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The Improvement of Machine-Tools Dynamic Behaviour with Adaptive Fuzzy Control Systems (8-th part)

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ABSTRACT

In this paper it is continued the presentation of an adaptive fuzzy controller developed for cutting processes.There are detailed: a fuzzy controller with an optimal rule base, through an automatic self-learning process. He is composed of the following three subsystems: a basic fuzzy controller; on-line adaptive regulating scaling factors for various cutting conditions; an off-line self-learning subsystem for modifying the rule base. The design procedures for the proposed adaptive fuzzy controller are follows: define input variables, construct data base, construct rule base, generate inference output, on-line adaptive scaling factors.
In this work it is detailed: - the self-learning algorithm, compound from "performance measurement" and "self-learning mechanism"; - the controller run simulation.
***Keywords**: fuzzy controller, cutting processes.*

1. Introduction

This paper presents an adaptive fuzzy controller developed for cutting processes, under various cutting conditions. When machining conditions change significantly, applying adaptive control to the cutting process (by varying the table feedrate), allows a constant cutting force to be maintained.

The fuzzy controllers have the block diagram from the figure 1.

In **the previous parts of this paper** are detailed: fuzzy sets, linguistic variables (the 1-st part), the rule base, the fuzzification, the normalisation, the scaling factors (the 2-nd part), the atomic fuzzy proposition, the compositional rule of inference, the Mamdani implication (the most used for the fuzzy control), the multiple rules with crisp input (the 3-rd part), the composition based inference, the individual-rule based inference, the defuzzification (which is realised with the methods of the: maximum, abscissa of the weight centre, etc.) (the 4-th part), the conversion between the fuzzy variables and the crisp quantities, the achievement of a control table, the adaptive fuzzy control (the adaptive component of this consists of two parts: the performance monitor and the adaptation mechanism) (the 5-th part), a fuzzy controller with an optimal rule base, through an automatic self-learning process, composed of three subsystems (a basic fuzzy controller, on-line adaptive regulating scaling factors for various cutting conditions, an off-line self-learning subsystem for modifying the rule base); the design procedures for the proposed adaptive fuzzy controller are follows: define input variables, construct data base, construct rule base (the 6-th part), generate inference output, define output from defuzzification, on-line adaptive scaling factors (the 7-th part).

2. Fuzzy controller with an optimal rule base

In [5] is proposed a fuzzy controller (fig. 2) with an optimal rule base, through an automatic self- learning process.

3. Self-learning algorithm

Using equations (4 and 5, from [3]) yields a very elementary rule base; further modifications of the rule base is still required to achieve

