Fuzzy Inference System for Automated Surface Finishing Process

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ABSTRACT
In this work, we propose fuzzy systems inference to solve the problem of automated surface finishing. We applied Mamdani and Takagi-Sugeno to this problem. We used the actual machine set up and surface finish measures as inputs and analyzed the prediction accuracy for the surface finish.

Keywords*: Fuzzy System Applications, surface finishing, automated manufacturing*

1. INTRODUCTION
Zadeh [1973, 1975, 1979] provided the fundamentals machinery for fuzzy set-based approximate reasoning and inference [1]. In rule-based fuzzy systems, the relationships between input and output variables are represented by means of fuzzy if-then rules of the following general form: **if** antecedent proposition **then** consequence proposition. Depending on the form of the consequence, two main types of rule-based models are distinguished: Mamdani and Takagi-Sugeno models [2].
The objective of this work is to apply different membership functions and rule-based model defuzzification to surface machining processes. Mamdani and the Takagi-Sugeno models with Triangle and Pi membership functions have been used. For each model, the structure of reduced set of rules is presented. The simulation experiments showed that the system could be used to effectively predict desired surface quality.

2. FUZZY MODELS
In this work, we present two main types of rule-based models Mamdani and Takagi-Sugeno.

2.1 Mamdani Model
Zadeh has introduced the basic linguistic fuzzy models in 1973 and Mamdani has introduced his model for control systems in 1977 [2]. Fuzzy if-then rules are of the general form:
R_i : **If** x is A_i **then** y is B_i

where: A_i and B_i (i=1,2,...,k) are the membership values of the input and output variables $x \in X \subset IR^p$ and $y \in Y \subset IR^q$ [2-4].

2.2 Takagi-Sugeno (TS) model

Takagi-Sugeno model is based on control variables that are characterized by singleton or linear functions of the process state variable [4]. Sugeno inference is represented by:

R^i : **If** x_1 is $A^1{}_1$ **and** x_2 is $A^i{}_2$ **and** ... x_m is $A^i{}_m$ **then** $y^i = a^i{}_0 + a^i{}_1 x_1 + ... + a^i{}_j x_j + ... + a^i{}_m x_m$

where: IR^i (i= 1,2,...,n) denotes the *i*-th fuzzy rule, x_j (j=1,2,...,m) are input variables [5,6].

3. FUZZY SYSTEM INFERENCE FOR SURFACE FINISHING

Two sources of information for building the fuzzy system are the prior process knowledge and actual collected surface machining data. The prior knowledge is of approximate nature (qualitative knowledge), which originates from manufacturing experts.

The following steps were followed:

- define the application field (surface machining).
- select the input and the output variables (feed rate, cutting tool nose radius, and surface quality).
- formulate the available knowledge in terms of 25 fuzzy if-then rules.
- validate the system using actual data (actual machining set up).

3.1 The Application

Automated surface machining process control is essential to the performance of computer automated manufacturing processes. Quality of machined parts is one of the most important parameters in manufacturing process. Fuzzy system can simulate the human behavior to obtain the desired quality of the machined parts [7]. The machine set-up represents the desired target surface. The proposed fuzzy system is intended to deal with the optimum machine set-up parameters.

3.2 Input / Output Variables

Machining conditions are important factors that impact system performance and accuracy. The main factors affecting the work-piece surface quality are cutting tool (material and nose radius), work-piece material, feed rate, speed and depth of cut [8-12].

The proposed system accepts the cutting tool nose radius and feed rate as inputs and provides the surface quality as target output.

3.3 Fuzzy Rule Base

There are three variables used in this work as shown in Table (1):

Feed rate : [Very Low (VL), Low (L), Medium (M), High (H) & Very High (VH)]

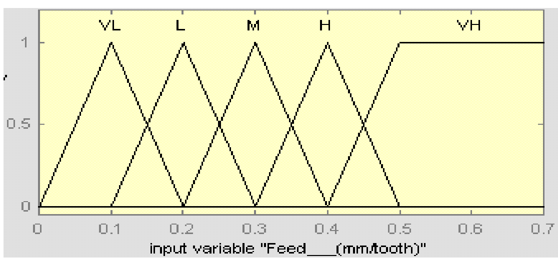
Nose radius : [Very Small (VS), Small (S), Medium (M), Large (L) & Very Large (VL)]

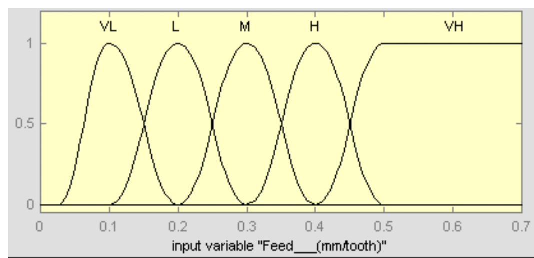
Surface quality : [Very Fine (VF), Fine (F), Little Fine (LF), Medium (M), Little Rough (LR), Rough (R) & Very Rough (VR)]

The choice of a suitable membership function influences the fuzzification outcome value. Different shapes can be utilized to construct membership functions (Gaussian, Triangular, …, etc.). Figures (1 and 2) show the Triangle and PI membership functions used in this work.

