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Predicting Force in Single Point Incremental Forming by Using Artificial Neural Network

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ABSTRACT

In this study, an artificial neural network was used to predict the minimum force required to single point incremental forming (SPIF) of thin sheets of Aluminium AA3003-O and calamine brass Cu67Zn33 alloy. Accordingly, the parameters for processing, i.e., step depth, the feed rate of the tool, spindle speed, wall angle, thickness of metal sheets and type of material were selected as input and the minimum vertical force component was selected as the model output. To train the model, a Multilayer perceptron neural network structure and feed-forward backpropagation algorithm have been employed. After testing many different artificial neural network (ANN) architectures, an optimal structure of the model i.e. 6-14-1 was obtained. The results, with a correlation relation between experiments to predicted force,-0.215 mean absolute error, show a very good agreement.

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1. INTRODUCTION

Sheet metals are manufactured by the rolling processes. Sheet metals have various applications starting from a simple sheet metal tray to complicated parts used in aircraft, automotive, construction. The other applications are household appliances, food & beverage containers, boilers, kitchen equipment, office equipment etc. A flat sheet metal is formed into complicated shapes by using the die and punch. The sheet metals are ductile in nature. They can be formed only to a certain limit. Beyond these limit failures like necking and fracture occurs. Many research groups are still investigating process feasibility and developing finite element (FE) codes for the SPIF. Several analysis tools are described in the proceedings [1-4]. Theoretically, the Yielding criteria, strains along with its hardening and thickness variations during the deep drawing of forming process has been established [5] which helps to understand the straining behavior of the thin sheet during incremental sheet metal forming (ISF). In this technique, no need of die and punch as in case of deep drawing. Of course, the deformation is incremental, local in nature and gradual. These enhance the limiting strain during ISF. It is a growing process; therefore, a wide analysis is required to develop the theory of incremental forming [6, 7]. At present, a number of research works have been carrying out in this field to enhance the process capability of SPIF. The conventional press forming processes become costlier for even small batch production because of the dedicated punch & die, hydraulic press required for forming. In conventional forming, the varying strain path and severe strains reduce the formability of complex shapes. These types of problems can be resolved by using SPIF. Early work in SPIF indicated that the maximum formable wall angle could be a good indicator for material formability [8].

The formability involution of aluminum grade Al 1050 using PAM-STAM software package to analyze the behavior of incremental forming on aluminum foils [9] and verified by using FEM [10]. The DHP (deoxidized high phosphorous) copper and AISI 304 steel sheets have been formed through ISF to evaluate the process suitability [11]. The ball end tool used in SPIF which moves incrementally in the predetermined path until the end of the program [12], further micro-forming using pointed tools [13] and conical end tool has been successfully done on ISF. A FEM model

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developed on ABAQUS to predict the behaviour of the sheet during ISF to analyse the effect of process parameters like advancing speed, forming in the characteristics of the parts (thickness, geometrical accuracy, roughness) [14]. The formability evaluation on negative ISF has been carried out [15] on pure titanium in cold state ISF [16] and on annealed and pre-aged aluminum AA-2024 grade sheets [17] with varying process parameters. The influence of process parameters on the forming forces have experimentally investigated and analytical results demonstrating the relationship between the respective process parameters and the induced forces [18-22]. An inverse method has been done for adjusting the material parameters for SPIF by FEM simulations called 'the line test' on aluminium alloy AA3103 with classical tests and compared with parameters accuracy of the tool force prediction [23] followed by impact of forming parameters on steel DC05 have investigated and confirms forming forces mostly dependent on the size of the wall angle, tool diameter and vertical step sizes of the tool [21]. The constitutive laws (an elastic-plastic law coupled with various hardening models) confirms the thickness of the metal sheet which is a crucial parameters for prediction of an accurate force [24]. Three level box-behnken design of experiments (DOE) approach correlated with quadratic mathematical models for the considered responses i.e. minimizing sheet thinning rate and the punch loads generated in this forming process [25].

2. EXPERIMENTAL INVESTIGATION: MATERIAL, TOOL, AND MACHINE

2. 1. Material The miniaturization trend always finds part with high quality; the body part of aluminium and brass are very demanding in many industries such as aerospace, automobile etc. therefore, commercially available AA 3003-O and calamine brass Cu67Zn33 alloy are taken for experients. The composition of constituents on samples has been found by using scan electron microscopy (SEM). The SEM results shown in Table 1.

The ultimate tensile strength of both metals have been tested on "INSTRON" Series IX automated materials testing system in the department of polymer engineering, Birla Institute of Technology, Mesra. The sample is prepared as per American society for testing's and materials (ASTM) standard E8 as shown in Figure 1 and corresponding stress-strain curve in Figure 2.