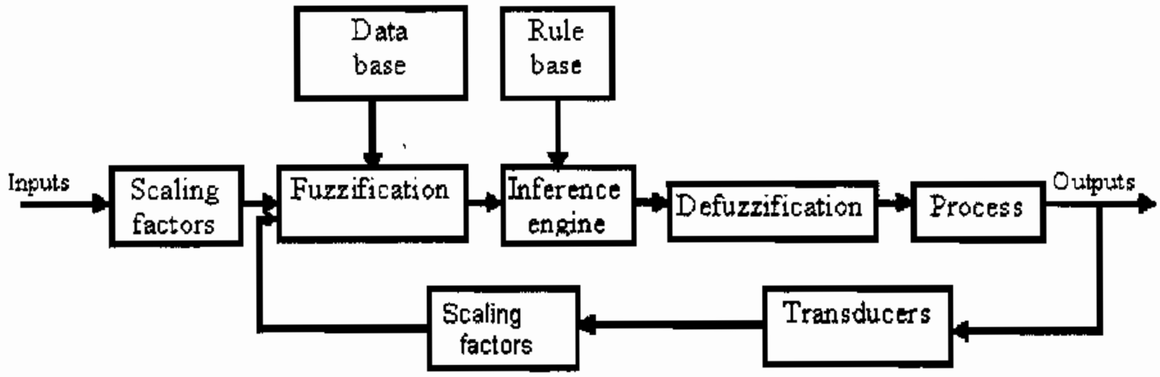

Fig. 1

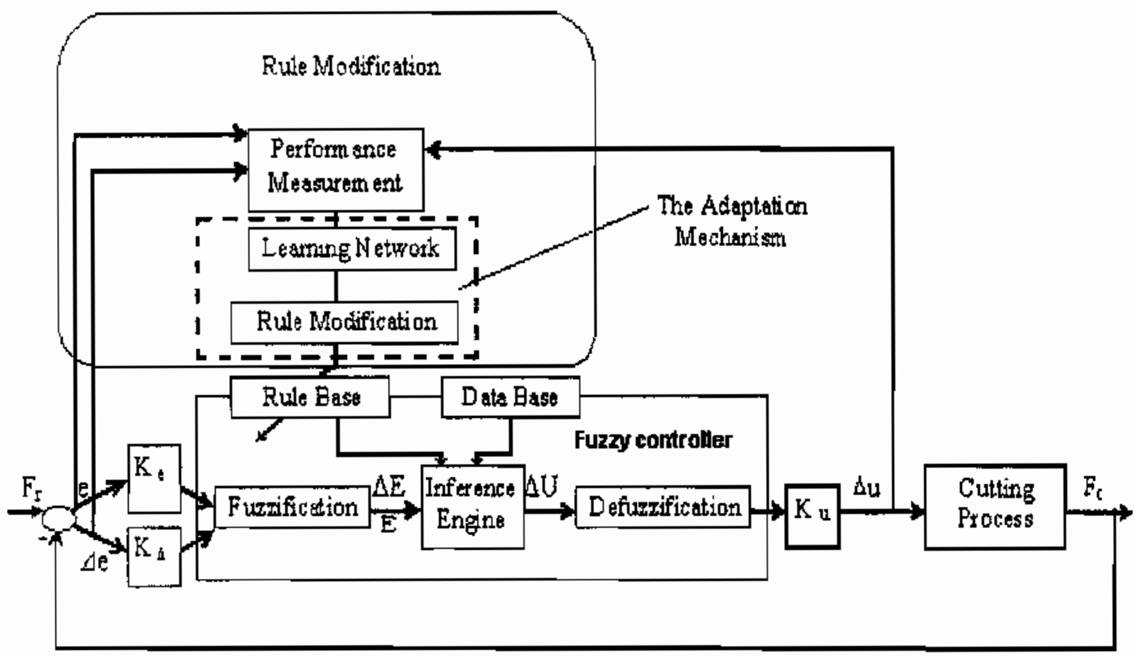

Fig. 2

better control performance. To update the controller, what is needed is **the appropriate correction for the process-input.**

a)- <u>Performance Measurement</u>

Since the present control goal is to maintain a cutting force within a tolerance band, the target set is selected around a zero error, as: $T = \{ NZ , PZ \} = \{ L_4 , L_5 \}$. (1)

In a adaptive fuzzy controller the control performance is given by four elements: $e\,(nT - mT)$, $\Delta e\,(nT - mT)$, $\Delta u\,(nT - mT)$ and $e(nT)$. These values can be described by fuzzy sets:

$$E\,(nT - mT)] = F\,[\, e\,(nT - mT)] \;;$$
$$\Delta E\,(nT - mT)] = F\,[\, \Delta e\,(nT - mT)] \;;$$
$$\Delta U\,(nT - mT)] = F\,[\, \Delta u\,(nT - mT)] \;;$$
$$E\,(nT) = F\,[\, e\,(nT)] \;, \qquad (2)$$

where F represents the process of fuzzification and these four subsets belong to a linguistic value set (3, from [3]): $\{ L_1 , L_2 , \ldots , L_8 \}$, denoted-respectively-by : L_i , L_j ,$L_{K\,ij}$, $L_{p\,ij}$

Therefore, a data set D_n representing at each sampling instance, may be defined as follows: $D_n = \{ i , j , K_{ij} , p_{ij} \}$,

$$(n = 1 , 2 , \ldots , N) \;, \qquad (3)$$

where N is the number of sampling points.