Table (1): Variable range

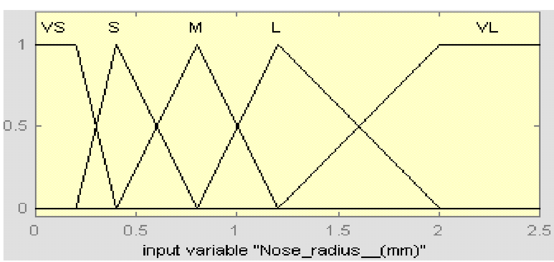
Feed Rate (mm/tooth)		Nose Radius (mm)		Surface Quality (μ m)	
Item	**Range**	**Item**	**Range**	**Item**	**Range**
Very Low	.025 - .200	Very Small	.05 - .40	Very Fine	0.2 - .75
Low	.100 - .300	Small	.20 - .80	Fine	.50 – 2.5
Medium	.200 - .400	Medium	.40 – 1.2	Little Fine	.75 – 5.0
High	.300 - .500	Very Large	.80 – 2.0	Medium	2.5 – 10
Very High	.400 - .600	Large	1.2 – 2.5	Little Rough	5.0 – 15
				Rough	10 – 20
				Very Rough	15 - 25

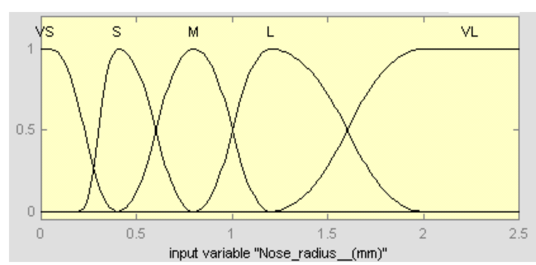




(1-a) Feed rate membership

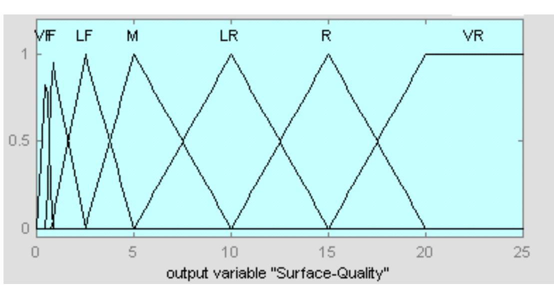
(2-a) Feed rate membership

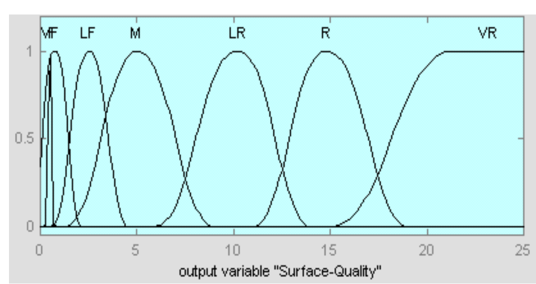




(1-b) Nose radius membership

(2-b) Nose radius membership





(1-c) Quality surface membership

Figure (1): Triangle membership function

(2-c) Quality surface membership

Figure (2): PI membership function

Fuzzy Rules Definition

Rules selection and evaluation are two important tasks during the design phase of the fuzzy inference system. The proposed fuzzy system is based on the expertise in the field of machining and metal cutting. A special rule reduction has been tested in the lab. The total number of rules is 25, they are e.g.

IF nose radius is **Very Small**
AND feed rate is **Very Low**
THEN quality surface is **Medium**

The rule view surface for Mamdani model and the rule firing Sugeno model are shown in Figures (3 and 4).

