Modelling of Single Point Incremental Forming Process for Al6061 Sheets using Artificial Neural Network

Rajeev R[1] Dr. C. Raju[2]
[1,2]Department of Mechanical Engineering
[1,2]College of Engineering Trivandrum, India

Abstract— Single Point Incremental Forming (SPIF) process is a dieless forming process with promise for prototyping and manufacturing of low production runs. This paper presents a model of Al6061 sheet Single Point Incremental Forming process using Artificial Neural Network(ANN). The parameters used for modelling are tool diameter, feed rate, spindle speed, vertical step depth and sheet thickness. Forming time, Formability and Spring back are the answers to the modelling. The technique of supervised machine learning is used to create an ANN model for SPIF the model created is tested and verified with another experiment with different set of process parameter values.

Keywords: SPIF, ANN, Supervised Learning, Al6061 Sheets, Modelling

I. Introduction

The current global economy situation has placed importance on developing new technologies to convert raw materials into final products as quickly as possible at the lowest cost of processing. Mason first described the process principle of asymmetric incremental sheet forming in 1978 and it was further developed and in 1994 Matsubara introduced a new family called incremental sheet forming (ISF). In ISF, a series of small incremental deformations use computer numerical control (CNC) milling machine and a specially designed tool form the sheet into the final productISF can be classified as single point incremental forming (SPIF) and multi point incremental forming (MPIF) based on the number of contact points between tool and sheet metal. ISF was initially developed for the sheet metal processing of car manufacturers. Now it is extensively applied on polymers and composites sheets too by many other industrial applications like rapid prototypes to make a variety of asymmetric complex shapes for the automotive industry and the nonautomotive industries such as in aerospace industries, biomedical applications and appliances.

Several studies on formability in SPIF have been conducted. Leszak[1] patented in a sheet forming process incrementally. Kim and Park[2] discovered the effect of certain process parameters on the formability of an aluminum sheet in incremental forming. Shanmuganatan et al.[3, 4] conducted Finite Element Analysis on conical frustum component profile formation and found the component's thinning effect and variation. Ham and Jeswiet[5] developed the SPIF Forming Limit Diagram(FLD) methodology. Single Point Incremental Forming (SPIF), a state of the art technique, was suggested by C. Pandivelan et al.[6] on alloy sheets of aluminum AA 6061 and its forming limit was experimentally determined. The straight groove and cupping tests were performed using a ball-ended tool in the CNC vertical milling machine.

Researchers combined artificial neural network (ANN) and genetic algorithm (GA) in certain metal forming processes to investigate and optimize the relationship between control factors of the forming process. In the radial forging process, Sanjari et al.[7] used the artificial neural network and genetic algorithm method to optimize radial force and stress inhomogeneity. Using an FEM equivalent model, artificial neural networks and genetic algorithms, Yu et al.[8] also developed an integrated approach for optimal path design of press bend formation.

The objective of the current research is model SPIF process for Al6061 sheets using ANN .L18 orthogonal array used for conducting the experiments.

II. Materials and Methods

A. Experimental Setup

Aluminium 6061 sheets were cut into in square array with dimensions of 150 mm (length) X 150 mm (width) X 1 mm (thickness). Circles with 2 mm diameter and 0.05 mm depth were engraved using a laser grid engraving machine on the Aluminium 6061 sheets. The tool consisted of EN8 steel and various diameter (8 mm, 10 mm and 12 mm) hardened steel balls were placed at the bottom of the SPIF tool shank using grease. The SPIF process was carried out at Precision engineering works, Thuvakudi, near Trichy, with a Leadwell Vertical Machining Centre with Fanuc OM CNC milling machine. Coconut oil was used as the lubricant to obtain a good surface finish on the deformed part. A CNC program for controlling the tool movement at speeds of 300 rpm, 450 rpm and 600 rpm was coded in the CNC milling machine's computer control unit. For experimental tests, a feed rate of 300 mm / min, 600 mm / min and 900 mm / min was maintained while the vertical step depth was varied (0.4 mm, 0.5 mm and 0.6 mm). Figure shows the SPIF experimental setup and SPIF process operations of Aluminum 6061 sheet blanks. 1.

