Optimization of Multi-Pass Laser Bending by means of Soft Computing Techniques

F. Lambiase*, A. Di Ilio and A. Paoletti
Dept. of Industrial and Information Engineering and Economics, University of L'Aquila, Viale V. Ponte Cre稳健, 67100 AQ, Italy

* Corresponding author. Tel.: +39 0862 434343; fax: +39 0862 434303. E-mail address: francesco.lambiase@univaq.it

Abstract
The relatively small angle produced after each laser-bending pass and the long time lapse between consecutive passes highly limits the laser bending process productivity. In the present study, different strategies have been carried out in order to overcome such limitations, including forced cooling of sheets as well as optimization of process parameters.

A series of experimental tests were conducted on thin sheets made of AISI 304 stainless steel. The variation of the bending angle achieved by multi-pass laser experiments, the minimum interval time between consecutive scans and the maximum temperature reached during the process were modelled by means of an Artificial Neural Network as well as the bend angle achieved per pass. Finally, an iterative procedure was developed to determine the optimal processing conditions that allow the production of a given bending angle. From an industrial point of view, the proposed procedure represents a preliminary version of a module for laser bending process automation and control.

Keywords: Laser; Productivity; Optimisation; Sheet metal; Artificial intelligence

1. Introduction
Laser forming is a non-contact process for thin metal sheets, which exploits a high thermal gradient induced by a high-power laser beam. The absence of hard tooling and contact forces, die and lubrication, high flexibility, possibility of automation represent the major advantages of such forming techniques over conventional processes [1]. On the other hand, the main shortcut of laser forming lies in a reduced bending angle per pass, which leads to employment of multiple passes to achieve practical deformations. In addition, the complex thermo-mechanical phenomena arising during the laser interaction with the sheet surface increase the difficulty in the process design and the choice of process parameters. In literature, experimental and theoretical studies have been carried out to understand the influence of process parameters involving analytical models, numerical simulations, empirical models as well as Artificial Intelligence techniques. Finite element simulations of the laser forming process have been extensively developed to study and optimize the process parameters [2-4]. Although the great flexibility of FE models, accurate temperature and stress field predictions require fine measurements of the mechanical and thermal properties of the sheet metal as well as their variation with temperature. In addition, also the laser absorption coefficient and its variation with temperature, require accurate measurement. On the other hand, empirical modelling as well as soft modelling techniques (such as Artificial Neural Networks) allow overcoming such problem by directly mapping the effect of operative process conditions on final bending angle. Empirical models have been recently developed to assess the effect of the main process conditions on the edge effect [5] and bending angle [6]. Process optimization by Artificial Intelligence-based models has been carried out to identify the optimal conditions in tube Laser bending [7] and control the springback in laser assisted bending [8].
Many of the previous mentioned researches mainly dealt with modelling and optimization of single pass laser bending. However, as above-mentioned, the achievement of practical deformation often require multiple passes. In order to avoid excessive material oxidation or even material melting, a certain cooling time should be waited after each pass when Multi-Pass Laser Bending (MPLB) is performed with a dramatic increase in the process productivity. A few researches have been carried out in order to reduce the waiting time after each pass by utilizing different cooling media [9, 10].

In this paper, a new approach is proposed to optimize the process parameters in MPLB by the concurrent employment of different soft-computing techniques.

The effect of the main process conditions, i.e. scanning speed, laser beam power, and number of passes on bending angle, maximum process temperature and waiting time were modelled by an Artificial Neural Network. Therefore, an optimization procedure based on a Genetic Algorithm was carried out to assess the optimal process conditions, i.e. laser power, scanning speed, waiting time and number of scans to produce a given bending angle.

2. Experimental setup

Laser forming tests were conducted on a thin sheet made of AISI304 stainless steel with 1.0 mm of thickness. The tests were conducted by means of a diode laser ROFIN model DL010 having a maximum power of 1.0 kW operating in continuous wave mode. The laser beam has a rectangular spot of 3.6 mm × 0.8 mm.

The bending angle is measured on-line by means of an inductive sensor placed at the workpiece bottom surface. The sensor measures the z-displacement of a given point of the sheet shifted by 20 mm from the line path. The temperature of the upper surface was measured by an infrared camera type ThermaCAM S65 HS, with a temperature range of 0°-1500 °C. The temperature of the lower surface is measured by means of a k-type thermocouple. The experimental angles produced with single pass achieved in [11, 12] were used to train the ANN. On the other hand, test involving multi-pass were carried out in this investigation to measure the variation of the bending angle per pass according to the main process parameters. Figure 2 depicts the experimental equipment adopted in this study.

