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Tool Life Modelling Using RBE-DSS Method and LESFRI Inference Mechanism[1]

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1. Introduction

The right selection of cutting parameters for machining operations plays a crucial role in achieving the desired economical and quality goals. A key issue of the optimization models developed as a solution of this problem is the reliable prediction of tool life, which is strongly related to the identification of the functional relationship between the tool life and its main influential factors, i.e. the cutting speed and the feed rate.

Several models have been describing this topic, e.g. exponential [19], Taylor [19], corrected Taylor [19], Gilbert [2], Kronenberg [14], etc. and their parameters can be estimated from experimental tests using some optimization methods. However, the estimation capability (approximation accuracy) of these methods decreases when one increases the studied interval of cutting speed and feed rate. Thus soft computing techniques like fuzzy systems and neural networks, which proved to be universal function approximators [17, 24] when some conditions are fulfilled, can find a much promising application area.

The objective of the present study is the justification of practical applicability of sparse fuzzy systems for modelling real-life problems, and particularly in this paper the fuzzy modelling of tool life in milling, using the rule base generation method RBE-DSS [7] and the inference mechanism LESFRI [5] is studied.

The rest of this paper is organized as follows. Section 2 recalls some basic concepts of fuzzy reasoning and sparse rule bases. Section 3 presents the inference technique LESFRI followed by a survey on the model identification method RBE-DSS in section 4. The results are presented and discussed in section 5.

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2. Fuzzy reasoning in sparse systems

Fuzzy reasoning is based on IF-THEN rules, whose antecedent and consequent parts are linguistic terms (fuzzy sets). The early developed inference techniques, also called compositional or classic methods (e.g. Zadeh [26], Mamdani [16], Takagi-Sugeno [22] or Larsen [15]), require a full coverage of the input space, i.e. for each enabled input value (observation) the knowledge base of the system should contain at least one rule whose antecedent part overlaps the observation at least partially. This condition can be expressed by ε>0 in

$$\arg\max_{\varepsilon}\left(\min_{i=1}^{N}\left\{\max_{j=1}^{n_i}\left\{t\left(A_{i,j},A_i^*\right)\right\}\right\}\geq\varepsilon,\forall A_i^*\subset X_i\right),\ \varepsilon\in[0,1],\qquad(1)$$

where X_i is the i^{th} dimension of the antecedent space (universe of discourse), A_i^* is the fuzzy set describing the observation in the i^{th} antecedent dimension, A_{ij} is the j^{th} linguistic term of the i^{th} antecedent dimension, t is an arbitrary t-norm, n_i is the number of the linguistic terms in the i^{th} antecedent dimension, N is the number of the antecedent dimensions and $\arg\max_{\varepsilon}(.)$ finds the value ε for which the expression in parentheses reaches its maximum.

Rule bases fulfilling condition (1) with ε>0 are called dense ones (see Fig. 1). Usually they contain a large number of rules that increases exponentially with the number of input dimensions. This effect was one of the main reasons that led to the development of fuzzy systems that are able to produce the output relaying only on the relevant rules. Generally they apply so called sparse rule bases (see Fig. 4), i.e. their rule bases ensure only the fulfilment of (1) for ε=0.

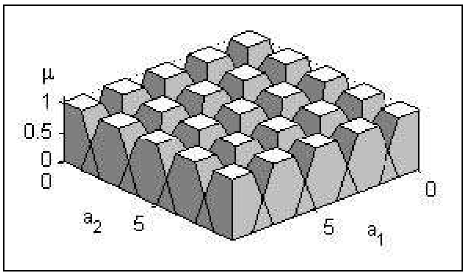

Figure 1. Antecedent space of a dense rule base

Since the classical fuzzy inference methods are able to work with sparse rule bases, new solutions for fuzzy reasoning had to be developed. Starting from the early 1990s several such methods have been published. They form two main groups depending on the applied approach.

The members of the first group calculate the conclusion directly from the observation and some rules. Here belongs the most known and firstly developed KH (Kóczy and Hirota) [12] method, and its modified and enhanced versions like the MACI [23] proposed by Tikk and Baranyi, which avoided the abnormal conclusion by introducing a coordinate transformation and the FIVE published by Kovács and Kóczy [10, 11] that solved the task of rule interpolation in the vague environment.

