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Application of multiple regression and neural networks to synthesize a model for peen forming process planning

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Analysis and modelling

ABSTRACT

Purpose: this paper aims to present a simple method to synthesize an empirically-based model that permit to estimate the maximum displacement of a plate when a shotpeening process values are known.

Design/methodology/approach: This approach regards the difficulty to develop a mathematical model to describe the relationship between the shot peening process variables (shot diameter, impact velocity, static preload and coverage) and the curvature of the piece. Such a model was generated through the application of statistical inference methods – multivariable regression and neural networks – to a set of experimental data concerning the application of peen forming processes to a group of 215 aluminium 7050 alloy rectangular plates.

Findings: Although the estimated displacements from both models comply reasonably well with the experimental data, the obtained results exposed the superiority of the regressive model concerning accuracy.

Research limitations/implications: Shot peen forming, a die less forming process, is one of the most successful methods to produce slight and smooth curvatures on large panels and plates. Through the application of a regulated blast of small round steel shot on the piece surface, a thin internal layer of residual compressive stress causes the elastic stretching of the shotted surface, giving rise to a permanent non-plastic deformation of the whole piece. Although this forming process has been used since the fifties, especially by the aerospatial industry, a scientific method for peen forming process planning has not been developed yet.

Originality/value: The referred model can be used as an engineering tool to aid setting up a peen forming process in order to produce a desired curvature on a given plate.

Keywords: Peen forming; Artificial neural network; Aluminium alloy 7050

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1. Introduction

Shot peen forming is a plastic cold work process that modifies the shape of a metallic plate or panel through the impact of a regulated blast of small round steel shots on its surface. The dynamic pressure of each sphere against the surface causes a local plastic deformation; consequently, a thin compressive residual stress is generated, giving rise to elastic stretching of the worked surface. As illustrated by Fig. 1, the residual stresses and the ellastic recovery due to the superficial stretching, introduces a permanent convex shape on the piece. Furthermore, a beneficial side effect results from the distribution of compressive residual stresses near the worked surface - a significantly increase in the fatigue life of the piece as well as in its corrosion fatigue strength.

Traditionally, peen forming process planning is performed on a trial-and-error basis, using, as the unique controllable variable, the measure of Almen intensity [1], i.e., the highest deflection assumed by a small standard rectangular steel blade fastened to a standard jig (Almen gauge) when submitted to the same shot peening process during the time required for deformation to saturate.

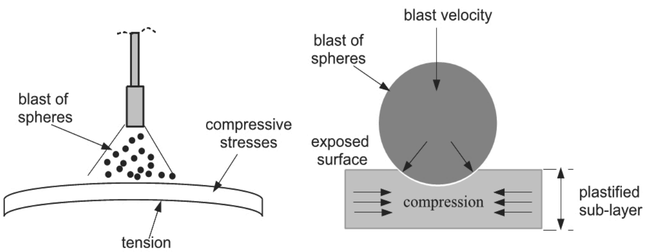

Fig. 1. Peen forming general schema

As exposed in [2], the simplicity of this method is one of the main attributed explanations for its extensive use in the industry; however, since Almen intensity combines the effects of several intrinsic variables of the process (velocity of impact, average diameter and hardness of the spheres, incidence angle, mass flow and exposure time), that measure is not adequate to feedback a closed-loop controlled peen forming process, an aim that has been pursued for very a long time, especially by the aerospatial industry.

According to [3], one of the most demanded problems to be solved concerning industrial application of peen forming is the development of a scientific methodology to synthesize a process plan able to generate a surface with a previously desired shape from a given blank - plate or panel.

Although there are several instruments capable to measure the intrinsic variables of peen forming processes in real time [4,5], there is not yet a mathematical model relating the shot blast variables to the ones responsible for the structural behaviour of the formed piece.

Aiming to evaluate the influence of velocity, size and shot characteristics on the variables that affect the local shape of the attacked surface - the contact force time and the residual stress field, Meguid et al. [6,7] developed a shot peening mathematical model using dynamic elasto-plastic analyses related to single and double impact events. However, the computational cost to extend the application of such a model to the overall shotted area would be too-high.