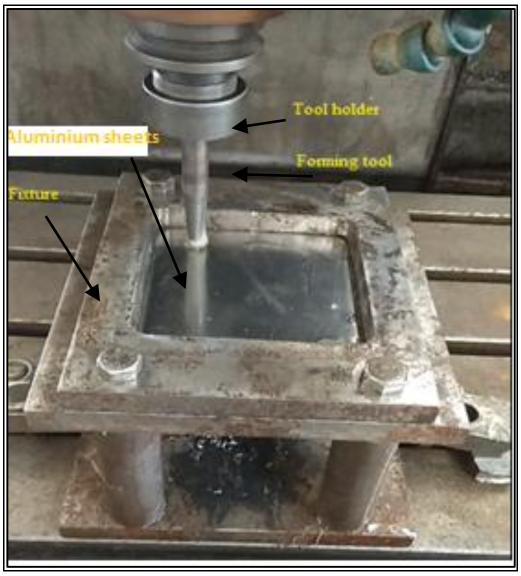

Fig. 1: Shows SPIF process experimental setup and

The CNC program specially prepared for SPIF is fed into the CNC. The forming tool travels both horizontally and vertically as per a NC part program based tool path, forming a desired frustum cup shape from the blank sheet metal. After the forming of each plate the tool, feed rate, spindle speed etc. are changed in accordance of L18 orthogonal array. The sheets were arranged individually one by one to perform the forming process. The time taken and given Vertical step depth are directly obtained from the CNC machine itself.

B. Experimental procedure and plans

Different process parameters and aluminum 6061 sheet SPIF levels are shown in Table 1. The design of experiments is performed using an L18 orthogonal array. 18 Frust cup shaped parts were made using the various process parameter combinations shown in Table 1

Process Parameters	Level 1	Level 2	Level 3
Spindle speed(rpm)	300	450	600
Vertical step depth (mm)	0.4	0.5	0.6
Feed rate (mm/min)	300	600	900
Tool diameter (mm)	8	10	12
Sheet thickness(mm)	0.8	1	1.2

Table 1: Process parameters

Time taken for SPIF, Formability and Spring back are the responses that are taken for modeling. A digital USB microscope was used to measure the large and small diameters of the deformed circles already engraved on Aluminum 6061 sheets. For the measurement of formability, major true strain and minor true strain are calculated.

Major true strain,(ε_{major}) = $\ln(d_m/d_c)$.

Where d_m is the major diameter of the ellipse and d_c is the diameter of the circular grid.

Minor true strain,(ε_{minor}) = $\ln(d_i/d_c)$.

Where di is the minor diameter of the ellipse.

Formability = Major true strain + Minor true strain.

Spring back (S) = D-d

Where D is the depth of the formed part and d is the actual depth of the formed part measured using the coordinating measuring machine

C. Modelling SPIF with ANN

The modelling of SPIF is carried out with ANN technique .Matlab 2015a is used for training of Neural Network .Supervised learning technique is applied here for training .The fitting app in matlab is used for training purpose. In fitting problems neural network map between a data set of numeric inputs and a set of numeric targets. The Neural Fitting app will select data, create and train a network, and evaluate its performance using mean square error and regression analysis. The training data used are shown in table 2 and 3 respectively. Out of 18 samples 14 are used for training, 3 are for validation and one for testing. A Single hidden layer with 25 neurones is used in the network.. Bayesian regularization algorithm is used for training purpose. This algorithm usually takes longer, but for difficult, small or noisy datasets can result in good generalization. Training stops in accordance with adaptive weight reduction.

