Fuzzy-RIM Based Optimal Parameter Selection Method: Application to High Speed Milling Manufacturing Process of Thin Aluminum Alloy Structures

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Abstract

This work represents the selection of alternatives for the realization of high speed milling in aluminum alloy material, obtained by applying the Ideal Method. The analysis carried out taking into account the uncertainty values, determined that of the selected criteria, the deformation of the part is the one with the greatest influence. By modeling with the FRIM method, it was possible to determine the parameters of cutting speed (Vc= 200-400 m/min) and main cutting force (Fz = 0.20 N) allowing us to perform the milling operation guaranteeing to minimize the deformation of the thin-structured part.

Keyworks: RIM, Fuzzy, High Speed Milling, AHP.

Introduction

In industrial processes, quality is defined as an extension in which the product is built according to the design specifications and the application of the manufacturing requirements according to the functionality of the components that conform it. In high-speed machining processes, the most prominent sectors in which high standards of part quality prevail are automotive and aeronautics. With in-line production models, the main difficulty that appears is the quality evaluation process outside the process, causing losses due to defects that appear in the final part. Because of this, it is necessary to incorporate automated and learning methods as a predictive solution to improve the finish, taking into account machining parameters.

At present, there is a diverse literature where ways and methods are sought to improve quality levels in high speed processes. Researches have approached this problem from different points of view and use different techniques. [1], demonstrates the effectiveness of applying two different classification methods with machine learning, Bayesian networks and neural networks to predict surface roughness in high speed machining. From the accelerated competition in the search for higher production levels but with low costs without affecting the environment [2], he applies grey relational analysis in establishing multi-objective optimization with minimum lubricant usage, milling parameters in improving surface quality and tool wear. Within the research on artificial roughness we find the use of optimal prediction methods of milling parameters, [3],[4] with the mathematical model Particle Swarm Optimization (PSO) validated through experiment and theoretical research to make clear the results and the relationship that is established between the parameters demonstrating the versatility and capacity that is achieved surface roughness in milling processes. [5] He adds edemas the action caused by the cutting speed on the second peripheral angle and the main diameter showing its influence on the surface texture; he uses for this purpose neural network back propagation in the prediction of the final result. In a similar proposal [6], he takes into account in his analysis the influence of vibrations on the tools; he predicts the final state of surface roughness using AI through a Gaussian regression model. Fuzzy logic has been found in research is used, [7] with an Adaptive Neuro-Fuzzy Inference System (ANFIS) model manages to estimate and predict the grade obtained in the high speed milling process; several runs are employed with steel material, with coated carbon insert. In ferrous and non-ferrous materials such as EN24 steel alloys, with the influence of cutting parameters with ball-shaped inserts, the behavior of Ra is studied [8], in the experiment the tungsten coated carbide steel tools are handled, the method used is through a Behnken box based on RSM method and the speed in rpm in CNC machines is taken into account. [9] With the infinite analysis method and from the effect of hybrid parameters in machining, it is possible to analyze the tool wear and surface roughness; it is related to the dimensions of the part, the clamping and the amplitude reached by the vibrations in the machining process. The tool wear is investigated under conditions of constant value of cutting speed during different periods of time. [10] [11] enrich in their studies the action of cutting forces in high speed milling processes in stainless steel parts with martensitic composition (1Cr13) and its optimization in order to improve the surface quality of the parts. With a model where the relationship between the cutting parameters depth of cut, feed, cutting speed and feed per tooth and with the cutting force to predict the surface roughness is established. The fundamental AI tools implemented are neural networks and radial basis functions. In his contribution [12] establishes how the monitoring of tool conditions is necessary in high speed milling processes and its evaluation establishes important criteria in the Ra values achieved in production. It applies AI efficiently to establish clusters that are used in the final diagnosis and proposals for the tool monitoring system.

In the case of advanced optimization techniques with AI, we have the case of [13] with methods of developing a model to improve the surface roughness in high speed ball milling process in finishing operation, with the methodology based on design of experiment. The union of the complex function and teaching-learning based optimization algorithm focuses on determining optimal parameters of the cutting process. In the same way [14], in his tests on manganese alloys (AZ91D and AZ31) taking into account the dynamic actions that appear in the milling process with changes in cutting forces and vibrations. [15] Analyzes for this same type of tools in finishing operations in high speed milling with hardened steel alloys 42CrMo4. By combining the sustainable model of neural networks, basic radial function and multithreaded perceptron it is achieved to predict the state of best behavior of the cutting forces in this type of alloys. The relationship established between high speed and computer numerical control in milling conditions to a large extent the degree of quality in the surface finish of the parts [16] this concept in finishing operations, helical milling, cutting tools with their characteristics is obtained learning with control scenarios to the cutting parameters. The optimal conditions in the milling of AISI 1045 steel parts has in its processes costs in the manufacture of parts, by employing artificial intelligence mechanism allows us to decrease these values and also achieve that the quality of good quality surfaces in fast fabrications, [17] his research is done from seven parameters in two experiments.

