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Springback control in laser-assisted bending manufacturing process by using a fuzzy uncertain model

Gennaro Salvatore Ponticelli[a,b,*], Stefano Guarino[b], Oliviero Giannini[b], Flaviana Tagliaferri[b], Simone Venettacci[b], Nadia Ucciardello[a], Gabriele Baiocco[c]

[a]*University of Rome 'Tor Vergata', Department of Enterprise Engineering, Via del Politecnico, 1, 00133, Rome, Italy*
[b]*University of Rome 'Niccolò Cusano', Department of Engineering, Via Don Carlo Gnocchi, 3, 00166, Rome, Italy*
[c]*University of Rome 'Roma Tre', Department of Engineering, Via V. Volterra, 62, 00146, Rome, Italy*

* Corresponding author. *Tel.:* +39-0672597168. *E-mail address:* ponticelli@dii.uniroma2.it

Abstract

This study wants to propose a fuzzy model able to describe the inherent uncertainties related to a laser-assisted bending process and it is aimed at controlling of the springback phenomena, for a different set of laser process parameters. The process maps obtained are used to select the operational parameters in order to obtain the desired process output, providing as additional information how much the uncertainty of the model and the process varies by changing those operational parameters. The fuzzy model has also been used to assess the optimal parameters in order to satisfy the requirement of the least-cost.

Keywords: Fuzzy logic; Springback; Laser-assisted bending

1. Introduction

Manufacturing technologies have experienced gradual but revolutionary changes in the last decades, passing from the introduction of numerical controlled machines, as well as robotics, to rapid prototyping, environmentally sustainable technologies, etc. At the same time, there has been the development and the need of new materials and products, giving rise to new concepts and targets: attributes like quality, reliability, cost, life-cycle prediction, delivery and service, have come more and more into focus. In fact, the evolution of new materials and the request for more precise processing operations have made traditional manufacturing processes unsuitable for modern engineering [1]. For this reason, innovative and advanced production processes have been introduced to address the needs of modern industry especially when dealing with technological frontiers. In this light, lasers are considered a valuable alternative, thanks to their ability in providing an elevated level of accuracy, consistency, control, and flexibility in almost every manufacturing sector. In this context, research in lasers development, process optimisation and modelling/simulation plays a critical role in advancing laser materials processing science and technology.

In order to keep up with the new challenges, laser manufacturing industries must be able to select appropriate strategies, processes, product designs, materials, equipment, etc. However, the decisions to be made to set-up the process are complex, since in a laser manufacturing process a wide range of alternative options must be evaluated, and the choice of the best one is frequently made on a set of conflicting criteria [2,3]. There are very different decision-making situations in the manufacturing environment and the evaluation of alternative process designs in order to meet the productivity and final quality requirements is one of the most relevant. In fact, both these aspects are governed by a complex interaction of many process parameters, ranging from those connected with the laser source, to those concerning the thermal and mechanical properties of the processed material.

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In order to enhance the decision-making process, very detailed knowledge of the laser manufacturing process itself is required. In order to improve such knowledge, we have two possible alternatives: performing experiments and/or modelling. In the first case, laser parameters are usually adjusted and tuned one by one to provide the quality desired [4–8], but this consumes exhaustive amounts of resources, both in terms of time and money, and on the same time, laser quality cannot be easily predicted. In this light, modelling appears to be very helpful and surely the only solution in order to speed up the characterization of the processes and therefore their optimization. In particular, the aim should be the development of a physical model able to simulate in a very precise way the entire process, starting from the generation of the laser, to the interaction between the laser and the material and hence on the quality obtained. However, in most cases, this is not possible because of the strong dynamic nature of the laser process. For this reason, empirical modelling can be considered a valuable solution, and very often the only available tool able to make researchers and manufacturers capable of predicting and controlling the final quality of the laser process. It is worth to state here that these empirical models exist only thanks to the experiments and are valid only within the "space" that is tested. In fact, they are exclusively built and then validated on the basis of the experimental findings, within the intervals of the investigated parameters.