Schiffner and Helling [8], on the other hand, constructed a simplified model to simulate the evolution of residual stresses caused by shot peening, assuming that load is quasi-static and the external dynamic forces due to impacts could be represented by time dependent load functions. Since such hypotheses are very strict, it is necessary to include in the model the specific material laws concerning deformation rate effects and the influence of friction on the multiple impacts.

The difficulties briefly appointed before might explain why several authors [9-11] emphasize that the inclusion of experimental data is the only feasible approach to synthesize a mathematical model suitable to be applied in closed-loop control of peen forming processes.

2. Design of experiments

Aiming to develop an experimentally-based methodology to generate a mathematical model for peen forming, a series of designed experiments was performed, encompassing 216 equally groups of 400 mm x 50 mm rectangular plates made in aluminum 7050 and 7475 alloys with four equally distributed thicknesses - 2 mm, 5 mm, 10 mm and 15 mm. These workpieces were peenformed on a specially designed CNC shotpeening machine at the Metallurgical Laboratory of Sao Paulo Institute of Technology (IPT) and using all the necessary instruments to measure the relevant process variables - average shot size, average impact shot velocity, coverage and static preload. Concerning this last variable, it is important to stress that the residual stress compressive depth increases when a shotpeened plate is submitted to a permanent elastic flexion [12].

Experiments were carried out according to a test matrix encompassing two to three variation levels for each process variable – three for d (shot diameter) and v (impact velocity) and two for c (coverage) and t (static preload). Levels for d are independent (0.7 mm, 1.3 mm and 3.2 mm), but *high* and *low* levels for coverage and velocity are defined according to the shot diameter used in the respective experiments; in the case of preload t, two levels were considered - no preload, i.e., t=0, and t=0.9Py, i.e., a distributed load of resultant P applied at the middle spam of the plate in order that a maximum stress of 90% of the yield stress is achieved somewhere in the plate. The structural behaviour of the workpiece was characterized by the measured maximum displacement obtained after applying the peen forming process.

In this work we present and analyse the data generated by the experiments executed to identify the effects of the above referred process variables - d, v, t and c - on the displacement f, measured at the mid-spam of a given Al-7050 plate of thickness e. The levels of variables concerning the process and the workpiece are shown in Table 1, whereas Table 2 presents some examples of the complete matrix of 216 experiments spanning a non-exponential set of combinations and three replicate for each experimental condition.

Table 1.
Variables levels

e(mm)	d(mm)	v(m/s)	t(kN)	c(%)
2	0.6	12.5	0.594	0.66
5	1.4	16.9	1.336	0.85
10	3.175	18.5	2.672	0.92
15		22.4	4.008	2.00
		28.6	10.688	
		61.2	26.718	
		72.2	53.348	
			80.156	

Table 2.
Subset of the matrix of experiments

e (mm)	d (mm)	v (m/s)	t (KN)	c (%)	f (mm)
5	0.6	50.20	1.336	2.00	1.174
5	0.6	50.20	1.336	2.00	1.085
5	0.6	50.20	26.718	0.66	2.097
5	0.6	50.20	26.718	0.66	1.960
5	0.6	50.20	26.718	2.00	2.575
5	0.6	50.20	26.718	2.00	2.496
5	0.6	50.20	26.718	2.00	2.474
5	0.6	61.20	1.336	0.85	1.426
5	0.6	61.20	1.336	0.85	1.502

3. Statistical analysis

Using Statistica™ software, two methodologies were applied to synthesize a peen forming empirically-based model from the available experimental data - one based on variance analysis (ANOVA) followed by linear regression; the other generated by one MLP neural network. Both models establish a quantitative relationship between the plate maximum deflexion and the process and structural variables.

As indicated in Table 3, the application of a factorial regression method, using second-order interactions among variables, gave rise to a multiple correlation factor equal to 0.83. After a simple inspection of Fig. 2, however, one can observe that the distribution of residues concerning the predicted values has a nonlinear biased tendency, a clear signal that the proposed regression method was not well-fitted to the data.