The multi-objective analysis related to surface roughness is found in [18], where the optimization of the lubricating fluid in milling processes on parts made of AISI 1045 material is presented. It establishes a predictive mathematical model where the effects of minimum lubrication are observed and the machining parameters are examined to determine the optimum conditions with minimum surface roughness and minimum energy consumption. [19] carries out the multi-objective methodology, where the cutting parameters (Vc, Ap and f) are optimized for a turning process with martensitic stainless steel material (AISI 420), minimizing the surface roughness with the required cutting force is achieved. [21] It presents the RIM method, as an improvement of the MCDM TOPSIS and VIKOR tools.

The object of research of this work is to determine the best alternative that minimizes the deformation in parts of thin aluminum alloy structures when performing high speed milling operations. For this, the novelty of the fuzzy set theory and its arithmetic is used in its solution, with the best solutions from the intermediate values, with the ideal reference method (RIM) and uncertainty analysis.

Materials and Methods

High-speed milling operations were performed on Quick Machining Center Jet AV1612, equipped with HEI-CNC-System from DENHAIN with precise machining control with a maximum spindle speed of 20,000 rpm and feed speed of 25 m / min. The workpiece selected for the experiment of an Al 5083 alloy in rectangular shape with dimensions of 140 mm × 70 mm × 5 mm. The chemical composition and physical properties of the workpiece material are collected in **Table 1** and **Table 2** respectively.

Table 1. Chemical composition of aluminum alloy 5083.

Elemento	% Presente
Si	0.4
Fe	0.4
Cu	0.1
Mn	0.4-1.0
Mg	4.0-4.9
Zn	0.25
Ti	0.15
Cr	0.05-0.25
Al	Balance

Table 2. Physical properties of 5083 aluminum alloy

Propiedades	Valor
Density	2650 kg/m^3
Melting point	570 °C
Modulus of elasticity	72 GPa
Electrical resistivity	0.058×10^{-6} Ω-m
Thermal conductivity	121 W/m-K
Thermal expansion	25×10^{-6} /K

Table 3. Mechanical properties of aluminum alloy 5083.

Temper	H32	0/HIII
Proof stress 0.2 % (MPa)	240	145
Tensile strength	330	300
Shear strength (MPa)	185	175
Elongation A5 (%)	17	23
Hardness Vickers	95	75

RIM algorithm with fuzzy numbers

Based on the considerations made above, regarding the form of the calculation of the minimum distance to the Reference Ideal and the normalization function, it is possible to proceed to the application of the RIM algorithm. In this case, the algorithm to be followed is described:

Step 1. Definition of the working context.

Its purpose is to establish the conditions of the working context, where for each criterion Ej has to be defined; the rank Rj , the Reference Ideal IRj and the weight Wj associated to each criterion.

Step 2. Obtaining of the decision matrix V, where the valuations issued (Vij) represent triangular fuzzy numbers.

$$V = \begin{pmatrix} V_{11} & V_{12\ldots} & V_{1n} \\ V_{21} & V_{22\ldots} & V_{2n} \\ & & \vdots \\ V_{m1} & V_{m2} \cdots & V_{mn} \end{pmatrix} \qquad (1)$$

Step 3. Normalization of the valuation matrix V as a function of the ideal solution.

$$N = \begin{pmatrix} f(V_{11}, t_1, S_1) & V_{12\ldots} f(V_{12}, t_2, S_2) \ldots & f(V_{1n}, t_n, S_n) \\ f(V_{21}, t_2, S_2) & f(V_{22}, t_2, S_2) \ldots & f(V_{2n}, t_2, S_2) \\ \vdots & \vdots & \vdots \\ f(V_{m1}, t_1, S_1) & f(V_{m2}, t_2, S_2) & f(V_{mn}, t_n, S_n) \end{pmatrix} (2)$$

Step 4. Calculation of the weighted normalized matrix P through:

$$P = N \otimes W = \begin{pmatrix} n_{11} \cdot w_1 & n_{12} \cdot w_2 \ldots & n_{1n} \cdot w_n \\ n_{21} \cdot w_1 & n_{22} \cdot w_2 \ldots & n_{2n} \cdot w_n \\ \vdots & \vdots & \vdots \\ n_{m1} \cdot w_1 & n_{m2} \cdot w_2 & n_{mn} \cdot w_n \end{pmatrix} (3)$$

Step 5. Calculation of the variation to the ideal and non-ideal solution for each alternative Ai .