The use of empirical models introduces, however, a new source of uncertainty related to the simplification and the inherent lack of knowledge led from the adoption of empirical models themselves. For this reason, there is a need for mathematical tools able to guide the decision-making process in environments characterized by high uncertainty. Therefore, decision-making has moved from the concept of probability to the concept of possibility, in which the most important aspect is the meaning of the information that is measured [2]. The inherent attitude of fuzzy logic to perform decision-making and deduce control actions has led to the study of a new field of decision analysis, the fuzzy decision-making, which consists in making decisions under complex and uncertain environments where the information can be assessed with fuzzy sets and systems [9,10]. In particular, the fuzzy technique is able to take into account both the random error, e.g. that is associated to the variability of the process, and the systematic error, e.g. that is due to the inability to physically replicate in a precise way the process itself or simplification introduced in the model. The fuzzy model is, therefore, able to propagate all the sources of uncertainty at the input level to the output quantities [11–14].

During a conventional bending process, the material is stressed beyond the yield strength but below the ultimate tensile strength going against a plastic deformation, which leads to a change in the shape of the material [15]. In general, it is a flexible process by which many different shapes can be produced. However, achievement of sharp bending angles with small fillet radius requires sophisticated devices involving customized expensive moulds and huge presses, resulting in long processing time and thus in high costs [16]. Application of laser in bending processes of metal sheets helps to overcome some of these limitations: it is flexible and easy to control; precise and small bend angle can be obtained [17]; at elevated temperatures, material's formability increases. Heat affected zone is small as the laser beam has a narrow, concentrated and controlled area of irradiation. Therefore, negligible springback occurs in the cooling phase, and a higher working accuracy can be achieved [18]. However, managing of springback is known to be very difficult since it depends on multiple concurrent variables such as the material properties of workpiece, its interaction with the mould and the design of the loading device [19,20]. On the contrary, properly tuning the laser parameters, the thermal flux radiated to the workpiece can be accurately managed [21,22].

In this context, the present work was divided into two main activities: performing experiments and developing fuzzy models. For the first one, the study, the definition, the design and the analysis of a laser-assisted bending manufacturing process was carried out. Then, based on the experimental findings, an innovative fuzzy uncertain model was developed and successfully applied. In particular, the Transformation Method is used to propagate these uncertainties to the delta angle [23,24] in order to find the optimal laser operational parameters able to satisfy the requirement of a nil springback effect.

2. Materials and Methods

The bending process was performed on two substrates of AA 6082 T6 aluminium alloy of 19 mm, 69 mm and 2 mm in length, width and thickness respectively, through two subsequent steps: first, the substrates were mechanically bent by means of built-ad-hoc equipment. Then, the surface was laser treated while maintaining the substrates constrained in order to minimize the springback phenomena. Table 1 reports the properties of the substrates.

Table 1. Mechanical properties of AA 6082 T6 aluminium alloy.

Property	Value	Unit
Density	2.70	$g \cdot cm^{-3}$
Hardness	95	Vickers
Ultimate Tensile Strength	290	MPa
Yield Strength	250	MPa
Thermal conductivity	170	$W \cdot m^{-1} \cdot K^{-1}$

The mechanical bending was performed through a three-point loading system able to induce a pre-scheduled initial deflection in the plastic range on the aluminium substrates (2, 4 and 8 mm), as shown in Fig. 1. For the laser treatment, a 1.5 kW high-power diode laser source (ROFIN-SINAR DL015) with 940±10 nm wavelength was used. During this step, a constant argon flux of 25 L/h was flushed on the substrate surface for protection and isolation purposes. Initial deflection, laser power, scan speed, number of passes and defocusing distance were the experimental factors investigated according to the developed full factorial plan based on Design of Experiment (DoE), which is reported in Table 2, for a total of 324 tests including the three replications performed.

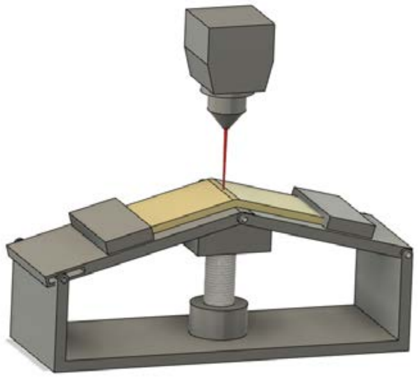

Fig. 1. Experimental set-up. The aluminium specimen is highlighted in gold, while the laser beam in red.

