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Original Article

Use of the support vector machine (SVM) algorithm to predict geometrical accuracy in the manufacture of molds via single point incremental forming (SPIF) using aluminized steel sheets

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ABSTRACT

In the present work, the use of the support vector machine (SVM) algorithm is proposed to generate models that allow predicting the geometrical accuracy of molds manufactured via single point incremental forming (SPIF) using aluminized steel sheets DX51D AS120 B CO. For this purpose, 27 molds were manufactured, using the dummy technique, and employing different process parameters (tool diameter, spindle speed, feed rate, step size) and toolpath strategies (contour-parallel, spiral, radial). The molds manufactured were geometrically characterized by means of a coordinate measuring machine: the transverse profile of each mold was measured and compared with the expected theoretical profile. Three geometrical values were extracted from this comparison: the area between the two profiles, the moment of inertia of this area with respect to the Y-axis and the difference in height between the two profiles at the mid-point of the mold. The geometrical accuracy of the mold increases if these values decrease. The model that achieved the best results is the one associated with the area between the theoretical and real profiles (correctly classified instances = 90%; kappa statistic = 0.8). This model was generated using the LibSVM (linear kernel) algorithm and evaluating only three of the five parameters (strategy, tool diameter and step size). In addition, process maps were drawn up to show briefly which values generate higher geometrical accuracy in the molds: contour-parallel strategy, tool diameter equal to 12 mm and small step size values.

1. Introduction

The single point incremental forming (SPIF) process is used for manufacturing prototypes or small batches of parts, avoiding the use of presses and dies [1]. Usually, the process is carried out in a machining center [2]: a frame, where the sheet is fixed, is mounted on the machine table; a semi-spherical tool, placed on the spindle, is responsible for progressively

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deforming the sheet, following the path programmed in the numerical control. The most important parameters in the SPIF process are [3]: tool diameter, spindle speed, feed rate, and step size. The strategy used to generate the tool path is also important; the most common strategies are contour-parallel and spiral [4].

The advantages of the SPIF process are as follows: it is a relatively low-cost process; it allows a large number of metallic and polymeric materials to be deformed; it is a process that has a short learning curve, as machining centers are common and well-known machines; it allows materials to be deformed beyond conventional deformation limits [5]; parts with relatively complex geometries can be formed [4].The main limitation of the process is the geometrical accuracy of the parts [6], due to phenomena such as springback, sheet bending and pillow effect [7,8].

1.1. *Use of machine learning to improve geometrical accuracy*

To improve the geometrical accuracy of parts manufactured by incremental forming, some authors propose the use of machine learning algorithms [9,10]. Khan et al. [11] developed a classification intelligent methodology that allows the prediction of springback in the SPIF process. Akrichi et al. [12] used different algorithms (back-propagation neural network, deep belief network and stacked autoencoder) to predict roundness and position deviation in parts manufactured using SPIF. Thiery et al. [13] used an artificial neural network to predict the pressure levels that are required to obtain the desired geometry in an incremental deformation process with an active medium.

In the present work, the use of the Support Vector Machine (SVM) algorithm is proposed to manufacture molds using SPIF with a higher geometrical accuracy. SVM is a classification algorithm widely used in industry [14]: Wuest et al. [15] proposed the use of cluster analysis together with SVM as a means to improve quality monitoring in a manufacturing process; Priore et al. [16] used the SVM algorithm to perform dynamic scheduling in flexible manufacturing systems; Lingitz et al. [17] studied the use of SVM in lead time prediction in a semiconductor industry; Lee at al [18]. used SVM to predict the quality of parts manufactured by metal casting; Hu et al. [19] proposed a method to diagnose fused deposition modelling (FDM) printing faults caused by the variation of temperature field; Aoyagi et al. [20] used the SVM algorithm to predict whether parts manufactured in a powder-bed fusion type additive manufacturing process would have high or low porosity. However, in the literature there are hardly any references that have used SVM in the field of sheet metal forming [10].

1.2. *Forming of bimetallic sheets: aluminized steel*

In recent years, the manufacture of parts using SPIF from bimetallic sheets has gained interest; in this regard, different properties can be obtained on each side of the part: resistance to corrosion, high electrical or thermal conductivity, high mechanical properties, food contact. Ali et al. [21] studied the formability and failure analysis of Al/stainless steel; Honarpisheh et al. [22] experimentally verified the maximum depth and thickness that can be obtained in a hyperbolic part when using an Al-1050/Cu sheet; Liu and Li [23] studied the formability, surface roughness, thickness variation and forming forces in the deformation of Al/Cu sheets obtained by cold roll bonding. However, no work has been found concerning the forming of aluminum-coated steel by SPIF.