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(p_{ij} - w_j\right)^2} \;\; y \;\; d_i^- = \sqrt{\sum_{j=1}^{n} \left(p_{ij}\right)^2} \qquad (4)$$

Where i = 1,2,...m, j=1,2,...n and pij are the values of the matrix P.

Step 6. Calculation of the index relative to the ideal solution of each alternative Ai, through the expression:

$$R_i = \frac{d_i^-}{d_i^+ + d_i^-} \text{ , donde: } 0 \leq R_i \leq 1,\ i\text{=1,2,…m} \qquad (5)$$

Step 7. Ordering of the alternatives Ai in descending order from the relative index Ri . If the alternative has an index Ri close to the value 1, it will indicate that it is very good, however if this value descends approaching the value 0, we will interpret that the alternative should be rejected.

Results and Discussion

Analytical Hierarchical Process (AHP).

(Saaty, 1987), with the Analytical Hierarchical Processes method, presents a general theory of scaled measurement of discrete and continuous values by equating multilevel values to create a hierarchical structure.

Step 1. Development of the model for the business.

It is defined through a hierarchical structure for the problem by matching the criteria and sub-criteria from the highest level to the lowest level by going through the alternatives.

Step 2. Derive priorities (weights) for the criteria.

Six sub-tasks are developed in this step:

a) The comparison matrix is established for each hierarchical level, the comparisons are made in pairs with the scale of values from 1 to 9.

b) The weights are normalized from the comparison of the criteria, the geometric mean is calculated for each row and the main rows are normalized in the comparison matrix. (A2) is the main geometric matrix.

c) The matrices A3 and A4 are evaluated by A3 = A1 * A2 and A4 = A3/A2.

d) Find the maximum value of landa ʎmax , calculated from the average of matrix A4.

e) Evaluate the consistency index (CI) as shown in formula x.

$$CI = (ʎ\max - N)/(N - 1)$$

f) The consistency ratio (CR) is calculated as the ratio of CI and Random Index (RI), where RI is the random ratio obtained by different orders of the matrix pairwise comparison. Generally, a consistency ratio of 0.1 or less value is considered good enough, reflecting an unbiased judgment of the decision maker.

Step 3. Consistency check (Correct assignment or not of weights).

Now, compare the matrix of alternatives in pairs with respect to how best they satisfy each of the criteria considered.

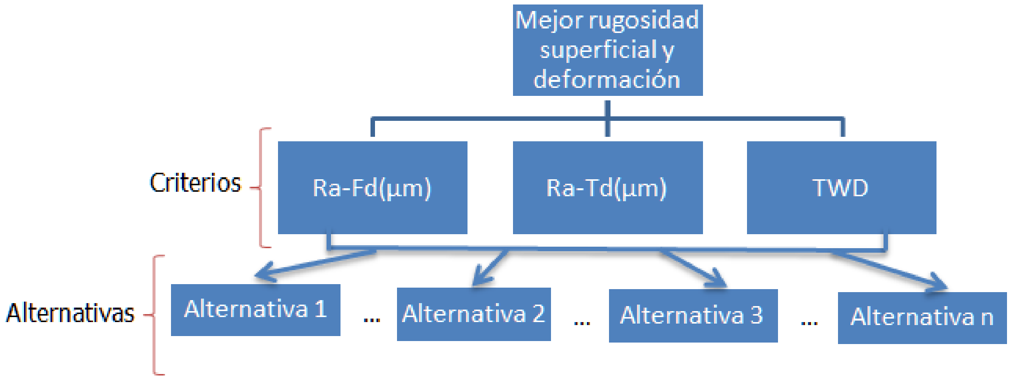
Step 4. Obtain the overall priorities (Final synthesis model).

Depending on the overall performance values obtained, the best and worst preferred values for the problem are given. The normalized relative weight (w) of each criterion with respect to the corresponding normalized weight is obtained by summing all the criteria of the alternative.

AHP method for weight evaluation.

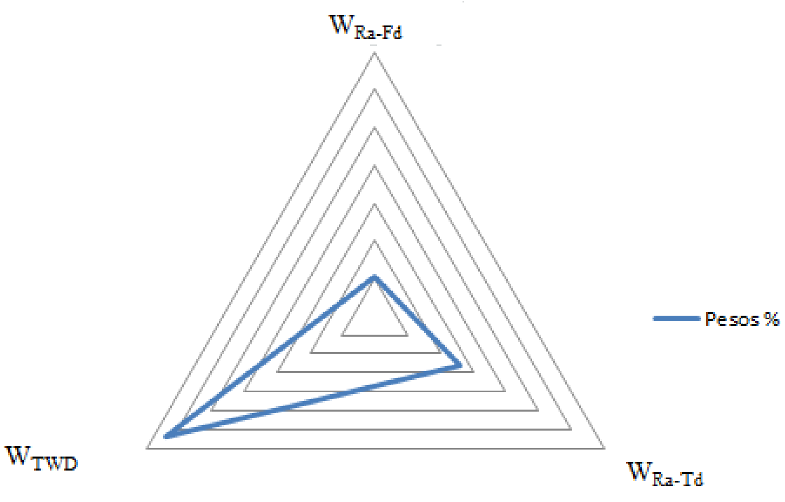
After establishing the business model, **Figure 1**, we proceed to calculate the weights using the AHP method.