Due to the limitation of the adopted equipment, the maximum scanning speed was 60 mm/s; on the other hand, in order to avoid excessive material oxidation, the minimum scanning speed (v) was set to 15 mm/s. the laser power (P) ranged between 260 and 550 W, while the maximum number of scans (n) was 16.

2.1. Modeling deformation and thermal fields by ANN

A number of analytical models which assume the sheet as a semi-infinite medium have been developed to predict the temperature variation produced with a single and multiple laser scans [13, 14]. However, as demonstrated in [11][15], such models fail to predict the temperature variation produced by the laser radiation on thin metal sheets, especially during the cooling phase. Similarly, the prediction of the bending angle produced with laser bending is still a challenging issue. Actually, the prediction of the deformation field by means of analytical solutions is often affected by high limitations resulting from restrictive assumptions e.g. neglecting the thermo-mechanical behaviours variation with temperature, absence of plastic anisotropy, as well as neglecting of the variation of the material emissivity with temperature.

In order to overcome such limitations, semi-empirical models as well as Artificial Intelligent techniques represent an attractive possibility since they directly “learn” from experimental data. Because of the high flexibility, Artificial Neural Networks have been employed in a wide range of engineering fields as well as for process design and automation e.g. shape rolling sequences [16] either design of clinching tools [17].

In this investigation, an Artificial Neural Network (ANN) was developed to predict the bending angle \( \theta \), the cooling time \( t_c \) and the maximum temperature \( T \) produced with different laser scanning schemes. A series of preliminary ANN configurations were tested and finally, a feed-forward ANN with three layers (input, hidden and output layer) was adopted with one hidden layer composed by ten neurons. The input layer comprises three neurons (scanning speed, laser power and number of scans) and the output layer, is composed by four neurons namely bending angle after first pass, variation of bending angle per pass, maximum
temperature T and cooling time tc. A Levenberg-Marquardt algorithm is adopted to train the ANN by minimizing the difference between the ANN predictions and the experimental data. Experimental data were divided into three sets: 60% of samples were used for training, 15% for cross validation and the rest for testing. The Network training was stopped as the mean square error of the cross validation set stopped decreasing which meant that the network started to interpolate data rather than modelling (overtraining).

3. Results And Discussion

3.1. Interpretation of the experimental results

The variation of the bending angle with process parameters is reported in fig.2 (a). As can be observed, under high values of scanning speed and low power, the bending angle yields low values; this is due to the low thermal stress produced. As the power is increased either the scanning speed is decreased, resulting in an increase of the interaction time, higher values of bending angles are produced. However, excessive increase in the laser power and extremely low values of scanning speed result in the reduction of the bending angle. Actually, when working under such processing conditions, the extremely low value of scanning speed produce a smoother temperature gradient in thickness direction resulting in a lower bending angle. In addition, such conditions often lead to material oxidation and even melting.

Fig. 1. (a) Variation of bending angle with power and scanning speed; (b) Variation of Cumulative bending angle with number of passes.

Fig. 1 b depicts the variation of the cumulative bend angle produced with repetitive laser scans. As can be observed, for relatively low values of scanning speed, the bend angle increases almost linearly with the number of scans; on the other hand, as the scanning speed reduces an almost constant bending angle per pass is achieved. On the other hand, as the scanning speed increases, the bending angle per pass reduces with the number of passes. Edwardson et al. [18] have deeply studied such a phenomena. Possible reasons of such non-linearity have been reported in literature including, material strain hardening, variation of absorption coefficient, section thickening, residual stress and variation of the geometry during the process which moves the sheet surface from the focal plane.

In order to evaluate the variation of the bending angle per pass, a parameter which accounts such a non-linearity was introduced $\gamma_n (n,v,P) = \alpha_n (v,P)/(\alpha_1 \times n)$. As can be inferred, $\gamma_n$ is lower or equal then unity that means the increase of the number of passes has a detrimental effect on the laser bending efficiency. Particularly, this coefficient yields unity for low scanning speed while it shows an almost bilinear trend for higher levels of the scanning speed.

Fig. 3 depicts the variation of the cooling time measured under different conditions i.e. power and scanning speed. From figure 3 it is revealed that, the cooling time decreases almost linearly with laser power. This is due to a minor absorbed energy which has to be dissipated during the cooling phase. The trend of the cooling time with the scanning speed show an exponential decay. Indeed, higher scanning speeds result in a lower interaction time (which result in a lower amount of heat to dissipate during the cooling phase). In addition, higher scanning speed allow produce higher temperature gradients which further increase the heat dissipation rate.