Table 3.
Correlation coefficients for the factorial model

Dependent Variable	Test of SS Whole Model vs. SS Residual				
	Multiple R	Multiple R^2	Adjusted R^2	F	p
f	0.92	0.84	0.83	70.21	0.00

Table 4.
Correlation coefficients for logarithmic factorial model

Dependent Variable	Test of SS Whole Model vs. SS Residual (ln)				
	Multiple R	Multiple R^2	Adjusted R^2	F	p
ln(f)	0.98	0.97	0.97	1353.5	0.00

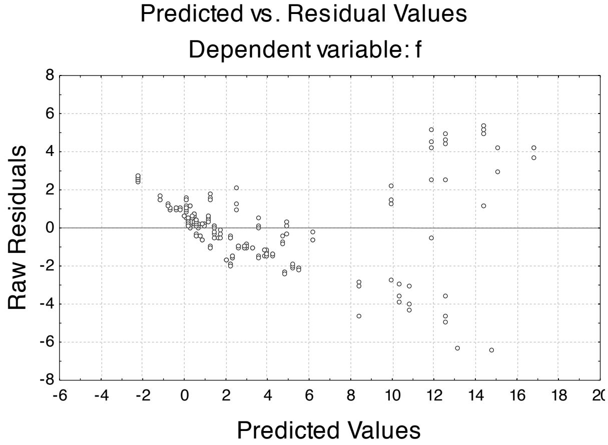

Fig. 2. Distribution of residual values for the predicted value of the displacement

To overcome the difficulties that caused the above approach to fail, a factorial regression with second-order interactions among the logarithms of the variables was adopted; the correspondent multiple correlation coefficient associated to this model was then 0.97 (see Table 4). Considering the excellent fitting of the data to this second regression model, as illustrated by Fig. 3, the following simple exponential expression for the displacement *f* was proposed:

$$f = Ke^{x_1} d^{x_2} v^{x_3} t^{x_4} c^{x_5} \tag{1}$$

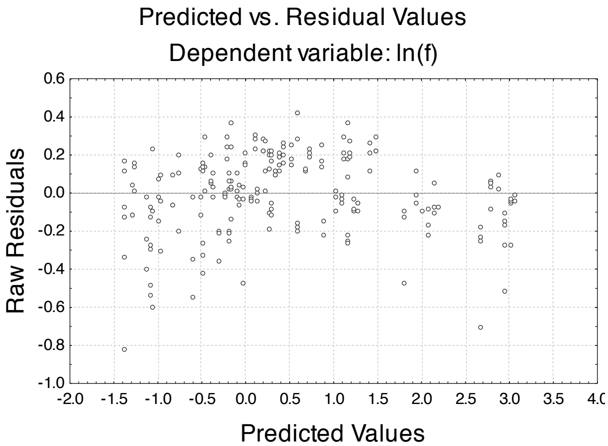

Fig. 3. Distribution of residues for the predicted value of the logarithm of the displacement

After applying a logarithmic transformation to Equation 1, in order to obtain a linear expression, a multiple linear regression model was adopted to synthesize the following relationship between *f* and the other variables of the process.

Using the regression analysis technique associated to the least square method, the coefficients of the empirically-based model were finally estimated (see Table 5). As it can be seen in Table 4, the high correlation coefficients obtained in this case demonstrate the well-fitness of this model to the experimental data.

$$\ln(f) = \ln(K) + x_1 \ln(e) + x_2 \ln(d) + x_3 \ln(v) + x_4 \ln(t) + x_5 \ln(c) \quad (2)$$

Substituting in Equation 1 the coefficients shown in Table 5, the following regression model for peen forming process planning is finally achieved:

Table 5.
Estimated coefficients for Equation 1

Dependent Variable	Test of SS Whole Model vs. SS Residual			
	ln(f)	ln(f)	ln(f)	ln(f)
	Param.	Std. Err.	t	p
Intercept	2.70143	0.155946	17.3229	0.000000
ln(e)	-2.24536	0.040615	-55.2846	0.000000
ln(d)	0.79752	0.047005	16.9665	0.000000
ln(v)	0.30836	0.036529	8.4416	0.000000
ln(t)	0.29868	0.009753	30.6235	0.000000
ln(c)	0.24815	0.025704	9.6543	0.000000

$$f = 14.9 e^{-2,245} d^{0,798} v^{0,308} t^{0,299} c^{0,248} \quad (3)$$

As mentioned before, not only classical regression methods were applied to the experimental data in order to synthesize a quantitative model for peen forming; another approach, based on the use of neural networks, was also attempted.