2. 2. Forming Tool A cylindrical rod of 40C6 steel of 07 mm diameter was used as tool. One face of the rod was grooved in such a way that the half part of 06 mm diameter bearing ball inserted in the groove (Figure 3).

TABLE 1. Composition of constituent in AA3003 and Cu67Zn33 alloy

Constituent (%)	AA3003	Cu67Zn33
Al	98.12	-
Si	0.628	-
Fe	0.705	-
Cu	0.05	66.90
Sn	-	-
Co	0.08	-
Mg	1.2	-
Zr	0.05	-
Zn	-	35.06
Pb	-	0.01

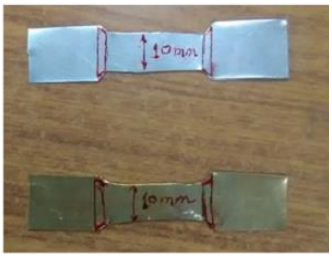

Figure 1. Samples for ultimate tensile testing of both AA3003 and Cu67Zn33 alloy

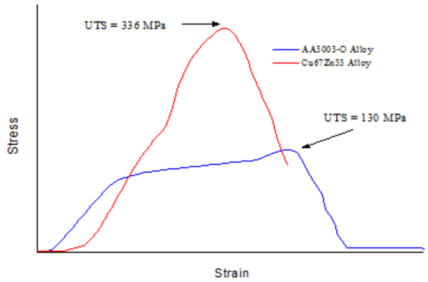

Figure 2. Stress-strain curves of test sample of AA3003 and Cu67Zn33 alloy

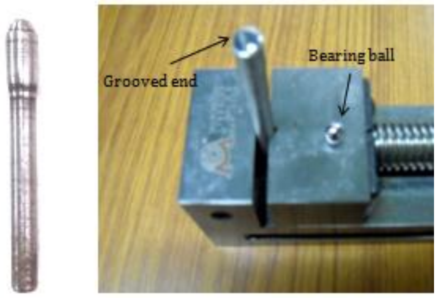

Figure 3. Preparation of forming tool and final shape of forming tool

Once the bearing ball is worn out due to forming, it can be replaced easily to a new bearing ball which results the saving of new tool preparation and manufacturing cost.

2. 3. SPIF Machine The SPIF is carried out on CNC vertical milling center MIKROTOOLS DT-110 shown in Figure 4 in the Department of Production Engineering, Birla Institute of Technology, Mesra, India. The machine having specifications such as Travel: x-axis: 200 mm, y-axis: 100 mm and z-axis: 100 mm, Spindle speed: 0 -3000, Feed rate: 1-2000 mm/min and Position accuracy: +/-1 micron/100 mm.

3. EXPERIMENTAL DESIGN: DOE

The forces imposed by the tool on the clamped worksheet has been measured through Kistler 9265B six-component force dynamometer shown in Figure 5. It is connected with a multichannel charge amplifier 5017A which have the capacity to measure the three force components i. e. F_x, F_y, and F_z in the range of -15 to 30 KN. In the present study, the online signals of only vertical force component F_z captured.

The experiments have been conducted with the aim to identify the relation that exists between each parameter and the minimum veritcal force component F_z. The taghchi design of experiment (DOE) is adopted for experiments. The experimental set has been designed according to the orthogonal array of L_{32} with two levels.

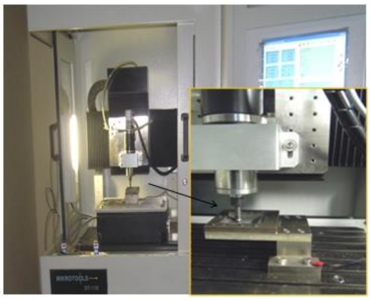

Figure 4.CNC machine and SPIF set-up for experiment

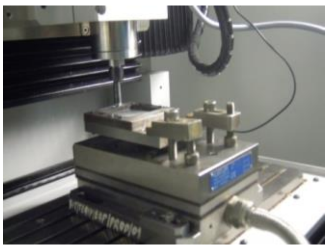

Figure 5. Arrangement of force dynamometer during incremental forming

The input parameters T_d, Δz, f, R, θ, T and M indicates tool end diameter, step depth, the feed rate of tool RPM, wall angle, the thickness of metal and the types of material respectively. These input variables are chosen for experiemnts based on litrreture review and the level of input variables are set by trail and error pivot experiments. The responses of vertical force component F_z are shown in Table 2.