Figure 1. Hierarchical model for calculation of the weights



The value of the weights are calculated as $W_{Ra\text{-}Fd}$ = 0.10473, $W_{Ra\text{-}Td}$ = 0.25828 and W_{TWD} = 0.63699, their graphical representation is observed in **Figure 2**. The value of ʎmax = 3.03851. The coefficient Ratio CR = 0.03702989, the same takes a value less than the permissible CR < 0.1.

Figure 2. Graphical representation of the weights.



Fuzzy-RIM

	Ra-Fd(µm)	Ra-Td(µm)	TWD
A	(4.260,4.864,4.495)	(3.844,3.854,3.918)	(0.051,0.052,0.056)
B	(6.056,5.833,6.538)	(5.432,6.264,5.394)	(0.106,0.105,0.105)
C	(4.263,5.436,6,056)	(3.938,4.681,5.432)	(0.049,0.067,0.105)
D	(4.147,5.416,6.540)	(3.851, 4.842,5.394)	(0.041,0.076,0.106)
X	(4.132,4.432,4.243)	(3.422,3.422,3.304)	(0.021,0.031,0.033)
Y	(4.231,4.232,4.222)	(4.242,3.222,3.312)	(0.102,0.102,0.101)

Table 1. Decision matrix

	Ra-Fd(μm)	Ra-Td(μm)	TWD
A1	0,7352	0,2648	0,7352
A2	0,0311	0,9689	0,0311
A3	0,3963	0,6037	0,3963
A4	0,7080	0,2920	0,7080
A5	0,0807	0,9193	0,0807
A6	-0,3887	1,3887	-0,3887
A7	0,1981	0,8019	0,1981
A8	-0,0351	1,0351	-0,0351

Table 2. Normalized Valuation Matrix

Ra-Fd(μm)	Ra-Td(μm)	TWD
0,0770	0,068	0,468
0,0033	0,250	0,020
0,0415	0,156	0,252
0,0741	0,075	0,451
0,0084	0,237	0,051
-0,0407	0,359	-0,248
0,0207	0,207	0,126
-0,0037	0,267	-0,022

Table 3. Normalized and weighted matrix.

Ra-Fd(μm)	Ra-Td(μm)	TWD	di+
0,0008	0,0361	0,0285	0,1687
0,0103	0,0001	0,0004	0,0198
0,0040	0,0105	0,1479	0,3845
0,0009	0,0334	0,0346	0,1860
0,0093	0,0004	0,3429	0,5856
0,0212	0,0101	0,7825	0,8846
0,0071	0,0026	0,2609	0,5108
0,0118	0,0001	0,4347	0,6593

Table 4. Variation to the positive reference ideal and calculation of di+

Ra-Fd(μm)	Ra-Td(μm)	TWD	di-
0,0059	0,0047	0,2193	0,4795
0,0000	0,0626	0,0004	0,2511
0,0017	0,0243	0,0637	0,2996
0,0055	0,0057	0,2034	0,4632
0,0001	0,0564	0,0026	0,2431
0,0017	0,1287	0,0613	0,4378
0,0004	0,0429	0,0159	0,2434
0,0000	0,0715	0,0005	0,2683

Table 5. Variation to the negative reference ideal and calculation of di-

	A1	A2	A3	A4	A5	A6	A7	A8
Ri	0,6524	0,7077	0,4265	0,6382	0,2905	0,3267	0,3188	0,2865

Table 6. Calculation of the Ri index

We conclude that under the criteria analyzed, the best alternatives are A2, A1 and A4, establishing a good approximation between them. The selection of the cutting speed (Vc= 200-400 m/min) and main cutting force (Fz = 0.20 N) parameters allows us to perform the milling operation guaranteeing to minimize the deformation of the thin-structured part.

Conclusions

Within the machining processes the occurrence of uncertainty in the measurements, it is necessary to have tools that minimize this problem, the following work used fuzzy set theory and arithmetic, it is also considered that the best solutions are not always found in the maximum or minimum values, but can be an intermediate value. In this work using Fuzzy and RIM (FRIM) and multicriteria analysis this situation is solved by performing high speed milling process to thin structures of Al 5083 alloys, minimizing the deformation of the part as the most critical criterion.

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