Fig. 2. Variation of the coefficient of non-linearity with number of passes and scanning speed.

3.2. Neural Network Modelling
Before discussing the results achieved by the developed ANN model, a brief analysis of the model accuracy is reported. Table 1 summarizes the main error indicators concerning the model predictions for the different outputs. As can be noted, the developed ANN models yield accurate predictions for all the analyzed signals. Although a general agreement was found between the ANN predictions and the experimental measurements, it can be noted that the cooling time is affected by the highest error. Indeed, the measurement of the cooling time, especially under high scanning speeds were relatively difficult from an experimental point of view and some inaccuracies were found. Nevertheless, acceptable estimations of the cooling time are found since the Round Mean Square Error (RMSE) is almost 4% and $R^2$ is 0.98.

Table 1. RMS error and correlation factor for ANN Networks of:
Nonlinearity coefficient, bend angle, Max Temperature and Cooling time.

|                          | SSE | $R^2$ | RMSE |
|--------------------------|-----|-------|------|
| Nonlinearity coefficient | 0.0065 | 0.995 | 0.01 |
| Bend angle, $\alpha$     | 0.02  | 0.991 | 0.03 |
| Max. Temperature, T      | 0.008 | 0.995 | 0.016|
| Cooling Time, $t_c$      | 0.053 | 0.98  | 0.042|

Further comparison of ANN predictions with experimental measurements is reported in Figure 4-6.

As shown in these figures, the comparison between the neural network predictions and experimental data reveals the good accuracy ANN model.

![Graph showing comparison between experimental data and network model of nonlinearity coefficient $\gamma_n$.](image1)

![Graph showing comparison between experimental data and network model of bending angle $\alpha$.](image2)

![Graph showing comparison between experimental data and network model of maximum temperature and cooling time.](image3)

3.3. Optimization

The proposed automatic procedure to optimize laser bending process design is aimed at defining the operational conditions to produce a given bending angle with the minimum processing time. Such procedure is based on the integration of an optimization engine and a model that predicts the bending angle and temperature evolution according to the selected operative conditions. The latter is substantially based on the calculation of the overall processing time given a guess of the operative conditions i.e. laser power ($P$) and scanning speed ($v$). The flow chart of the procedure is depicted in figure 9. The evaluation of the overall processing time is reported in the following steps:

1. initial Guess of the process parameters ($P$ and $v$);
2. evaluation of the maximum temperature achieved during the laser scan (T) by means of the ANN;
3. if the maximum temperature reached during the process is lower than the maximum available temperature $T_{\text{max}}$ (which can be a reasonable temperature which avoids excessive oxidation of the sheet surface or even melting) proceed with the calculation of the process conditions, otherwise perform a new guess of the process conditions;
4. calculate the bending angle produced with a single pass $\alpha_1$ and the coefficient of non-linearity $\gamma_n$ (ANN);
5. calculate the number of passes required to achieve the given bending angle $\alpha$;
6. calculate the cooling time between consecutive scans (ANN) and consequently the overall time required to produce the bending angle $\alpha$;
7. (Optimization) iteratively perform a new guess for the the process conditions until the calculated production time is minimized.
The variation of the production time with scanning speed and laser power calculated by means of the above mentioned procedure is depicted in Figure 8. As can be inferred, the surface describing the processing temperature for low values of the bending angle to achieve in discontinuous; actually, the reduction of the beam power or the increase of the scanning speed may lead to an increase in the number of required passes that consequently results in a increase in the processing temperature. According to the achieved results, the same bending angle can be achieved with a reduced number of passes and involving low scanning speeds either a higher number of scans and higher scanning speed. As figure 7 reveals, the latter solution allows an increase in the process productivity. Actually when high scanning speeds are adopted, the required cooling time reduces because of a lower interaction time with the laser beam. In addition, high scanning speeds promote steeper temperature gradients in thickness direction which further contributes to a faster surface cooling.