Using the neural networks module of Statistica™ software, a backpropagation learning based MLP with five neurons in the input layer, seven in the intermediate layer and one in the output layer (see Fig. 4), was adopted as a model synthesizer tool.

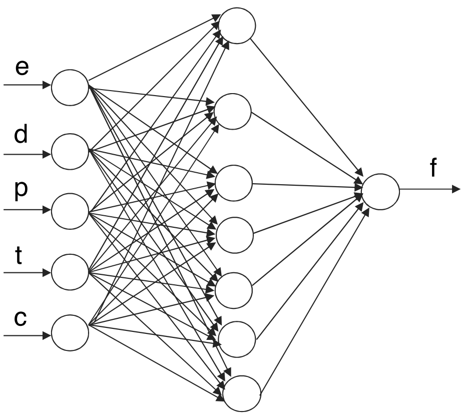

Fig. 4. *MLP* neural network adopted for the modeling synthesis

Following the recommendations from literature, 80% of the experimental data were randomly chosen to train the proposed neural network while the reminiscent 20% were destined to its validation. As shown in Table 6, the correlation coefficients obtained during the training and validation phases - respectively 0.9907 and 0.9913, indicated that the generated model is very well fitted to the experimental data.

Table 6.
Properties of the adopted neural network

Net. name	Training perf.	Test perf.	Training error	Test error
MLP 5-7-1	0.990720	0.991277	0.000511	0.000546
	Training algorithm	Error function	Hidden activation	Output activation
	BFGS 47	0.000546	Exponential	Identity

4. Predicted results

The data showed in Table 7 and the graphics of Fig. 5 permit to visually compare the measured (f_{EXP}) values with the respective predicted ones, either using the neural network (f_{ANN}) or the regression approach (f_{REG}).

The graphics of Fig. 5 indicate that there is a reasonable agreement among the experimental and predicted values. The average deviates of the displacements relative to the measured values, are given by:

$$e_{ANN} = \frac{1}{n}\sum_{i=1}^{n} \frac{\left| f_{ANN,i} - f_{EXP,i} \right|}{f_{EXP,i}} \times 100 = 29,3 \quad (4)$$

$$e_{REG} = \frac{1}{n}\sum_{i=1}^{n} \frac{\left| f_{ANN,i} - f_{EXP,i} \right|}{f_{EXP,i}} \times 100 = 18,4 \quad (5)$$

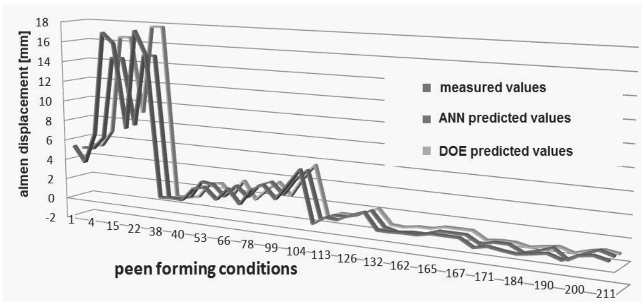

Fig. 5. Measured and predicted maximum displacements

Therefore, despite the extreme simplicity of the statistical inference method used, the model generated by the regression method was still more accurate than the one issued by the neural network. This is due, probably, to the small quantity of experimental data used to train the neural network, a fact that often restricts the application of neural networks to the solution of statistical inference problems [14].