Sheet thickness(mm)	Spinde speed(RPM)	Vertical stepdepth(mm)	Feed rate (mm/s)	Tool diameter(mm)
0.8	300	0.4	300	8
0.8	450	0.6	600	10
0.8	600	0.8	900	12
1	300	0.4	600	10
1	450	0.6	900	12
1	600	0.8	300	8
1.2	300	0.6	300	12
1.2	450	0.8	600	8
1.2	600	0.4	900	10
0.8	300	0.8	900	10
0.8	450	0.4	300	12
0.8	600	0.6	300	10
1	300	0.6	900	8
1	450	0.8	300	10
1	600	0.4	600	12
1.2	300	0.8	600	12
1.2	450	0.4	900	8
1.2	600	0.6	300	10

Table 2: Input data for training ANN

time(min)	Spring back(mm)	Formability
62.42	1.48	0.456
23.9	2.78	0.897
7.18	2.83	0.658
32.9	2	0.913
18.08	3.4	0.819
32.72	3.09	0.635
48.12	3.91	0.711
17.77	2.41	0.6579
22.33	2.59	0.78
7.47	3.04	0.987
63.93	1.77	0.73
52.18	1.3	0.7028
18.87	2.65	0.9288
44.55	2.95	0.793
37.68	2.77	0.718
16.1	2.82	0.7828
26.55	2.64	0.9688
59.63	1.15	0.7233

Table 3: Responses for training ANN

III. RESULTS AND DISCUSSIONS

A. Trained Neural Network Model

The training is stopped after 475 iterations with bayesian regularization training technique.An overall regression value of 0.9909 is achieved.The regresion analysis of responses (target) and trained data (output) is shown in fig 2.

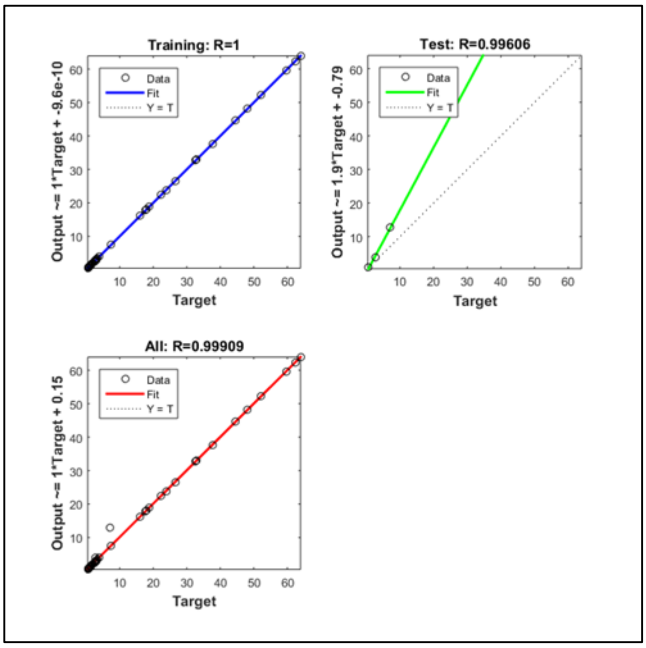

Fig. 2: Comparison of trained data and actual data after training

From fig.2 it is clear that the trained data and actual responses are very closer.This illustrates the modeling accuracy of ANN.

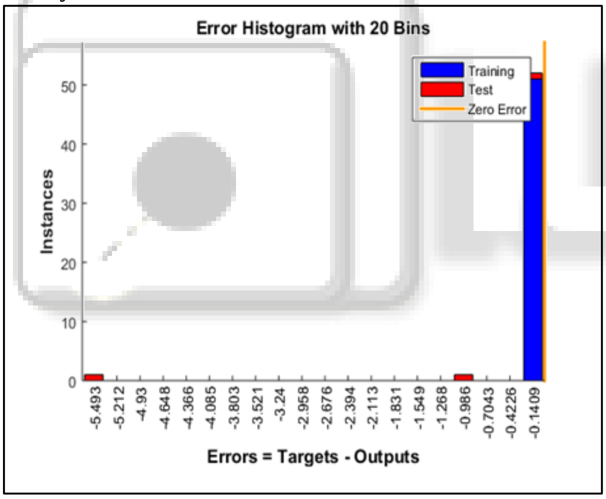

Fig. 3: Error histogram of trained data

The figure 3 depicts the error histogram of trained data.From the error histograms, it is evident that for most of the instances, there is very minimal or no error. The error values rise to a maximum only for very few instances and this can be attributed to the randomness of the real life conditions.