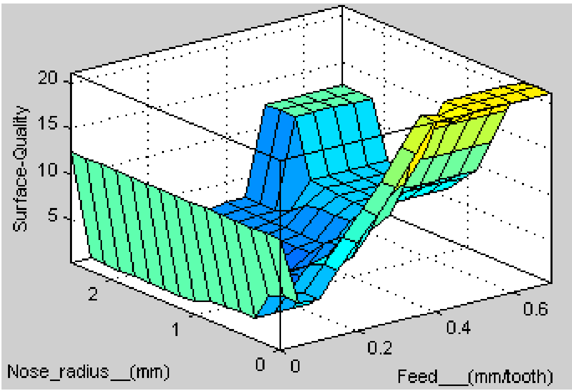


Fig. (3) Rule view surface for Mamdani model

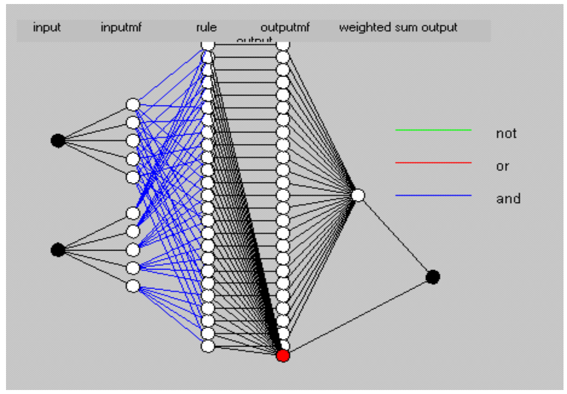


Fig. (4) Rule structure for Sugeno model

FUZZY INFERENCE SYSTEM RESULTS

The Mamdani and the Takagi-Sugeno models have been extensively used for the application. Figure (5) shows a sample run with Mamdani model and Figure (6) shows another sample run with Sugeno model.

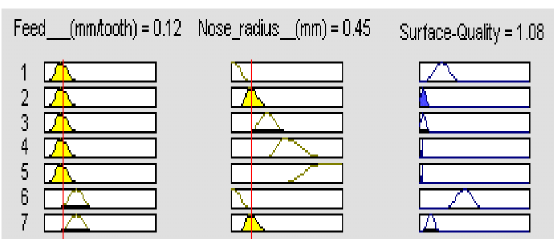


Figure (5):A sample run with Mamdani model

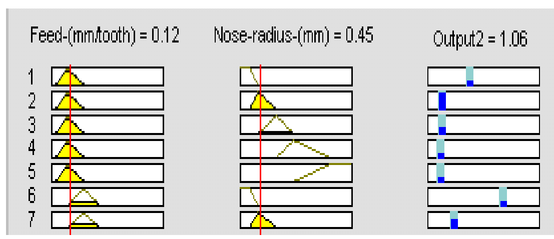


Figure (6): A sample run with Sugeno model

To simulate the actual machining condition, combinations of fuzzy inputs are run through sequential experiments at three different cutting tool nose radii and a wide range of feed rate values. The comparison between the accuracy of the above two systems is shown in Table (2) and Figure (7). Consistency between actual laboratory results and system output results are illustrated in Table (3). Figure (8) shows the prediction accuracy for the two models.

Table (2): System outputs

Nose Radius (mm)	No. of Experiments	Feed Range (mm/tooth)	Consistency between actual case and system outputs							
			Mamdani Model				Sugeno Model			
			Triangle		PI		Triangle		PI	
			No.	%	No.	%	No.	%	No.	%
0.396	14	0.10 - .050	13	93	10	71	10	71	10	71
0.792	11	0.05 – 0.60	10	91	8	82	6	55	6	55
1.192	5	0.20 – 0.70	5	100	5	100	5	100	5	100
Mean			94.7 %		84.3 %		75.3 %		75.3 %	

Table (3): Mean quality surface readings (µ m)

Nose Radius (mm)	Actual Surface Quality	Mamdani Model		Sugeno Model	
		Triangle	PI	Triangle	PI
0.396	8.5 (Medium)	5.78 (Medium)	5.44 (Medium)	**4.97 (Little Fine)**	5.01 (Medium)
0.792	4.94 (Little Fine)	4.33 (Little Fine)	3.9 (Little Fine)	**2.07 (Fine)**	**2.11 (Fine)**
1.192	3.91 (Little Fine)	3.56 (Little Fine)	2.91 (Little Fine)	2.85 (Little Fine)	2.83 (Little Fine)
Mean	5.78	4.56	4.08	3.3	3.32
%	100	79	71	57	57.4