The methods belonging to the second group follow the concepts of the generalized methodology of fuzzy rule interpolation (GM) [1], i.e. determine the conclusion by interpolating first a new rule corresponding to the position of the observation and next calculate the conclusion based on the dissimilarities between the observation and the antecedent part of the new rule. Relevant members of this group are among others the techniques suggested in [1], the LESFRI (Johanyák and Kovács) [5] that uses the method of least squares, the FRIPOC (Johanyák and Kovács) [4] and IGRV (Huang and Shen).

3. LESFRI

Owing to its advantageous properties we chose LESFRI (LEast Squares based Fuzzy Rule Interpolation) [5] as fuzzy reasoning method. It follows the concepts of GM (Generalized Methodology of fuzzy rule interpolation) [1] by calculating the conclusion in two steps.

Firstly a new rule is interpolated corresponding to the position of the input values, i.e. the reference points of the antecedent sets are identical with the reference points of the observation in each input dimension. The task of rule interpolation is solved in three phases. Firstly the antecedent membership functions are calculated using the FEAT-LS (Fuzzy sEt interpolATion based on method of Least Squares) [6] fuzzy set interpolation method. Next one determines the position (reference points) of the consequent linguistic terms of the new rule using an adapted version of the Shepard interpolation [18]. The last phase is the calculation of the shape of the consequent sets using the same set interpolation technique (FEAT-LS) as in the first phase.

LESFRI determines the conclusion in its second step using the single rule reasoning method SURE-LS (Single rUle REasoning based on the method of Least Squares) [5] that calculates the necessary modifications of the new rule's consequent sets based on the dissimilarities between the rule antecedent and observation sets.

3.1. FEAT-LS

The FEAT-LS method [6] aims the determination of a new linguistic term in a fuzzy partition based on a supposed regularity between the known sets of the partition. First all linguistic terms are shifted horizontally into the interpolation point (x^i on Fig. 2 left side) and next, one calculates the shape of the new set from the overlapped membership functions (A^i Fig. 2 right side).

FEAT-LS targets the preservation of the characteristic shape type of the partition (e.g. trapezoidal on Fig. 2) therefore it applies the method of the weighted least squares for the identification of the new set's parameters. The weighting is related to the original distance between the sets and the interpolation point.

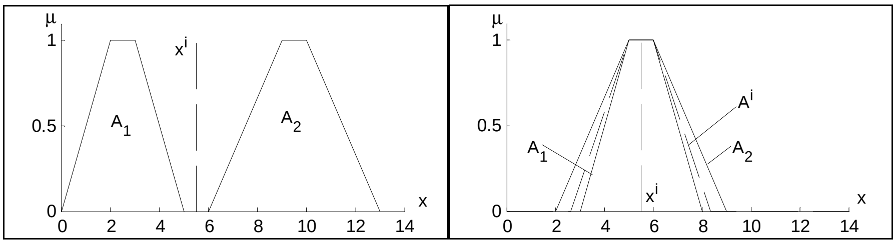

Figure 2. Original partition and interpolation point (x^i)

The calculations are done α-cut wise using only the α-levels corresponding to the characteristic points of the partition's default shape type.

3.2. SURE-LS

The revision method SURE-LS (Single rUle REasoning based on the method of Least Squares) [5] is a special fuzzy inference technique that takes into consideration only one rule for the determination of the conclusion. The method is applicable when its antecedent sets are in the same position as the observation sets in each antecedent dimension and the heights (maximal membership value) of all involved fuzzy sets are the same.

SURE-LS calculates the conclusion by modifying the consequent sets of the rule. This modification is related to the similarity between the antecedent linguistic terms and the observation sets, which is measured independently in each input dimension by the means of their fuzzy distance [13] (see Fig. 3) and is aggregated by calculating the average distance.

In order to keep low the computational complexity, which is an essential requirement in practical applications, only the α-levels corresponding to breakpoints (in case of piece-wise linear shape types) or characteristic points (in case of other shape types) are considered.

SURE-LS was developed for the case when all membership functions of a partition belongs to the same shape type (e.g. trapezoidal) and the corresponding break/characteristic points are situated at the same α-levels in case of each fuzzy set. In order to ensure this feature also in case of the conclusion the final shape is calculated using the method of least squares.