Aluminized steel is obtained through a continuous process during which the steel sheets pass through a molten aluminum-silicon bath. This type of steel is of great industrial interest as it is a material with excellent mechanical and forming properties, with a competitive cost and which can achieve food contact under certain conditions. One of the conditions that must be fulfilled is that the aluminum coating must be intact to avoid corrosion of the steel substrate.

Due to the inherent dynamics of the SPIF process, coatings can be damaged during deformation due to tool friction in case of direct contact. To avoid this, the dummy method is used, which consists of deforming two sheets at the same time [24]: an upper sheet or dummy, which is a sacrificial plate that avoids direct contact between tool and coating; and a lower sheet, which is the coated metal part to be obtained by deformation.

1.3. *Manufacture of molds via SPIF rapid tooling*

The manufacture of molds by traditional methods (machining) is expensive and only justified when such molds are to be used to produce a significant number of parts by means of, for example, plastic injection molding. There are several manufacturing processes where SPIF has been used as a rapid and cost-effective way to manufacture molds [25]: composite materials processing, low-pressure polymer processing, food processing [26].

Afonso et al. [25] studied the use of SPIF for the manufacture of the molds needed to produce composite parts. Using a single-stage helical toolpath strategy, a 12 mm diameter tool, a step size equal to 0.5 mm and a feed rate equal to 2500 m/min, they deformed a 2 mm thick sheet, and using a coordinate measuring machine they determined that the maximum deviation obtained on the walls of the molds was +6.4 mm, with an average deviation of +1.5 mm.

Afonso et al. [27] used SPIF to make thermoforming molds. In this case, the maximum deviation measured in the positive mold was +2.9 mm and in the negative mold was +6.8 mm [25]. Similar values were obtained in molds manufactured by SPIF for rotomolding processes [28].

Rodriguez-Alabanda et al. [26] proposed the use of SPIF to manufacture molds for the food sector. To evaluate the geometrical accuracy, these authors measured the area between the theoretical profile and the profile obtained after forming. In this case the values obtained were between 200 and 300 mm^2 for a truncated pyramid geometry of 130 mm side and 40 mm depth.

1.4. *Aim of the work*

In the present work, we propose the use of the SVM algorithm to predict the geometrical accuracy of molds manufactured by SPIF from DX51D AS120 B CO aluminized steel sheets. For this

Table 1 – Factors and levels used in the design of the experiment.

Factor	Low Level	Medium Level	High Level
Strategy	Contour-Parallel	Spiral	Radial
Tool Diameter (mm)	8	10	12
Spindle Speed (rpm)	500	1000	2000
Feed Rate (mm/min)	600	1200	2400
Step Size (mm)	0.4	0.8	1.2

purpose, a design of experiments (DOE) was elaborated using the following variables with influence in the geometrical accuracy [3]: tool-path strategy, tool diameter, spindle speed, feed rate and step size. From this DOE, 27 parts were manufactured using the dummy method to avoid damaging the aluminum coating. The longitudinal section of the parts obtained by this process was measured by a coordinate measuring machine (CMM); hence, the difference between the programmed profile and the profile obtained was evaluated. The values obtained were used to train models generated by two SVM algorithms (SMO and LibSVM) using different kernels. These models made it possible to anticipate whether a mold would have high or low geometrical accuracy depending on the manufacturing parameters used. Also, some process maps were generated that allowed us to clarify graphically which values of the parameters studied were associated with high geometrical accuracy in the molds.

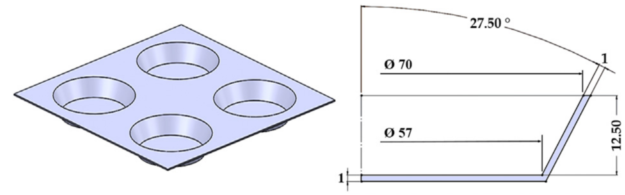

Fig. 1 – Typical tray used in food industry to make mini-burgers (left); dimensions of the geometry used in the study obtained from an industrial tray (right).

2. Materials and methods

This work aims to improve the geometric accuracy of molds manufactured by SPIF from aluminized steel sheets, using machine learning algorithms. The molds were manufactured in a machining center and measured in a CMM. The results obtained were used to train models generated by SVM algorithms.

2.1. *Mold making by SPIF and measurement by CMM*

To manufacture the parts, a sheet of aluminized steel DX51 AS120 B CO with dimensions 210 × 210 × 1 mm^3 was used. To avoid damaging the aluminum coating, the dummy technique was employed, which consists of placing a sacrificial plate on

Table 2 – Design of experiment L27 used in the present work.