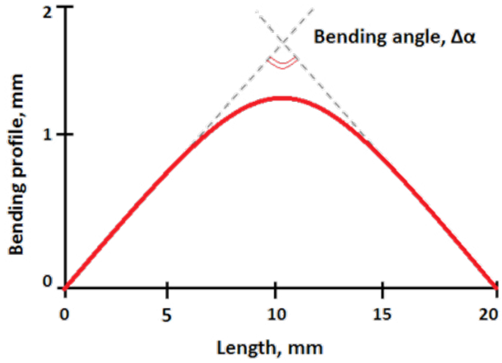

Fig. 2. Evaluation of the bending angles from a typical bending profile.

Table 2. Full factorial plan: 3 terms of *Id* · 2 terms of *P* · 2 terms of *Ss* · 3 terms of *R* · 3 terms of *Fd* = 3·2·2·3·3 = 108 experimental conditions. Each test was replicated 3 times: 108 · 3 = 324 tests.

Parameter	Value			Unit
Initial deflection (*Id*)	2	4	8	mm
Laser power (*P*)	500	-	800	W
Scan Speed (*Ss*)	3	-	5	mm/s
Number of passes (*R*)	1	2	4	-
Defocusing distance (*Fd*)	0	2	4	mm

It is worth to note here that an increase in the working distance between the laser head and the substrate surface (i.e. increasing of the defocusing distance) leads to an increase in the spot area and to a corresponding decrease in the power intensity the laser beam delivers on the substrate surface. Table 3 reports the values of the spot area and the power density for the different configurations.

Table 3. Spot area and power intensity for the different defocusing distances and laser powers.

Defocusing distance (mm)	Spot area (mm^2)	Power Intensity (W/mm^2)	
		P = 500 W	P = 800 W
0	3.58	139.66	223.46
2	4.33	115.47	184.76
4	5.08	98.43	157.48

After laser treatments, the substrates were taken away from the die and submitted to the characterisation process. The profiles of the bent substrates were measured by surface profiler in contact mode (inductive gauge, Taylor Hobson Surface Topography System CLI 2000). For each sample, 1 surface profile 20 mm long taken along the direction normal to the bending axis was stored. The profile of the substrates was measured twice: (i) after the mechanical bending, when the substrates were still clamped on the die; (ii) after the laser treatment, when the substrates were removed from the die. Finally, the bending angles were evaluated from the stored profiles (Fig. 2). In particular, the residual springback, i.e., the delta angle $\Delta\alpha$ between the angle achieved by mechanical bending of the constrained samples and the angle achieved by laser-assisted bending, with all constraints removed, was considered the experimental output of major interest. In fact, when $\Delta\alpha = 0$, a perfect compensation of the springback is observed.

3. Results and Discussion

3.1. Experimental and Statistical Analysis

The analysis of the experimental results was carried out by means of the ANOVA test, shown in Table 4, in which are listed only the significant effects for sake of briefness (p-value < 0.05, $\Pi > 1\%$, F-value > 3.87 for 1-DoF and F-value > 3.03 for 2-DoF). These results are also graphically represented by means of the mean effects and interaction plots (see Fig. 3 and Fig. 4). In particular, within this condition of significance, the results indicate that $\Delta\alpha$ is affected by all the control factors except for the *Fd* term. While, among the interaction terms, the delta angle is influenced by only the *Id*P* and *Id*R* terms. Although other interactions among experimental factors could be technically influential, their contribution percentage is largely lower than 1% and they can be considered negligible in the determination of $\Delta\alpha$.

Table 4. ANOVA table for the bending angle.