4. STATISTICAL ANALYSIS OF THE VERTICAL FORCE COMPONENT F_z

The statistical analysis is carried out with 95% confidence level by using Minitab 17.0.1 version for finding the significance of input variables. The "smaller is better" approach was chosen because the porpuse is to perform SPIF with low force component F_z.

$$F_z = -10log\frac{1}{n}\sum_{i=1}^{n} y_{ij^2} \quad (1)$$

where,y_{ij} is the observed response value.

The tool end diameter T_d was same for all experiments, therefore it is kept constant. Figure 6 corresponds to the main response plot for vertical force component F_z. It shows that the suitable combination of input variables for SPIF with minimum force as Δz = 0.1 mm, f = 20 mm/min, R = 2000, θ = 15^0, T = 0.4 mm, and M= Cu67Zn33 alloy respectively.

The analysis of variance ANOVA [26] of force component F_z is tabulated in Table 3. It indicates that the significance of input variables for SPIF with low force component F_z. Higher significance for SPIF with low F_z are found as wall angle θ (P=0.000) and step depth Δz (P=0.001) whereas other input variables are not significant for the SPIF. As per ANOVA, the SPIF of both materials should be carried out by keeping low wall angle and low step depth. The interaction of input variables i. e. feed rate and wall angle (p= 0.014) and RPM with the types of material (P=0.015) shows their significance for low F_z.

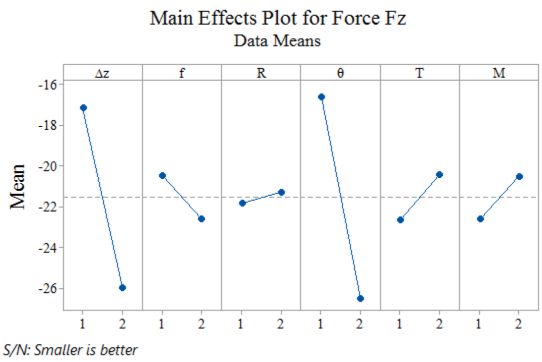

Figure 6. Response of input variables on vertical force component F_z

TABLE 2. The input parameters for experiments and output response i.e. vertical force component F_z

Exp. No.	Tool End Diameter (T_d) (mm)	Step depth (Δz) (mm)	Feed rate (f) (mm)	RPM (R)	Wall angle (θ) (°)	Tickness of metal (T) (mm)	Type of material (M)	Minimum F_z
1		0.1	20	500	15	0.2	AA3003	3.489
2		0.1	20	500	15	0.2	Cu67Zn33	3.723
3		0.1	20	500	45	0.4	AA3003	12.567
4		0.1	20	500	45	0.4	Cu67Zn33	30.275
5		0.1	20	2000	15	0.4	AA3003	3.324
6		0.1	20	2000	15	0.4	Cu67Zn33	2.044
7		0.1	20	2000	45	0.2	AA3003	12.498
8		0.1	20	2000	45	0.2	Cu67Zn33	13.321
9		0.1	100	500	15	0.4	AA3003	3.021
10		0.1	100	500	15	0.4	Cu67Zn33	5.286
11		0.1	100	500	45	0.2	AA3003	22.125
12		0.1	100	500	45	0.2	Cu67Zn33	8.972
13		0.1	100	2000	15	0.2	AA3003	8.483
14		0.1	100	2000	15	0.2	Cu67Zn33	6.699
15		0.1	100	2000	45	0.4	AA3003	6.097
16	0.6	0.1	100	2000	45	0.4	Cu67Zn33	7.934
17		0.7	20	500	15	0.4	AA3003	3.398
18		0.7	20	500	15	0.4	Cu67Zn33	9.091
19		0.7	20	500	45	0.2	AA3003	40.985
20		0.7	20	500	45	0.2	Cu67Zn33	42.968
21		0.7	20	2000	15	0.2	AA3003	7.415
22		0.7	20	2000	15	0.2	Cu67Zn33	5.848
23		0.7	20	2000	45	0.4	AA3003	48.364
24		0.7	20	2000	45	0.4	Cu67Zn33	37.994
25		0.7	100	500	15	0.2	AA3003	89.904
26		0.7	100	500	15	0.2	Cu67Zn33	3.321
27		0.7	100	500	45	0.4	AA3003	25.128
28		0.7	100	500	45	0.4	Cu67Zn33	42.724
29		0.7	100	2000	15	0.4	AA3003	89.823
30		0.7	100	2000	15	0.4	Cu67Zn33	6.353
31		0.7	100	2000	45	0.2	AA3003	20.965
32		0.7	100	2000	45	0.2	Cu67Zn33	35.022