Experiment	Strategy[a]	Tool Diameter, D (mm)	Spindle Speed, n (rpm)	Feed Rate, f (mm/min)	Step size, Δz (mm)
1	CP	8	500	600	0.4
2	CP	8	500	600	0.8
3	CP	8	500	600	1.2
4	CP	10	1000	1200	0.4
5	CP	10	1000	1200	0.8
6	CP	10	1000	1200	1.2
7	CP	12	2000	2400	0.4
8	CP	12	2000	2400	0.8
9	CP	12	2000	2400	1.2
10	SPI	8	1000	2400	0.4
11	SPI	8	1000	2400	0.8
12	SPI	8	1000	2400	1.2
13	SPI	10	2000	600	0.4
14	SPI	10	2000	600	0.8
15	SPI	10	2000	600	1.2
16	SPI	12	500	1200	0.4
17	SPI	12	500	1200	0.8
18	SPI	12	500	1200	1.2
19	RAD	8	2000	1200	0.4
20	RAD	8	2000	1200	0.8
21	RAD	8	2000	1200	1.2
22	RAD	10	500	2400	0.4
23	RAD	10	500	2400	0.8
24	RAD	10	500	2400	1.2
25	RAD	12	1000	600	0.4
26	RAD	12	1000	600	0.8
27	RAD	12	1000	600	1.2

[a] CP: contour-parallel; SPI: spiral; RAD: radial.

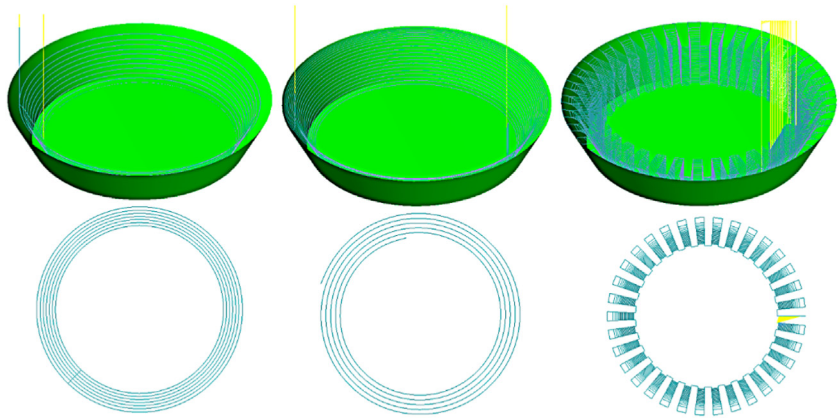

Fig. 2 – Strategies used in the tests: contour-parallel (left); spiral (center); radial (right).

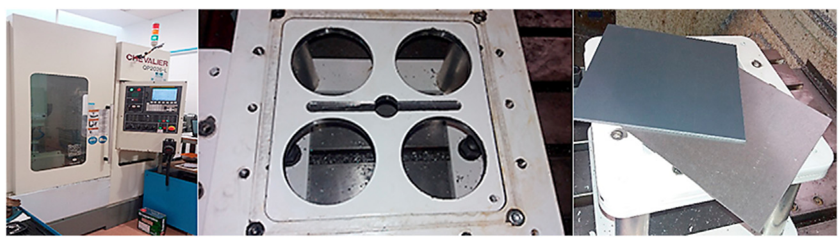

Fig. 3 – Machining center used to manufacture the molds (left); elevated frame and backing plate utilized to fix the sheets to the table of the machining center (center); PVC dummy and aluminized steel sheets employed as raw material to produce the molds (right).

the sheet to be deformed [24]. In this way, the punch deforms both sheets at the same time. In all the experiments carried out, the sacrificial plate is a PVC sheet with dimensions $210 \times 210 \times 3$ mm^3.

A design of fractionated experiments L27 was elaborated, with 5 factors and three levels, which are shown in Table 1. These values were chosen because they are compatible for both the base sheet (steel) and the dummy sheet (PVC). The values used in each test are shown in Table 2. The geometry of the part chosen for the study is used in the food industry to make molds for mini-burgers (Fig. 1). The manufacture of molds is one of the main applications of SPIF [25].

The model was designed using the SolidWorks software (release 2018). The generated file was imported from Mastercam, where the process parameters and toolpath strategy were defined. The strategies used to generate the toolpath were: contour parallel, spiral, and radial (Fig. 2). It should be noted that, while the parallel and spiral contour toolpaths have been widely studied in previous works, the study of the radial toolpath was included here for the first time. The motivation is to seek less aggressiveness in the way of attacking the material to avoid degradation of the protection dummy used.