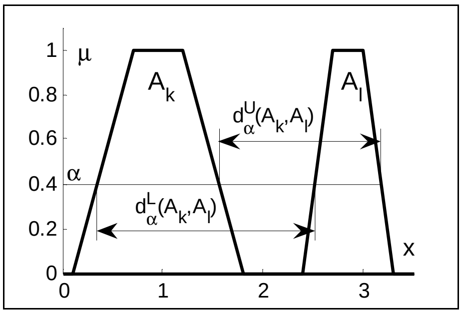

Figure 3. Lower ($d_\alpha^L(A_k, A_l)$) and upper ($d_\alpha^U(A_k, A_l)$) fuzzy distance at the α-level

4. Fuzzy model identification by RBE-DSS

The RBE-DSS (Rule Base Extension based on Default Set Shapes) [7] fuzzy model identification method provides the automatic creation of a sparse rule base with a low number of rules (low system complexity) from sample input-output data. The number of data points is not restricted. Although the system is tuned for a specific fuzzy reasoning method, several practical experiments showed good system performance also in case of reasoning with other methods that belong to the same FRIT family (e.g. the techniques that follow the concepts of the GM [1]).

The key idea of the Rule Base Extension is that one first creates two starting rules that describe the minimum and the maximum of the output. Next a parameter identification algorithm is started that tunes the parameters of the fuzzy sets and after each step evaluates the system by means of a performance index. If the amelioration of the performance index slows down or stops in course of the iteration a new rule is produced corresponding to the output point where the difference between the prescribed (measured value) and calculated (obtained by fuzzy reasoning) is maximal. The algorithm stops if either the prescribed maximal iteration number is reached or the performance index becomes better than a predefined threshold value.

4.1. Performance index

In course of the parameter identification process after each parameter adjustment the resulting parameter set is evaluated by calculating the system output for a collection of predefined input data, for which the expected output values are known. In order to compare the results obtained with different parameter sets a performance index is calculated after each system evaluation.

RBE-DSS supports the application of any kinds of performance indices that express the goodness of a fuzzy system with one numerical value, which decreases with the improvement of the system. A list containing several suitable performance indices was published in [8].

5. Fuzzy modelling of the tool life

In course of the tool life modelling we used results obtained by milling experiments carried out by carbide inserts DA20 and DA25. The data sets represented 9 experiments in the first case (DA20) and 15 experiments in the second one (DA25). In both cases two inputs (cutting speed – v_c in m/min and feed rate – f_z in mm/rev,tooth) and one output dimension (tool life – T in min) determined the fuzzy system.

We created separate models for the different carbide insert types using the RuleMaker [8] and FRI [9] Matlab ToolBoxes and applying RBE-DSS for rule base generation as well as LESFRI for fuzzy reasoning. The crisp output values were calculated applying centre of area (COA) defuzzification.

We used the relative value of the root mean square (quadratic mean) of the error (RMSEP) as performance index. We chose it owing to its easy interpretability and comparability to the range of the output. Its value [25] is calculated by

$$PI_{RMSEP} = \frac{1}{DR}\sqrt{\frac{\sum_{i=1}^{N}\left(T_i - \hat{T}_i\right)^2}{N}} \cdot 100 \quad [\%], \tag{2}$$

where DR is the range of the output, N is the number of the data points, T_i is the measured tool life in the i^{th} experiment and $\hat{T}_i$ is the tool life value obtained by the model for the inputs corresponding to the i^{th} experiment.

Both fuzzy systems apply sparse rule bases with 9 rules in the first case and 11 rules in the second one. Figure 4 visualizes the antecedent spaces of the rule bases. Each rule base is represented by a pyramid defined by the trapezoidal shaped antecedent fuzzy sets in the two input dimensions.

The generated fuzzy models were compared with former results [20, 21] obtained with models based on exponential tool life equation, Taylor tool life equation and corrected Taylor equation.

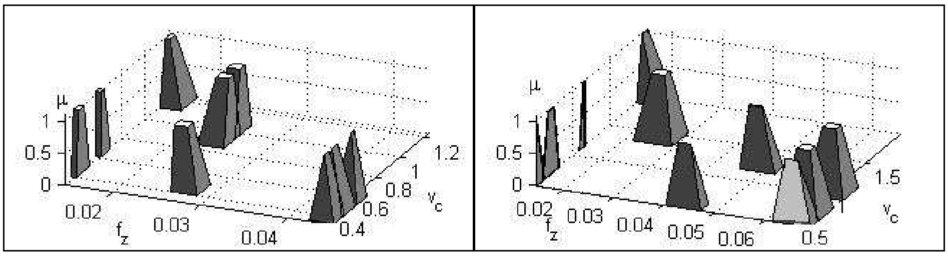

Figure 4. Antecedent space of the fuzzy systems DA20 (left) and DA25 (right)

As a comprehensive evaluation we can state that in case of both carbide insert types the fuzzy system proved to give better approximation of the measured data (see Tab. 1). The system modelling the functional relationship between the input and output in case of DA20 gave the overall best results.