Source	DoF	Adj.SS	Adj.MS	F-value	p-value	Π (%)
Id	2	14.93	7.466	13.01	0.000	1.232
P	1	500.91	500.914	872.58	0.000	41.345
Ss	1	27.18	27.179	47.35	0.000	2.243
R	2	419.47	209.734	365.35	0.000	34.623
*Id*P*	2	20.41	10.207	17.78	0.000	1.685
*Id*R*	4	22.13	5.532	9.64	0.000	1.827
Error	290	166.48	0.574	-	-	13.741
Total	323	1211.53	-	-	-	-

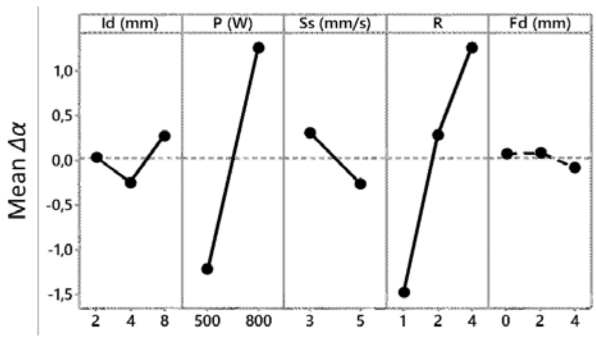

Fig. 3. Main effects plot for $\Delta\alpha$.

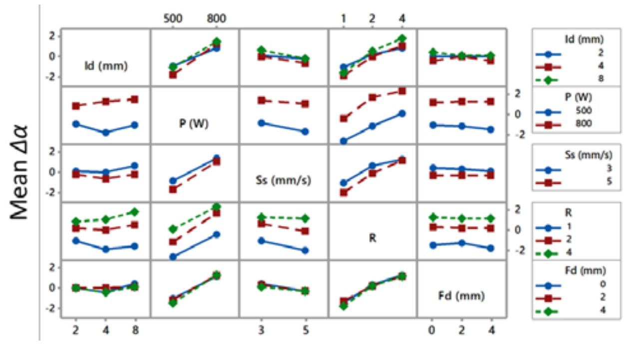

Fig. 4. Interaction plot for Δα.

The phenomena related to the shape correction by laser treatment of the substrate after mechanical bending when still constrained on the die can be explained considering two main effects: (i) inhibition of springback by selective heating and simultaneous annealing of the outermost layers of the substrate still under constrains [25]; (ii) extra-bending of the still constrained metallic substrate induced by thermal gradients inside the pre-bent material during the laser treatment [26]. In particular, the first effect can be considered to be due to the change in the material properties of the aluminium alloys during heating because of the change in the residual stress distribution inside the metallic substrate [27].

3.2. Fuzzy Uncertain Modelling

The results of the ANOVA test have shown that the laser-assisted bending process is characterized by a high variability due to the unpredictable factors which contribute more than 13% to the total Adj.SS (see Error in Table 4), thus conferring a certain degree of uncertainty to the experimental data processed. Moreover, the regression model is responsible for a systematic error between data and model results. In this context, the fuzzy model can be used to select the operational parameters in order to achieve a given value of the residual springback, taking into account both the variability of the process and the inherent inaccuracy related to the model.

Based on the results of the ANOVA test, an empirical model of the laser-assisted bending process has been proposed. It only considers the experimental parameters and their interactions whose calculated p-values are greater than 0.05, Fisher's factors are bigger than corresponding Fisher's factors tabulated and characterized by a percentage of contribution of, at least, 1%, i.e. *Id*, *P*, *Ss*, *R*, *Id*P* and *Id*R*.

Basically, the numerical formulation of the empirical model can be drawn as follows:

$$\Delta\alpha = k_0 + k_1 \cdot Id + k_2 \cdot P + k_3 \cdot Ss + k_4 \cdot R + \\ + k_5 \cdot Id \cdot P + k_6 \cdot Id \cdot R \qquad (1)$$

The empirical coefficients k_0, k_1, k_2, k_3, k_4, k_5 and k_6 are the calibration coefficients of the model, which were determined by nonlinear multiple regression analysis based on the whole experimental data set. Table 5 reports the values of the coefficients for the delta angle.

Table 5. Calibration coefficients for the delta angle.