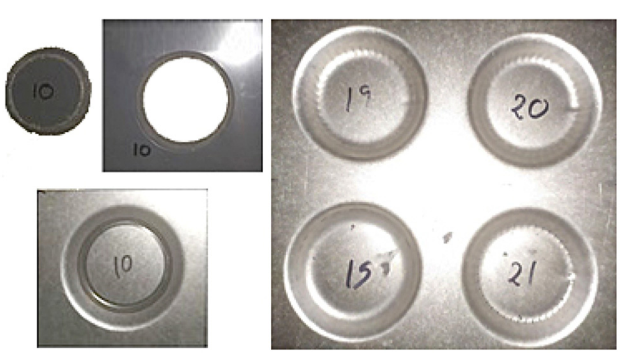

Fig. 4 – Molds manufactured during the experimental stage: damaged mold: the tool breaks the dummy sheet and removes the aluminum coating (food contact is lost) (left); correct molds: the dummy sheet does its job and protects the aluminum coating (possible food contact) (right).

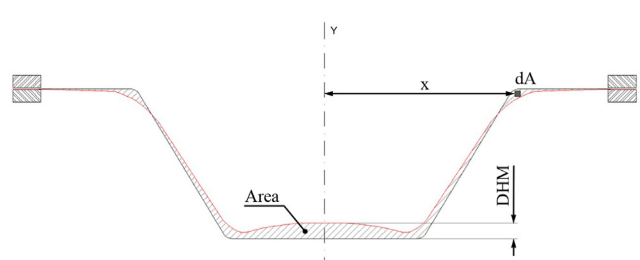

Fig. 5 – Geometrical parameters used to quantify geometrical accuracy as the difference between the design profile (black) and the profile measured experimentally (red): area, difference in height at the midpoint (DHM), and second moment of area respect y-axis.

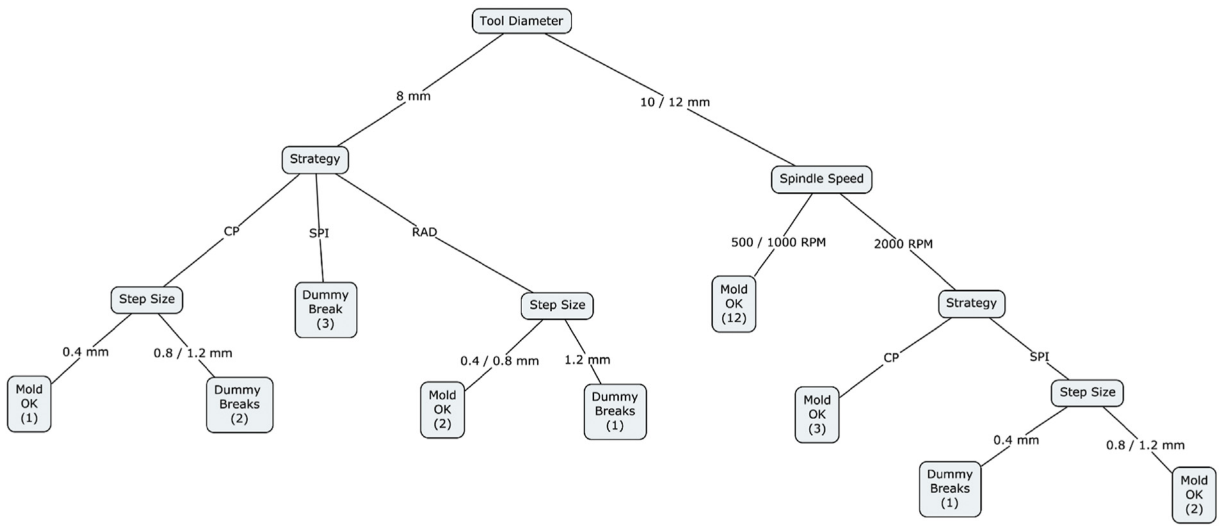

Fig. 6 – Tree diagram generated by the Random Tree algorithm: it is possible to observe which combinations of parameters generate damaged (dummy breaks) or correct molds (mold OK). The number between parentheses corresponds to the number of molds obtained in each case.

The molds were manufactured on a Chevalier QP-2026-L 3 axis machining center, equipped with a Fanuc 0i-M numerical control (Fig. 3, left). Three steel punches were utilized, with diameters of 8 mm, 10 mm, and 12 mm. To fix the sheets (Fig. 3, right), a raised frame with backing plate was used (Fig. 3, center). To prevent the PVC sheet from heating up and suffering damage due to friction with the tool, coolant was employed.

During the manufacturing process, it was found that some combinations of the parameters did not allow to obtain right parts: the tool broke the dummy plate and rubbed against the coating, damaging it (Fig. 4, left). Those molds were discarded, and only undamaged molds were studied (Fig. 4, right). To characterize them geometrically, a coordinate measuring machine Coord3 model ARES 07.07.05 was used to obtain the interior profile of each mold. To generate this profile, the coordinates of 20 points were measured along each mold; the generated CSV file was imported from SolidWorks, with the objective of overlapping the real profile with the theoretical profile. Thus, three geometrical parameters were determined

Table 3 – Process of selecting features in the dataset to model the problem studied. The most influential parameters are marked in bold.