Table 1. Performance indices calculated in case of exponential, Taylor, corrected Taylor and fuzzy models

	Exp.	Taylor	T. corr.	Fuzzy
DA20	1.1223 %	2.8816 %	4.7610 %	0.0473 %
DA25	0.7045 %	3.9486 %	7.2525 %	0.3315 %

Fig. 5 and 6 show the variation of the deviation (*dT*) between the calculated and measured tool life values in case of each modelling approach. The variable *dT* is plotted against the ordinal number of the data points (n_p).

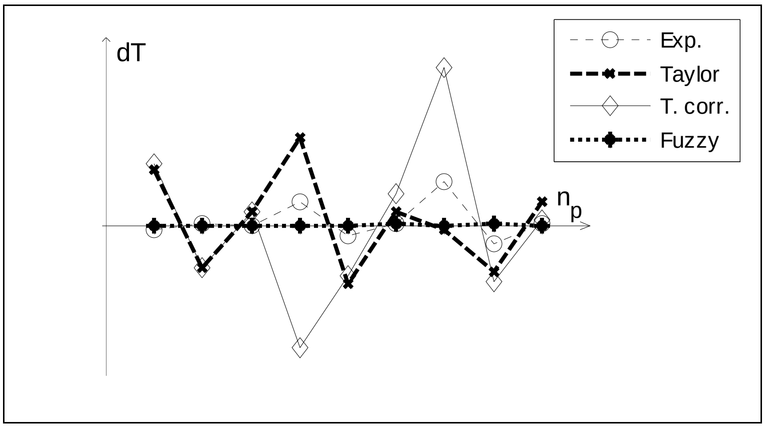

Figure 5. Deviation between the measured and calculated tool life values in case of the four models for DA20

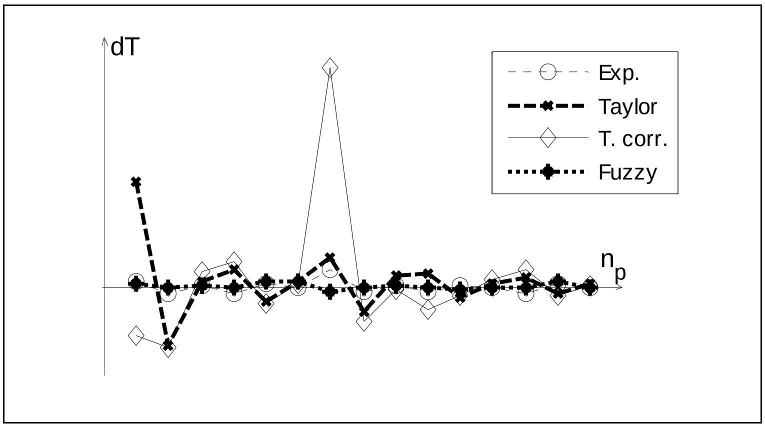

Figure 6. Deviation between the measured and calculated tool life values in case of the four models for DA25

Examining the individual deviations it is clearly observable that while in case of the Taylor and corrected Taylor models there are huge peek points, in case of the fuzzy model the curve describing the deviations is smoother.

The good approximation capability of the fuzzy model is also reflected by the Figure 7, where there is a well observable overlapping between the measured and calculated data points.