The relation (2) shows that the corresponding symbols i , j and $K_{i\,j}$ (at the past m sample instances) dominate the present performance measurement p_{ij} .

b)- <u>Self-learning mechanism</u> is formed by:

b1)- <u>Self-learning network</u>

All the D_n series will be processed in the self-learning network (which consist 8 x 8 = 64 nodes), as shown in figure 3, to generate a reinforcement $\Delta K_{i\,j}$, to modify the rule base. For each input D_n , the node (i , j) represents the firing of a corresponding state in the network. By processing performance measurement p_{ij}, we obtain a reinforcement $\Delta K_{i\,j}$, which represents the degree of **goodness**

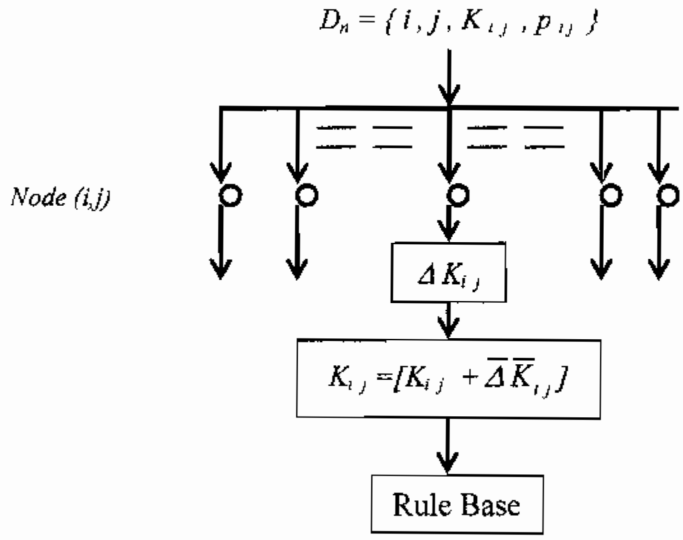

Fig. 3

or **badness** of the corresponding control action in the state. For example, if a *PB* control action (that means $K_{ij} = 8$) produces *NB* error after *m* samples (that means $p_{ij} = 1$), then reducing the control action will result in a smaller error.

The correction is defined in [5] as:

$$\Delta K_{ij} = \begin{cases} w(p_{ij} - 4), & if \ p_{ij} \leq 4; \\ w(p_{ij} - 5), & if \ p_{ij} > 4. \end{cases} \quad (4)$$

where *w* represents the weight, which size can be determined from either simulation or experimental analysis.

b2)- <u>Rule modification</u>

The new index K_{ij} will be:

K_{ij} = *the nearest integer to* ($K_{ij} + \overline{\Delta K}_{ij}$) , (5)

where $\overline{\Delta K}_{ij}$ is the mean values of ΔK_{ij} at each node (*i* , *j*) while processing a batch of data.

4. The controller run simulation

We consider the lathe of the semi – manufactured from figure 4, the parameters of the cutting process are:

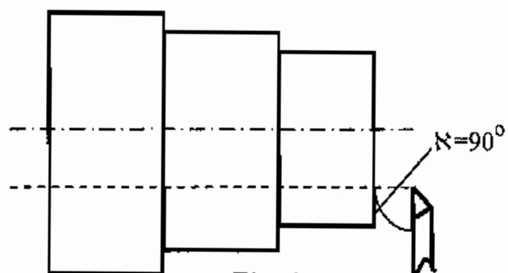

Fig. 4

$n = 1500$ *rot/min.* $= 25$ *rot/sec.* ; $s = 0{,}2mm$ / /*rot.*; the lengths $\ell_1 = \ell_2 = \ell_3 = 100mm$. ; the depths of cut $t_1 = 0{,}2$ *mm* ; $t_2 = 0{,}4$ *mm* ; $t_3 = 0{,}7$ *mm* ; the sampling time $\Delta T = 0{,}02s$. (6)

The cutting force - at lathe – has the components: F_x - the radial force (of repel), F_y - the tangent force (the main one) , F_z - the axial force (of advance). These components have the expressions [6]:

$$F_x = C_x (HB)^e \frac{1}{2}\left[1 + \left(\frac{\cos\aleph}{\cos 45^0}\right)^2\right] t^{0,9} s^{0,75} [daN]$$

$$F_y = C_x (HB)^e \left(\frac{\sin 45^0}{\sin\aleph}\right)^{0,25} t s^{0,75} [daN] \quad (7)$$

$$F_z = C_z (HB)^e \left(\frac{\sin\aleph}{\sin 45^0}\right)^{0,5} t s^{0,4} [daN]$$

in which: *t* is the depth of cut [mm]; *s* – the advance [mm/rot]; *HB* – the Brinell hardness of the processing material; ℵ - the main attack angle; C_x , C_y , C_z and *e* have the values from the table1.