Attribute Evaluator	Search Method	Attributes
Correlation based feature selection	Ranker	**0.56 Tool diameter** **0.37 Strategy** **0.18 Step size** 0.08 Feed rate 0.03 Spindle speed
Learner based feature selection	Bestfirst	**Strategy** **Tool diameter**

Table 4 – Results obtained in each experiment (OK or dummy breaks) and geometrical accuracy class (class 1 or class 2) achieved for each parameter (area, second moment of area respect to y-axis -SMA_Y- and difference in height at the midpoint -DHM-): class 1 is associated with high geometry accuracy and class 2 is associated with low geometry accuracy.

Exp.	Result	Area	SMA_Y	DHM
1	OK	Class 2	Class 2	Class 2
2	Dummy breaks	*	*	*
3	Dummy breaks	*	*	*
4	OK	Class 1	Class 1	Class 1
5	OK	Class 1	Class 1	Class 1
6	OK	Class 1	Class 2	Class 2
7	OK	Class 1	Class 1	Class 1
8	OK	Class 1	Class 1	Class 1
9	OK	Class 1	Class 1	Class 1
10	Dummy breaks	*	*	*
11	Dummy breaks	*	*	*
12	Dummy breaks	*	*	*
13	Dummy breaks	*	*	*
14	OK	Class 2	Class 2	Class 2
15	OK	Class 2	Class 2	Class 2
16	OK	Class 1	Class 1	Class 1
17	OK	Class 1	Class 1	Class 1
18	OK	Class 2	Class 1	Class 2
19	OK	Class 2	Class 2	Class 1
20	OK	Class 2	Class 2	Class 2
21	Dummy breaks	*	*	*
22	OK	Class 2	Class 2	Class 2
23	OK	Class 2	Class 1	Class 2
24	OK	Class 2	Class 2	Class 2
25	OK	Class 1	Class 1	Class 1
26	OK	Class 1	Class 2	Class 1
27	OK	Class 2	Class 2	Class 2

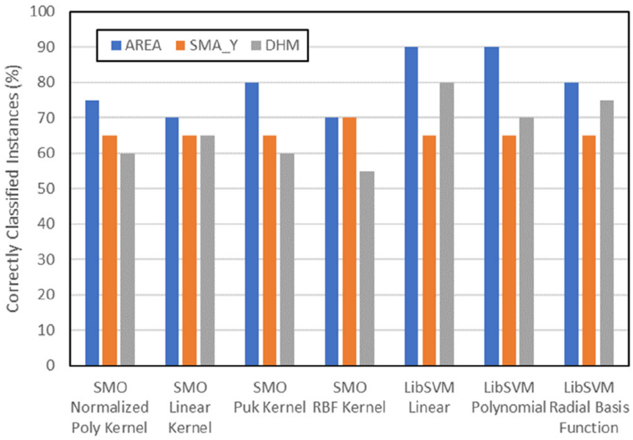

Fig. 7 – Percentage of correctly classified instances by the models generated by the algorithms (SMO and LibSVM) using the data corresponding to the geometric parameters defined: area, second moment of area respect to y-axis (SMA_Y) and difference in height at the midpoint (DHM).

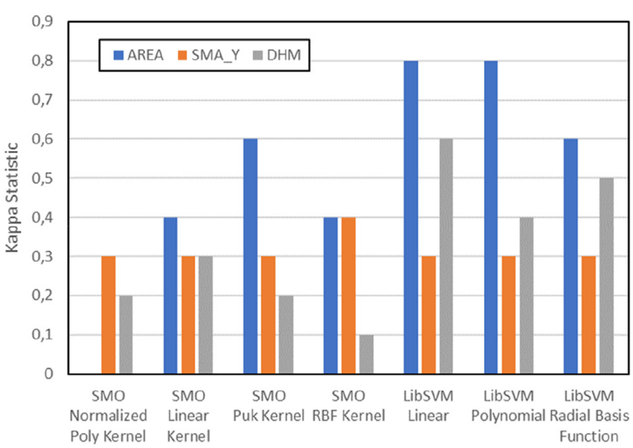

Fig. 8 – Kappa statistic obtained by the models generated by the algorithms (SMO and LibSVM) using the data corresponding to the geometric parameters defined: area, second moment of area respect to y-axis (SMA_Y) and difference in height at the midpoint (DHM).

Table 6 – Meaning of the Kappa statistic parameter.