Table 7.
Measured and predicted maximum displacement values

e	d	v	t	c	f_{EXP}	f_{ANN}	f_{REG}
mm	mm	m/s	kN	%	mm	mm	mm
2	0.600	50.200	0.594	0.660	5.389	5.572	5.392
2	0.600	50.200	0.594	0.660	3.790	5.572	5.392
2	0.600	50.200	0.594	2.000	6.821	6.723	7.099
2	0.600	50.200	10.688	2.000	17.102	14.704	16.844
2	0.600	50.200	10.688	2.000	16.072	14.704	16.844
2	0.600	61.200	0.594	2.000	7.682	8.062	7.545
2	0.600	61.200	10.688	0.850	17.491	15.103	14.481
2	0.600	61.200	10.688	0.850	15.067	15.103	14.481
5	0.600	50.200	1.336	0.660	1.156	0.756	0.878
5	0.600	50.200	1.336	0.660	1.222	0.756	0.878
5	0.600	50.200	1.336	2.000	1.174	1.101	1.156
5	0.600	50.200	26.718	2.000	2.474	2.877	2.832
5	0.600	61.200	26.718	0.850	2.689	3.058	2.434
5	0.600	72.200	1.336	2.000	1.648	1.871	1.293
5	0.600	72.200	26.718	0.920	2.868	3.177	2.612
5	1,400	10.200	1.336	2.000	1.487	1.223	1.392
5	1,400	10.200	26.718	0.600	3.079	2.540	2.528
5	1,400	22.400	26.718	0.600	3.628	3.544	3.222
5	1,400	28.600	1.336	2.000	2.408	2.484	1.912
5	1,400	28.600	26.718	0.600	3.949	4.151	3.473
5	1,400	28.600	26.718	2.000	5.530	5.844	4.682
10	1,400	12.500	2.672	2.000	0.517	0.981	0.385
10	1,400	12.500	53.348	0.600	1.277	1.264	0.698
10	1,400	12.500	53.348	0.600	1.198	1.264	0.698
10	1,400	16.900	53.348	0.600	1.818	1.464	0.766
10	1,400	16.900	53.348	2.000	2.257	2.397	1.033
10	1,400	18.500	2.672	0.600	0.716	0.638	0.322
10	1,400	10.200	53.348	0.600	0.710	0.222	0.656
10	1,400	22.400	53.348	0.600	0.784	0.532	0.836
10	1,400	22.400	53.348	0.600	0.773	0.532	0.836
10	1,400	22.400	53.348	2.000	1.038	0.912	1.127
10	1,400	22.400	53.348	2.000	1.026	0.912	1.127
10	1,400	22.400	53.348	2.000	1.016	0.912	1.127
10	1,400	28.600	2.672	0.600	0.316	0.682	0.368
10	1,400	28.600	2.672	2.000	0.574	1.233	0.496
10	1,400	28.600	2.672	2.000	0.382	1.233	0.496
15	3,175	12.500	4.008	2.000	0.250	0.441	0.336
15	3,175	12.500	80.156	0.600	0.441	0.237	0.610
15	3,175	12.500	80.156	2.000	0.675	0.643	0.822
15	3,175	16.900	4.008	0.600	0.245	0.218	0.273
15	3,175	16.900	80.156	0.600	0.706	0.330	0.669
15	3,175	16.900	80.156	2.000	0.886	0.794	0.902

5. Conclusions

Statistical methods based on multiple regression and artificial neural networks were applied to a data set generated by peen forming designed experiments with aluminium alloy plates, aiming to synthesize quantitative models relating the highest displacement of the plate with the respective variables of the process. Although the estimated displacements from both models comply reasonably well with the experimental data, the obtained results exposed the superiority of the regressive model concerning accuracy.

It is important to emphasize that, in spite of its extreme simplicity, the regression-based model, relating the maximum deflection f of a plate of thickness e with the four significant variables of peen forming processes (preload (t), average shot diameter (d), coverage (c) and average impact velocity (v)) can solve two typical shot floor industrial problems - indicate if a peen forming process can produce or not a given curvature to the plate and estimate the values of the parameters of the process able to produce the desired curvature.

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