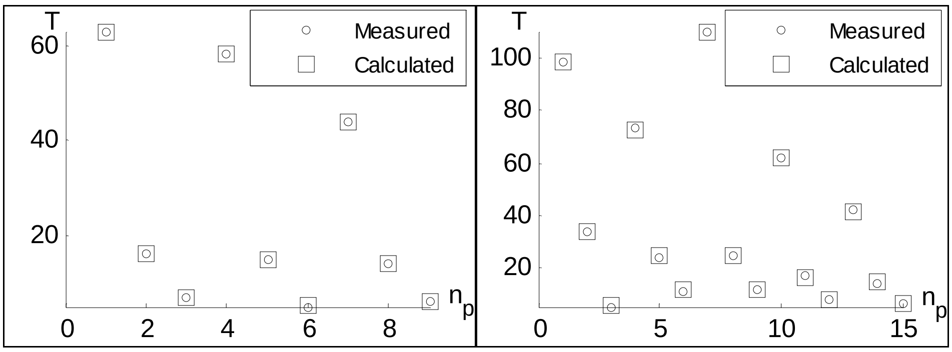

Figure 7. Measured and calculated data
DA20 (left) and DA25 (right)

6. Conclusions

This paper presented and evaluated the application of soft computing techniques for modelling of the tool life in case of milling operation using DA20 and DA25 carbide insert types. The applied fuzzy model identification technique was RBE-DSS [7] using the fuzzy reasoning method LESFRI [5]. Our goal was the generation of low complexity rule bases and the achievement of a better approximation than the previously published models.

The results showed that the selected method pair has proved to be a promising technique for tool life modelling. The established models can be used as supporting tool for researchers studying the machining operations. The enhancement of the applied methods and the study of their wider applicability are subject to further research work.

Appendix

Tool life models. In metal cutting, the most important economical factor is the *tool life (T* in min), i.e. the effective cutting time between two edge resharpening or – in case of indexable carbide inserts – edge change. The tool life is influenced in the highest degree by *cutting speed* (v_c in m/min). The relation between cutting speed and tool life is generally expressed in form of various *tool life models*. The most frequent exponential tool life model is originated with F. W. Taylor and can be written in form of

$$\lg v_c + m \,.\, \lg T = \lg C_v$$

where m and C_v are constant values (Taylor-equation).

Carbide tool materials. In modern metal cutting technology, the most frequently used tool (edge) materials are *cemented carbides*, consisting of hard *metal carbides* (WC, TiC, TaC, etc.) and *cobalt* as a binder material. Cemented carbides are produced by *powder metallurgy* technology, pressed into regular forms and sizes. According to the ISO-classification, the DA-grades used in our experiments (see Chapter 5.) are recommended for machining of steels. The carbide grade denoted by DA20 is harder (due to its less cobalt content) than that of DA25.

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Éltartam modellezés RBE-DSS és LESFRI segítségével

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Összefoglalás

A forgácsolási paraméterek helyes megválasztása lényeges szerepet játszik a kívánt gazdasági és minőségi célok elérésében. A feladat megoldásaként kidolgozott optimalizációs modellek egyik kulcskérdése a megbízható éltartam előrejelzés, ami szorosan kapcsolódik az éltartam és azt befolyásoló tényezők közötti kapcsolat megismeréséhez.

Dolgozatunkban lágy számítási módszerek éltartam területén való alkalmazhatóságát vizsgáltuk DA20 és DA25 anyagú keményfém marólapkákra. Az éltartamhoz kapcsolódó kis komplexitású fuzzy modelleket RBE-DSS módszerrel állítottuk elő, illetve a LESFRI következtetési technikát alkalmaztuk. Mindkét esetben sikerült a korábban közölteknél pontosabb modelleket előállítani.

Standzeitmodellierung mit RBE-DSS Methode und LESFRI Inferenz

Johanyák, Zsolt Csaba – Szabó, András

Zusammenfassung

Die richtige Auswahl der Schnittdaten spielt eine entscheidende Rolle bei der Erreichung der gewünschten Qualitäts- und Wirtschaftszielen. Eine zentrale Frage der Optimierungsmodelle, die als Lösung für dieses Problem entwickelt wurden, ist die zuverlässige Vorhersage der Standzeit, die in engem Zusammenhang mit der Identifizierung der funktionalen Beziehung zwischen der Standzeit und ihren wichtigsten Einflussfaktoren ist.

Dieser Artikel untersucht und bewertet die Anwendungsmöglichkeiten den Soft-Computing-Techniken für die Modellierung der Standzeit bei Fräsen in der Falle den Hartmetalleinsatztypen DA20 und DA25. Wir haben Fuzzy Modellen mit niedriger Komplexität hergestellt. Die angewendeten Techniken waren RBE-DSS [7] für Modellidentifizierung und LESFRI [5] für die Fuzzy Inferenz. Im Fall der beiden Modelle die resultierenden Performance-Indizes waren besser als die jenige die zuvor veröffentlicht wurden.