Range	Kappa
0.00	Poor
0.01–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.00	Almost Perfect

to characterize the geometrical accuracy obtained: (i) area between the two profiles; (ii) difference in height at the midpoint (DHM) of the profile; (iii) moment of inertia of the area with respect to the y-axis (Fig. 5). The area provides an average value relative to the geometric accuracy obtained for each mold; the DHM is used to determine whether adequate geometric accuracy has been obtained at the bottom of the mold; the second moment of inertia of the area is used to quantify whether geometric accuracy is acceptable at the mold walls.

2.2. *Generation of models via machine learning*

The geometrical results obtained were processed by WEKA. This software, using machine learning algorithms, allows extracting knowledge from datasets. First, the Random Tree algorithm [29] was used to generate a tree diagram that summarized the cases in which it was possible or not to produce the molds correctly.

Then, before using the SVM algorithm, the most relevant attributes were selected, and the less relevant ones were discarded. Two algorithms were used for this purpose: (i) the correlation-based feature selection algorithm (with ‘ranker’ as search method) and (ii) the learner-based feature selection algorithm (with ‘best first’ as search method).

The SVM algorithm allows to divide an initial set of data into two smaller sets; to do so, it looks for the hyperplane with the maximum margin among all possible options (the margin is the distance between the hyperplane and the closest points). The hyperplane is defined by support vectors, which are usually the points closest to the hyperplane and those that define it. Suppose we have a data set $\mathbf{x}_i \in R^d (i = 1, \ldots, N)$ and its corresponding labels $y_i \in \{+1, -1\} (i = 1, \ldots, N)$. The value of the labels $+1$ and -1 is used to represent the two classes (in this case, high geometrical accuracy, and low geometrical accuracy). When we have feature vectors $\phi(\mathbf{x})$ in the feature space converted from the input space, the decision function is given as follows:

$$f(\mathbf{x}) = \mathbf{w}^T \cdot \phi(\mathbf{x}) + b$$

where $f(\mathbf{x}) = 0$ represents the separation hyperplane.

Two SVM algorithms are available from WEKA: SMO and LibSVM. The SMO algorithm [30] is an improvement made from the original algorithm developed by Platt [31]. The LibSVM algorithm was developed by Chang and Lin [32]. The

Table 5 – Summary of the SVM algorithms that obtained the best results for the different geometric parameters studied.

Geometrical Parameter	SVM Algorithm	% Correctly Classified Instances	Kappa
Area	LibSVM linear	90	0.8
	LibSVM polynomial	90	0.8
Moment of inertia with respect to the y-axis	LibSVM linear	65	0.3
	LibSVM polynomial	65	0.3
Mold mid-point error	LibSVM linear	80	0.6
	LibSVM polynomial	70	0.4

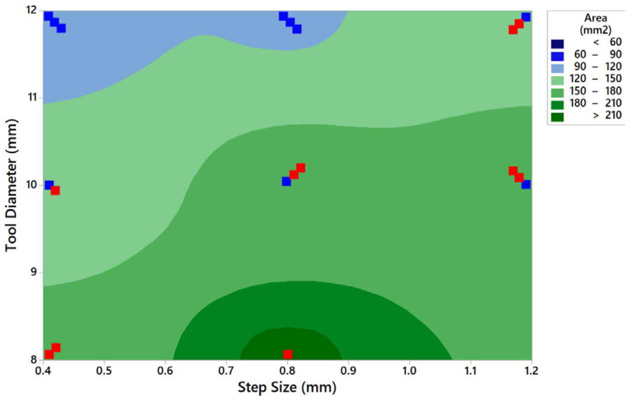

Fig. 9 – Geometrical accuracy map generated for the output variable 'area' as a function of step size and tool diameter variables. In blue, it represents the molds that have a smaller area between the real and the designed profile (better geometrical accuracy); in red, it represents the molds that have a larger area between the real and the designed profile (worse geometrical accuracy).

Fig. 11 – Geometrical accuracy map for the output variable 'difference of height at the midpoint' as a function of the step size and tool diameter variables. In blue, the molds that have a lower difference in height at the midpoint (better geometrical accuracy) are represented; in red, the molds that have a higher difference in height at the midpoint (worse geometrical accuracy) are represented.

SMO algorithm has several kernels; in this work the following were used: normalized polykernel, linear kernel, puk kernel and RBF kernel. The LibSVM algorithm also has several kernels, in this case the linear kernel, polynomial kernel and radial basis function were used.

3. Results

Some of the combinations of the parameters studied did not allow the manufacture of the right molds. Using the Random Tree algorithm generated a tree diagram that summarizes the different scenarios (Fig. 6).The algorithm only uses the factors that it considers to be most representative in each case: (i) to express the success or failure of molds fabricated with the 8 mm diameter tool, only the factors 'strategy' and 'step size' are necessary; (ii) for molds produced using tools with diameter 10 mm or 12 mm, an additional factor (spindle speed) has to be used. For example, molds fabricated with a tool diameter of 10/12 mm and a spindle speed of 500/1000 rpm have been produced correctly regardless of the strategy used.