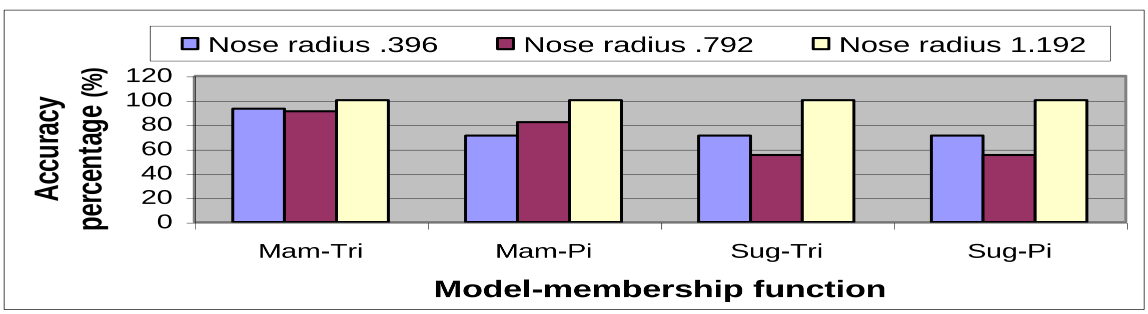


Figure (7): The comparison between Mamdani and Sugeno

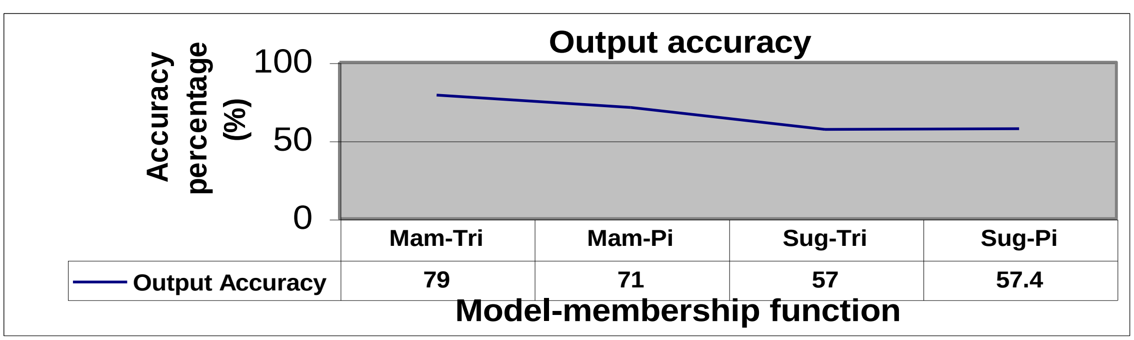


Figure (8): Output accuracy

CONCLUSION AND FUTURE WORK

The comparison between actual laboratory results on the machine set up and the proposed fuzzy inference outputs shows that the system can predict surface quality with:

- 94.7 % accuracy when using Mamdani model with triangle membership function.
- 84.3 % accuracy when using Mamdani model with Pi membership function.
- 75.3 % accuracy when using Sugeno model with triangle or Pi membership functions.

Also, the system shows that both models give good results at large nose radius (100 %). The applications using Mamdani model with, triangle membership function gave the best accuracy as shown in Table (3).

This work is a first step toward automated surface quality inspection. Future work remains to be done to allow the system to expand and measure the machine outputs for adaptive process control.

REFERENCES

1. M.J.Patyra and D.M.Mlynek, "Fuzzy Logic – Implementation and Applications", John Wiley & Sons, 1996.
2. R. Babuška, H.B. Verbruggen, and H. Hellendoorn, "Promising fuzzy modeling and control methodologies for industrial applications", ESIT'99, AB-02, Crete, Greece, June 1999.
3. M. Jamshidi, A. Titli, L. Zadeh and S. Boverie, "Applications of Fuzzy Logic – Towards High Machine Intelligence Quotient Systems", Prentice Hall, 1997.
4. L. C. Jain and C. W. de Silva, "Intelligent Adaptive Control – Industrial Applications", CRC Press, USA, 1999.
5. Hung T. Nguyen and Nadipuram R. Prasad, "Fuzzy Modeling and Control – Selected Works of M. Sugeno", CRC Press, 1999.
6. H. Hellendoorn and D. Driankov, "Fuzzy Model Identification – Selected Approaches", Springer-Verlag Berlin, Germany, 1997.
7. Y.S. Trang, H.Y. Chuang and W.T. Hsu, "Intelligent cross-coupled fuzzy feed rate controller design for CNC machine tools based on genetic algorithms", Int. J. of Machine Tools & Manufacture, V39, N10, Elsevier Science Ltd., 1999, pp 1673-1692.
8. D. K. Baek, T. J. Ko and H. S. Kim, "Optimization of feed rate in face milling operation using a surface roughness model", Int. J. of Machine Tools & Manufacture, V41, N3, Elsevier Science Ltd., 2001, pp 451-462.
9. Erik Oberg, Franklin D. Jones and Holbrook L. Horton, "Machinery's Handbook – A Reference Book for the Mechanical Engineer, Draftsman, Toolmaker and Machinist", Industrial Press Inc., New York, 1996.
10. Milton, C. Shaw, "Metal Cutting Principles", Oxford University Press, 1997.
11. Abdel Nasser Zaied, M. Zohdy and G. Barber, "An Expert Decision System For Optimum Tool Cutting Conditions" Submitted to IIE Transactions on Design and Manufacturing.
12. Abdel Nasser Zaied, M. Zohdy and G. Barber, " Improving Machining Quality Using Fuzzy Surface Quality System", Submitted to Journal of Manufacturing Systems.