Time(min)	Spring back(mm)	Formability
62.42	1.480000001	0.456000026
23.9	2.779999992	0.896999958
7.18	2.830000003	0.658000018
32.9	2.000000009	0.912999976
18.08	3.400000003	0.819000014
32.72	3.090000001	0.635000007
48.12	3.909999998	0.711000022
17.77	2.409999999	0.657900032
26.891414	2.142855843	0.824798641
7.47	3.04	0.986999988
63.93	1.770000001	0.730000004
52.18	1.300000011	0.702800029
18.87	2.650000001	0.928800017
44.55	2.949999999	0.792999957
37.68	2.769999998	0.71800001
16.1	2.820000009	0.782799996
26.55	2.639999994	0.968799979
59.63	1.150000008	0.723299982

Table 4: Responses after training

Table 4 shows the responses of trained SPIF model.If we compare this data with input response data for training the variation are very less.The model generated by applying Bayesian regularization algorithm has been given as,

$$Output=\sum\{purelin[LW * (\sum\sum tansig(X * IW + b))] + a\}$$

This equation represents the five input process parameters and three responses of the trained feed-forward ANN model in MATLAB. Here, MATLAB functions are' purelin' and' tansig' which calculate the output of the layer from its network input. Purelin provides a linear relationship between input and output, whereas tansig is a hyperbolic tangent sigmoid transfer function and is equivalent to' tanh' mathematically. In MATLAB simulations, Tansig is faster than tanh, so it is used in neural networks. LW and IW, respectively, are weights of connections between the input layer and the hidden layer and the input layer. The weights of the input bias connections and the hidden layers are respectively represented as b and a. The variable input was represented as X. After training the neural networks with Bayesian regularization algorithm, the networks were simulated to predict the time for SPIF,Formability, Spring back. The network learned training data-set with predicted validation data-set with 99.909% accuracy (Fig 2).

Time(min)	Spring back(mm)	Formability
-7.47e-09	-7.89e-10	-2.60e-08
-5.23e-09	8.17e-09	4.17e-08
-3.16e-09	-3.28e-09	-1.81e-08
-6.92e-09	-9.50e-09	2.44e-08
-3.32e-09	-2.76e-09	-1.43e-08
-8.70e-09	-7.12e-10	-7.48e-09
-1.57e-08	1.71e-09	-2.18e-08
-5.95e-10	8.14e-10	-3.18e-08
-4.561414	0.447144157	-0.044798641
5.99e-09	-4.73e-10	1.17e-08
-2.04e-08	-6.23e-10	-3.77e-09
-1.53e-08	-1.11e-08	-2.88e-08
6.88e-09	-8.49e-10	-1.73e-08
-1.27e-08	8.24e-10	4.26e-08
-1.59e-08	1.61e-09	-1.03e-08
-8.48e-09	-8.58e-09	3.88e-09
1.47e-09	5.73e-09	2.11e-08
-1.79e-08	-8.09e-09	1.83e-08

Table 5: Error in the trained model response from actual response

Table 5 depicts the error in training the data, ie, difference of trained data from actual data.From the error value it is clear that there is only a slight difference in the trained model than actual data except for one experiment.

IV. CONCLUSIONS

The following points have been concluded from this project:

- Modelling of SPIF process with ANN is carried out, and the model created has an accuracy of 99.909% .
- This model created is superior over RSM model that are created widely before the advent of ANN.
- Bayesian regularization algorithm provides a an accurate result over levenberg marquardt algorithm which is most commonly used.

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