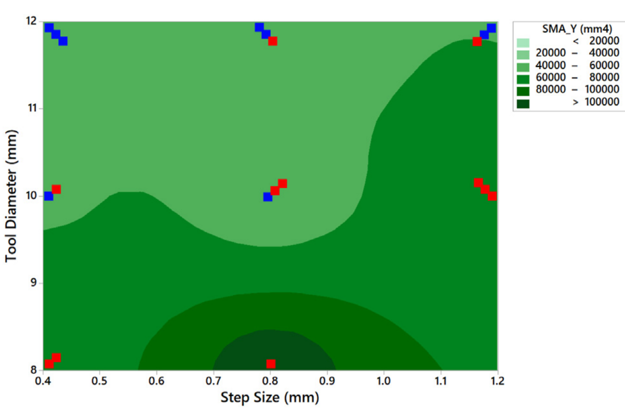

Fig. 10 – Geometrical accuracy map generated for the output variable 'second moment of area respect to y-axis' as a function of step size and tool diameter variables. In blue, the molds that have a lower second moment of area respect to y-axis (better geometrical accuracy) are represented; in red, the molds that have a second moment of area respect to y-axis (worse geometrical accuracy) are represented.

As can be seen in Fig. 6, most of the damaged molds are associated with the use of the 8 mm diameter tool. The pressure exerted by this tool was so high that the PVC sheet was broken. Thus, it should be noted that practically all molds manufactured using the radial strategy are correct.

Once the damaged molds were discarded, the geometrical data obtained from the right molds was analyzed. First, the most relevant attributes were selected for making predictions. For this, two evaluation algorithms were used (Table 3): (i) correlation based feature selection algorithm; (ii) learner based feature selection algorithm. This step allowed the selection of the three most relevant attributes: tool diameter, strategy, and step size. From this point, the attributes feed rate and spindle speed were discarded.

Then, different SVM algorithms were used to generate models capable of predicting whether a mold belongs to the class 1 (high geometrical accuracy) or to class 2 (low geometrical accuracy) depending on the values taken by the selected process parameters (Table 4). WEKA allows the use of two types of SVM algorithms: SMO and LibSVM. In addition, each of these algorithms allows the use of different kernels.

Figures 7 and 8 show the results obtained by the different SVM algorithms for the geometric parameters studied: area, second moment of area respect to y-axis (SMA_Y), difference in height at the midpoint (DHM). Figure 7 shows the percentage of correctly classified instances; Fig. 8 shows the kappa statistic values obtained by each model. As you can see, the algorithm that obtains better results is the LibSVM, with linear and polynomial kernel. Table 5 summarizes the values obtained by the algorithm with both kernels. The model based on the area parameter was the one that obtained a higher percentage of correctly classified instances (90%) and a higher kappa statistic (0.8). This kappa value is associated with substantial models (Table 6). The model related to difference in height at the midpoint is the one that obtained the second-best result (correctly classified instances = 80%, kappa statistics = 0.6). Last is the model relative to second moment of area respect to y-axis (correctly classified instances = 65%, kappa statistics = 0.3).

Figures 9–11 show the process maps elaborated from the experimental results. These maps allow visualizing which combinations of tool diameter and step size provide molds with a higher geometrical accuracy. As can be seen, the best results are associated with the use of high tool diameters and small step size values.

Finally, from the results shown in Table 4, Fig. 12 has been constructed. This figure shows the percentage of 'class 1' instances obtained for each geometrical parameter (area, SMA_Y, DHM) using the different strategies studied (contour-parallel, spiral and radial). As can be seen, the strategy that generates the highest percentage of molds with 'class 1' geometrical accuracy is the contour-parallel (CP) strategy.

4. Discussion

In the present work, the use of machine learning algorithms is proposed to improve the geometrical accuracy of molds for the food industry manufactured by SPIF from aluminized steel sheets. Specifically, the support vector machine (SVM) algorithm is used, which generates models that allow predicting whether a mold is going to have a high or low geometrical accuracy from the variables used in the process. For this purpose, 27 molds were made using different process parameters (tool diameter, spindle speed, feed rate, step size) and different toolpath strategies (contour-parallel, spiral, and radial) (Tables 1 and 2). During the manufacturing process, 7 molds were discarded because the tool broke the dummy plate and the aluminum coating was damaged (thus, no food contact was achieved, Fig. 4 and Table 4). Most of the breaks/damage occurred when the smaller diameter tool (8 mm) was used (Fig. 6). The right specimens were geometrically characterized using a coordinate measuring machine. Specifically, the longitudinal profile of the molds was measured. This profile was compared by means of computer software with the programmed profile, and three geometric parameters were calculated (Fig. 5): area between the real and theoretical profiles; moment of inertia of this area with respect to the y-axis; distance between the real and theoretical profiles at the midpoint. The geometrical accuracy increases when these geometrical parameters decrease. The geometric values obtained were used to train the models generated by two SVM algorithms implemented in WEKA software: SMO and LibSVM. Each of these algorithms has several kernels, which were also tested. The LibSVM algorithm obtained better results than the SMO. Among the kernels available for LibSVM, the 'linear' obtained the best results (Figs. 7 and 8, Table 5).

