0.17 mm).

This knowledge base was tested using the data from test 1, which was used for database construction. The average error of the estimation was 0.027 mm and the maximum error was 0.07 mm. To verify that this knowledge base may be applied in a general way, data from test 2 were tested. In this case the average error was obviously larger, 0.035 mm and the maximum error was 0.146 mm. This maximum error occurred once, for the last the cutting forces measurement, just after chipping of the cutting edge. The chipping did not cause an increase of the flak wear but resulted in the cutting force increase. Since both high value of VB_B and chipped edge mean tool failure, the discussed answer of the FUZZY-FLOU should not be considered as erroneous. Without this last results: the maximum error was -0.09 mm and the average was 0.03 mm.

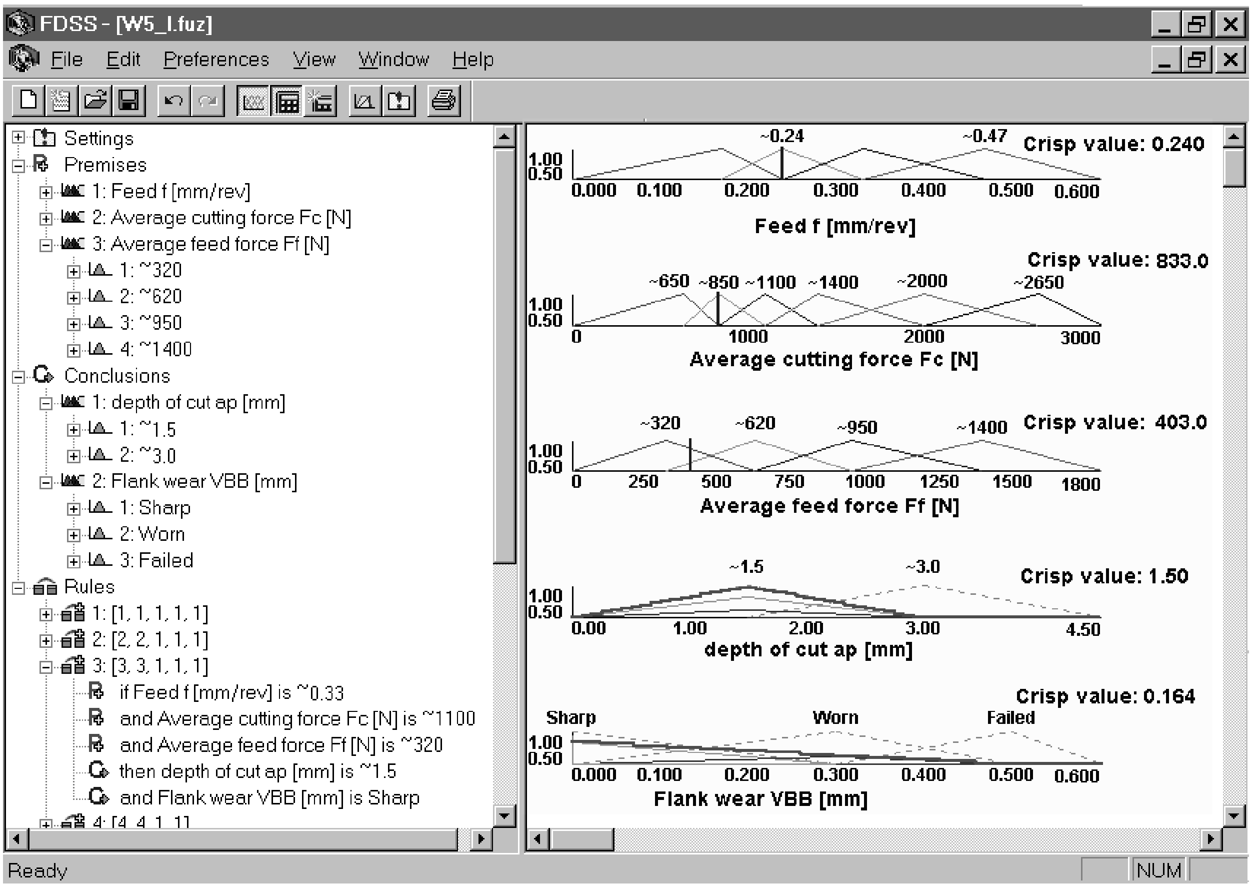

Fig 5. Screen layout of the software FUZZY-FLOU with the knowledge base structure (left), and the complete evaluation of the depth of cut and the flank wear (right).

In Figure 6 the measured and estimated by FUZZY-FLOU values of the tool wear obtained in both test are presented.

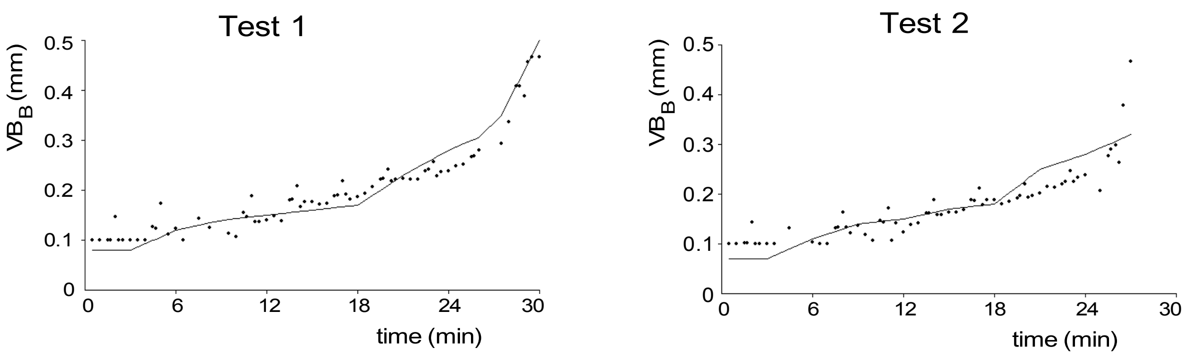

Fig. 6. Measured (continuous line) and estimated by FUZZY-FLOU (dots) values of the tool wear.

Here input data were the average (crisp) values of the cutting forces, however the FDSS gives also the possibility of using input data in the form of fuzzy values. This is particularly useful because the signal of the force measurement is often available only in the fuzzy form.

6. CONCLUSIONS

The results presented in this paper show that the application of the Fuzzy Decision Support System FUZZY-FLOU for the prediction of flank wear is simple and flexible. The knowledge base can be built easily without bothering about internal mechanism of the FUZZY-FLOU programme or mathematics concerning fuzzy logic itself, briefly described here in section 2.

The performance of the method holds promise for practical machine-shop application.

Further research is needed to broaden the basis for the input data, to improve modelling of linguistic values, and to examine the factors affecting the accuracy of system performance.

For this application the database is a very simple one.

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