Calibration coefficient	Value
k_0	-1.160845
k_1	-0.078028
k_2	0.001675
k_3	-0.071162
k_4	0.128883
k_5	0.000078
k_6	0.017459

Then, the regression model described by Equation 1 was considered as the starting model for the development of the related fuzzy regression model, which is written as follows:

$$\Delta\alpha^* = k_0^* + k_1^* \cdot Id + k_2^* \cdot P + k_3^* \cdot Ss + k_4^* \cdot R + \\ + k_5^* \cdot Id \cdot P + k_6^* \cdot Id \cdot R \qquad (2)$$

In the latter equation, all the coefficients are expressed as triangular fuzzy numbers and they are described by 8 α-cuts and the interval at each α-level is discretized with 2 points. For each α-cut, the transformation method requires, in a combinatorial scheme, the evaluation of the number of points within the α-cut to the power of the number of fuzzy parameters, 7 in this case, leading to 128 evaluations. Then, the transformation method requires that, for each α-cut, all these models are evaluated obtaining for each of them the hypersurface of the output quantity, i.e. delta angle, as a function of the process parameters, i.e. initial deflection, laser power, laser scan speed and number of repetitions. The fuzzy result for the given α-cut is then obtained by computing the envelope of these hypersurfaces. The results are presented in Fig. 5, in which the samples are ordered for increasing values of *Δα* provided by the starting regression model (blue line).

From the inspection of the fuzzy results reported in Fig. 5, several statements can be done: (i) the experimental results show a large data dispersion, in fact the variation between residual springback obtained by using the same operational parameters can be quite different; (ii) the fuzzy model does not include about 10% of the data points; (iii) the starting regression model does not provide a useful indication of the resulting springback; (iv) the uncertainty level related to the fuzzy model is not constant with respect to the parameter combination used during the experimental test and it is not centred on the specific data point (red asterisks). In fact, the extent of the input uncertainty in the model, due to the choice of a specific fuzzy confidence interval, is not only related to the accuracy of the regression model adopted but also to the variability of the process. This effect can be therefore considered the reason for a non-constant level of uncertainty. This is a new information that tells us how much faithful the model is in representing such experimental result. In other words, the wider the fuzzy bands and the higher the distance of the experimental finding from the black area, the higher the uncertainty and therefore the lower the representative capability of the model.

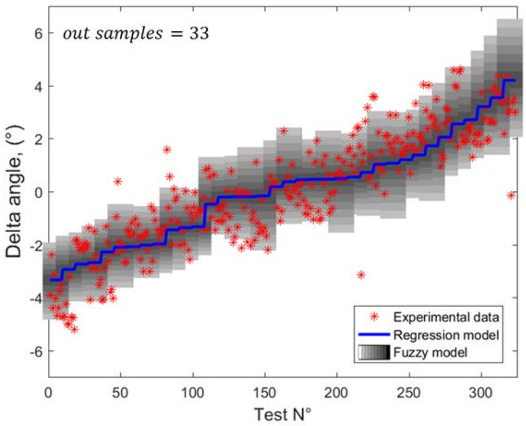

Fig. 5. Fuzzy map for the residual springback in terms of $\Delta\alpha$.

It is important to notice here that the large variability of the process is highlighted by the fuzzy model through a large band of uncertainty. This information is not available by considering just the regression model, nor directly obtained from the values of the confidence interval. Moreover, for this case study, the fuzzy results warn the analyst on the high level of uncertainty that is inherent with the technological process.

The proposed model can be also inverted in order to obtain the most suitable combination of the operational parameters leading to the desired output, which in this case is the highest productivity in terms of the least-time and therefore of least-cost. Therefore, it is possible to obtain the link between the optimal operational time (t_{op}), defined in the following equation, and the laser power, leading to a zero residual springback:

$$t_{op} = \frac{L \cdot R}{Ss} \quad (3)$$

In the latter equation, L represents the distance travelled by the laser beam, which in this case is coincident with the length of the substrates (i.e. 19 mm).

In order to obtain two-dimensional maps, it is necessary to fix the other parameters thus obtaining different maps for each parameter combinations (see Fig. 6).

As expected from the physics of the process, the number of repetitions has a direct influence on the process time and the corresponding power of the laser necessary to obtain a zero residual springback. The maps highlight that for R = 1 (Fig. 6A) laser power above 700 W is necessary to obtain the desired result. By increasing R to 2 and to 4, a larger range of P can be used. However, while changing laser power does not affect the uncertainty of the fuzzy model, increasing the number of repetitions has a negative effect on the uncertainty. Each of these maps provides a relation between t_{op} and P, so each can be used to select the optimal laser power level considering both time and uncertainty. In this case, it is therefore convenient to reduce the number of passes to R = 1 and use the necessary laser power P = 800 W. It is also important to notice that if one should do more than one repetition, the indirect fuzzy results point out that the uncertainty is lower when using higher laser power, i.e. P = 800 W for R = 2, and P = 700 W for R = 4.