The production time for the production of relatively high bending angles (i.e. \( \alpha > 10^\circ \)) shows three definite zones: a high productivity zone (dark blue) which results from high values of scanning speed and high values of power; a medium productivity zone (light blue) which are generated under high values of power and low values of scanning speed or medium values of power. Finally, a low productivity zone (yellow to red areas) which are characterized by extremely high values of the production time. To better understand the effect of process parameters on the production time, fig. 9 depicts the production time required to produce a bending angle of 10° with constant line energies i.e. \( LE = 5, 10, 15 \text{ J/mm} \). A close comparison of the curves representing the variation of the production time with scanning speed at different line energies reveals that, the higher the line energy, the lower the process time. Indeed, as can be inferred from the figure, low values of \( LE \) results in high values of the production time. Under such condition, a small thermal stress is produced since low values of power are adopted or excessively high values of scanning speed are utilized.
The following conclusions can be drawn:

- According to the prevalent deformation mechanism, the bend angle per pass can vary with the number of passes (pure temperature gradient Mechanism). On the other hand, lower scanning speeds which leads to a buckling-TGM deformation mechanism leads to an almost constant bend angle per pass;
- Artificial Neural Networks can be profitably used to predict and control the temperature evolution produced under given processing conditions as well and the bending angle and its variation with the number of scans.
- The developed procedure aimed at determining the optimal processing conditions to produce a given bending angle can contribute in the processing time compression;
- Laser bending productivity can be increased by the employment of path strategies involving: fast scans, high power

In conclusion, the integration of the Artificial Neural Network, used to map the effect of the process parameters on the produced angle and temperature profile, with the optimization engine has demonstrated to be a practical tool for laser bending process automation and control

References

[1] Vollertsen F, Hu Z, Niehoff HS, Theiler C. State of the art in micro forming and investigations into micro deep drawing. Journal of Materials Processing Technology. 2004;151:78-9.
[2] Shi Y, Lu X, Yi P, Liu Z. Effect of heating paths on strain distribution of plate in laser forming. The International Journal of Advanced Manufacturing Technology. 2012;66:515-21.
[3] Shi Y, Liu Y, Yi P, Hu J. Effect of different heating methods on deformation of metal plate under upsetting mechanism in laser forming. Optics & Laser Technology. 2012;44:486-91.
[4] Shi Y, Shen H, Yao Z, Hu J. Temperature gradient mechanism in laser forming of thin plates. Optics & Laser Technology. 2007;39:858-63.
[5] Ghadiri Zahrani E, Marasi A. Experimental investigation of edge effect and longitudinal distortion in laser bending process. Optics & Laser Technology. 2013;45:301-7.
[6] Hoseinpour Gollo M, Mahdavian SM, Moslemi Naeini H. Statistical analysis of parameter effects on bending angle in laser forming process by pulsed Nd:YAG laser. Optics & Laser Technology. 2011;43:475-82.
[7] Guan Y, Yuan G, Sun S, Zhao G. Process simulation and optimization of laser tube bending. The International Journal of Advanced Manufacturing Technology. 2012;65:333-42.
[8] Gisario A, Barletta M, Conti C, Guarino S. Springback control in sheet metal bending by laser-assisted bending: Experimental analysis, empirical and neural network modelling. Optics and Lasers in Engineering. 2011;49:1372-83.
[9] Lambiase F, Di Ilio A, Paoletti A. An experimental investigation on passive water cooling in laser forming process. The International Journal of Advanced Manufacturing Technology. 2013.
[10] Cheng J, Lawrence Yao Y. Cooling Effects in Multiscan Laser Forming. Journal of Manufacturing Processes. 2001;3:60-72.
[11] Lambiase F, Ilio A. A closed-form solution for thermal and deformation fields in laser bending process of different materials. The International Journal of Advanced Manufacturing Technology. 2013;69:549-61.
[12] Lambiase F. An Analytical Model for Evaluation of Bending Angle in Laser Forming of Metal Sheets. Journal of Materials Engineering and Performance. 2012;21:2044-52.
[13] Lambiase F, Di Ilio A, Paoletti A. Prediction of laser hardening by means of Neural Network. Procedia - CIRP2012.
[14] Nath AK, Gupta A, Benny F. Theoretical and experimental study on laser surface hardening by repetitive laser pulses. Surface and Coatings Technology. 2012;206:2602-15.
[15] Lambiase F, Ilio A. A closed-form solution for thermal and deformation fields in laser bending process of different materials. The International Journal of Advanced Manufacturing Technology. 2013.
[16] Lambiase F. Optimization of shape rolling sequences by integrated artificial intelligent techniques. The International Journal of Advanced Manufacturing Technology. 2013;68:443-52.
[17] Lambiase F, Di Ilio A. Optimization of the Clenching Tools by Means of Integrated FE Modeling and Artificial Intelligence Techniques. Procedia CIRP 2013;12:163-8.
[18] Edwardsson SP, Griffiths J, Dearden G, Watkins KG. Temperature gradient mechanism: Overview of the multiple pass controlling factors. Physics Procedia. 2010;5:53-63.