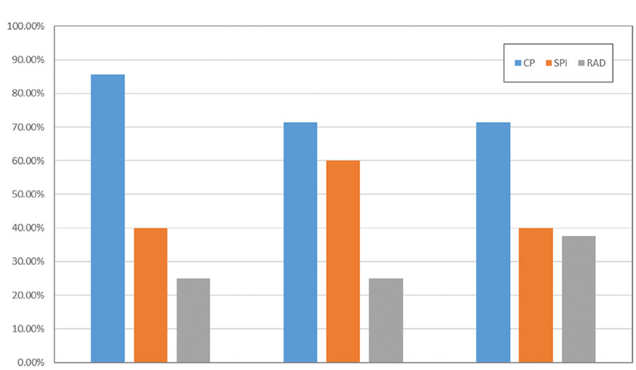

Fig. 12 – Percentage of 'class 1' instances obtained for each geometrical parameter (area, second moment of area respect to y-axis -SMA_Y-, difference of height at the midpoint -DHM-) using the different strategies studied (contour parallel -CP-, spiral -SPI- and radial -RAD-).

4.1. *Geometrical accuracy in SPIF via SVM algorithms*

The authors found hardly any references in the literature studying the improvement of geometrical accuracy by machine learning on parts manufactured by incremental deformation. The few works found usually use neural networks to try to solve the problem: Zwierzycki et al. [33], who used TensorFlow to predict geometrical accuracy in incremental sheet forming processes in architectural parts; Akrichi et al. [34] used multilayer perceptron to predict SPIF quality. The results of neural networks are usually slightly better than those obtained by SVM [35]; however, neural networks are black boxes difficult to understand by the uninitiated, while SVM is an easy technique to interpret [10].

The model generated by LibSVM to predict the area between the real and theoretical profiles reached a 90% success rate and a kappa equal to 0.8 (substantial). These values are like those obtained by other authors who have studied the defects in parts made of sheet metal using other metal forming processes. For example, Dib et al. [35] considered as acceptable average percentages of correctness 85% for base algorithms (without assembler). In another work, Dib et al. [36] claimed to obtain, through SVM, a 92.01% success rate when predicting failures derived from springback in parts manufactured by U-bending from DP600 sheet metal. This percentage is slightly higher than achieved here (90%), although it is true that Dib et al. worked with data from simulations.

4.2. *Geometrical accuracy maps*

The process maps generated in this work show that the molds manufactured by SPIF and dummy technique with higher geometrical accuracy are those manufactured using a contour-parallel strategy, a tool diameter equal to 12 mm and small step size values. These results are consistent with those found in the literature for SPIF without sacrificial sheet. Lu et al. [8] stated that the strategy is one of the most delicate aspects to achieve a better geometrical accuracy; it also indicates that the most used strategy is the parallel contour. On the other hand, Gatea et al. [3] affirmed that increasing tool diameter and reducing vertical step size can lead to a reduction in springback. Lu et al. [37] proposed a method to obtain a better geometrical accuracy using a contour-parallel strategy where the step size values were recalculated as a function of the springback measured during the process. Although some authors noted the influence of feed-rate and spindle-speed in the geometrical accuracy of parts manufactured by SPIF without dummy sheet [38], in this work this influence was not detected.

5. Conclusions

The authors propose the use of the SVM algorithms to generate models that can predict the geometrical accuracy of molds manufactured by SPIF from DX51 aluminized steel sheets. For it, a total of 27 molds were made, using different process parameters and different strategies to generate the toolpath. With the help of a coordinate measuring machine, the longitudinal profiles of the molds were geometrically characterized. These data were used to train the generated models. The model that achieved the best results were generated using the LibSVM algorithm with a linear kernel (instances correctly classifying equal to 90%; kappa statistic equal to 0.8); this model was trained with data relating to the area between the actual profile manufactured and the theoretical profile. These values are considered as excellent in the bibliography. From the process maps obtained, it can be concluded that the molds manufactured with a contour-parallel strategy, a 12 mm tool diameter and a 0.4 mm step size are classified as instances with high geometrical accuracy.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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