Table 1

Material	Hardness *HB*	C_x	C_y	C_z	e
Steels and	≤ 170	18.13	27.9	11.16	0.35
Al alloys	> 170	2.32	3.57	1.43	0.75

Therefore , the resultant cutting force F , which is controlled to be constant, is defined as:

$$F_C = \sqrt{F_x^2 + F_y^2 + F_z^2} \; . \quad (8)$$

We calculate $F_{ext} = F\ (t_{ext}\ )$,

$$(\ ext = min\ ,\ max\ )\ ; \quad (9)$$

$$t_{med} = (\ t_{min} + t_{max}\ )\ /\ 2\ .$$

We take the reference force:

$$F_r = F\ (\ t_{med}\ )\ , \quad (10)$$

and the relation (3, from [4]) is replaced with:

$$K_e = \begin{cases} 0{,}2\ daca\ |F_r - F_C| \leq 0{,}1 \cdot F_r \\ 1\ daca\ |F_r - F_C| > 0{,}1 \cdot F_r\ , \end{cases} \quad (11)$$

0,1 being *the tolerance half-band* of *10 %*.

We calculate: $E_{ext} = (\ F_r\ - F_{ext}\ )\ K_e$,

$$(\ ext = min\ ,\ max\ )\ ;$$

$$E_m = MAX\ (\ /E_{min}\ /\ ,\ /E_{max}\ /\ )\ .$$

We apply the relations (11, from [1]) :

$$E_n = \left(\frac{6}{E_m}\right) \cdot E\ \ ;\ \Delta\, E_n = \left(\frac{6}{\Delta E_m}\right) \cdot \Delta\, E\ . \quad (12)$$

The normalised sizes E_n and $\Delta\, E_n$ are shown in figure 2 (from [2]), ΔU is in figure 3 (from [3]), and the primary rule base is in table 1 (from [3]).

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Ameliorarea comportării dinamice a masinilor-unelte cu sisteme de control fuzzy adaptive (partea a 8-a)

Rezumat

In lucrare se continua prezentarea unui controler fuzzy adaptiv dedicat proceselor de aschiere. Anterior s-au detaliat: un controler fuzzy cu o baza optimala de reguli, realizata printr-un proces automat de auto-instruire. El este compus din trei subsisteme: un controler fuzzy de baza; factori de scara reglati adaptiv on-line pentru diferite conditii de aschiere; un subsistem auto-instruibil off-line pentru modificarea bazei de reguli. Etapele proiectarii controlerului fuzzy adaptiv propus sunt: definirea variabilelor de intrare, construirea bazei de date, construirea bazei de reguli, generarea iesirii din inferenta, factori de scara adaptati on-line.

In aceasta parte a lucrarii se detaliaza: - algoritmul de auto-instruire, compus din "masurarea performantei" si "mecanismul de auto-instruire"; - simularea functionarii controlerului.

L'amélioration du comportement dynamique des machines-outils avec des systèmes de contrôle fuzzy adaptatifs (8-eme partie)

Résumé

En cet article c'est continué la présentation d'un contrôleur fuzzy adaptatif développé pour des processus de coupe. Ils sont détaillé: un contrôleur fuzzy avec une base optimale de règle, par un processus autodidacte automatique. Il se compose de trois sous-ensembles suivants: un contrôleur fuzzy de base; des facteurs de graduation réglées adaptatif on-line pour différents états d'usinage; un sous-ensemble autodidacte off-line pour modifier la base de règle.
Les procédures de conception pour le contrôleur fuzzy adaptatif proposé sont: définissez les variables d'entrée, construisez la base de données, construisez la base de règles, produisez de la sortie d'inférence, facteurs de graduation adaptatifs on-line.
En cet ouvrage c'est detaille: -l'algorithme autodidacte qui est compose par „l'evaluation de performance" et „le mechanisme d'adaptation"; -la simulation de fonctionement du contrôleur.