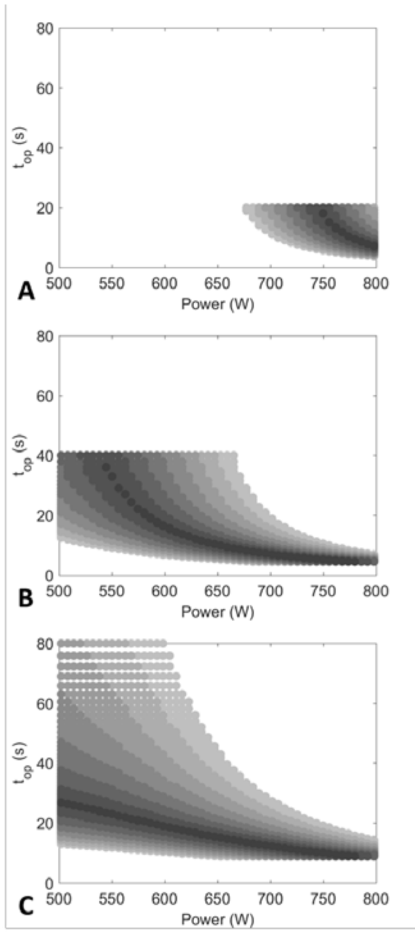

Fig. 6. Fuzzy uncertainty maps for Id = 2 mm, A) R = 1; B) R = 2; C) R = 4.

4. Conclusions

Probabilistic analysis can provide a quantitative way to account for the uncertainties in input parameters. However, in many practical conditions, the amount of data is frequently limited, and the distribution type of the uncertain variable may not be known. This situation makes the application of the probabilistic approach difficult. Moreover, some uncertainties relating to measured parameters in a generic process may, in fact, be non-stochastic but rather cognitive, arising from incomplete knowledge. The lack of information is generally reflected by the lack of a physical model of the process, and often an empirical model is used. Under such conditions, it appears to be reasonable to adopt fuzzy set theory because of the inherent ability of fuzzy logic to make a decision and deduce control actions under complex and uncertain environments only requiring mean, minimum, and maximum values of the uncertain parameters.

This work presents a methodology to obtain such a fuzzy model from the experimental data available from an experimental campaign and its application to a case study dealing with laser assisted bending process. In particular, the use of this fuzzy model is aimed at evaluating the best input parameters combination in order to obtain a nil residual springback.

The input parameters were considered as triangular fuzzy numbers, and the Transformation Method was used to handle uncertainty propagation to the residual springback.

The phenomena related to the shape correction by laser treatment of the substrate after mechanical bending when still constrained on the die are essentially ascribable to two different reasons: (i) inhibition of springback by selective heating and concurrent annealing of the outermost layers of the substrates still under constraints; (ii) extra-bending of the still constrained metallic substrate induced by thermal gradients inside the pre-bent material during the laser treatment.

The large variability of the process is highlighted by the fuzzy model through a large band of uncertainty that occurs in all the process maps generated. This information is not available by considering just the nominal regression model, nor directly obtained from the values of the confidence interval.

Since one of the main targets of a manufacturing process is to obtain the desired result in the shortest possible time, the fuzzy model was inverted in order to assess the optimal parameters needed for this purpose, imposing a nil residual springback as output. By applying a single laser scan and the highest laser power of 800 W gives the best result in terms of operating time and uncertainty level. In particular, with such level of input parameters, it is possible to ensure the inhibition of the springback phenomenon with an operating time of 20 s.

Fuzzy solutions can be very helpful in predicting, controlling and managing springback in V-shaping of thin aluminium sheets. Expert systems can be therefore a viable alternative to analytical and finite element models. It can allow the definition of practical tools for automation and process monitoring as well as facilitate the development of first approximation modulus very useful to the practitioners for the control of bending process of workpiece with simple geometry.

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