TABLE 3. Analysis of variance for vertical force component F_z

SOURCE	DF	Seq SS	Adj MS	F	P
Δz	1	626.12	626.119	21.65	0.001
f	1	35.44	35.444	1.23	0.294
R	1	2.21	2.207	0.08	0.788
θ	1	785.82	785.825	27.18	0.000
T	1	40.51	40.508	1.40	0.264
M	1	34.51	34.512	1.19	0.300
$\Delta z * f$	1	21.07	21.071	0.73	0.413
$\Delta z * R$	1	12.11	12.112	0.42	0.532
$\Delta z * \theta$	1	0.35	0.352	0.01	0.914
$\Delta z * T$	1	48.95	48.953	1.69	0.222
Δz * M	1	0.92	0.923	0.03	0.862
f * R	1	3.50	3.499	0.12	0.735
$f * \theta$	1	258.69	258.692	8.95	0.014
$f * T$	1	93.39	93.386	3.23	0.103
$f * M$	1	4.83	4.831	0.17	0.691
$R * \theta$	1	41.27	41.271	1.43	0.260
$R * T$	1	8.28	8.284	0.29	0.604
$R * M$	1	248.14	248.137	8.58	0.015
$\theta * T$	1	98.15	98.153	3.39	0.095
$\theta * M$	1	0.39	0.387	0.01	0.910
$T * M$	1	7.40	7.401	0.26	0.624
Error	10	289.15	28.915		
Total			31 2661.21		

These input variables must be controlled during the SPIF of aliminum AA3003-O and Cu67Zn33 brass alloy.

5. VALIDATION OF EXPERIMENTAL RESULTS OF FORCE COMPONENT THROUGH ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural network (ANN) is a computer-based numeric solution for optimisation. ANNs are considered as nonlinear statistical data modeling tools where the complex relationships between inputs and outputs are modeled without having a complete knowledge of relationships between inputs and outputs [27, 28]. However, to generate a valid model, the large amount of data is required for its training and testing, consequently, an extensive period of time is needed for a standard ANN. The better ANN analysis constitutes the network configurations and factors. Therefore, it is required to fix the factors during the investigation. Also, over-fitting should be avoided during the training phase. The dataset for validation (which is independent of the training set) recommended for measuring the error during the analysis. The neural network (NN) stops when the value of error function is minimum (early stopping method).

In the manufacturing process, the output data sets may vary due to assignable causes. Consequently, in ANN, the original dataset putting in training and test sets. Properly trained networks tend to give meaningful answers with inputs parameters that they have never seen. Typically, the introduction of new input leads to an output like the correct output for input vectors used previously in training and that is like the new input being presented. This generalization property makes it possible to train a network on a representative set of input/output pairs and get very good results without training the network on all possible input/output pairs.

A variety of ANN network algorithms has been proposed by researchers for the modeling purpose such as Elman BP, Time-delay BP, Cascade-forward BP, Radial Basis, Self-Organizing Map, and Perception. The feed forward back propagation (FFBP) algorithm [29-32] is widely utilized by investigators for the prediction of surface roughness in SPIF. The BPNN is also applied by the researchers in different manufacturing field such as milling, cutting, turning operations, even in hardness of Al2024-multiwall carbon nano tube [33] for finding the error such as mean square error (MSE), mean absolute error (MAE),root mean square error (RMSE) etc.

For the present research work, feed forward (FF) neural network structure 6-6-1 is developed (Figure 7). The sigmoidal transfer used for hidden layer neurons whereas the linear activation function used for output.

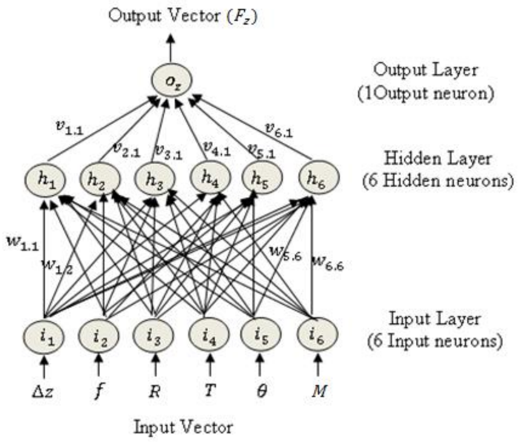

Figure 7. Structure of 6-6-1 feed-forward network

A three-layer feed-forward network with sigmoid hidden neurons and linear output neurons is developed by using MATLAB, version 7.10.0.499 (R2010a) (Figure 8). Two stopping criteria has been adopted, i.e., sufficient accuracy on the test set and the maximum number of iteration (the first activated).

The ANN model adopted for the present study is summarised below.

5. 1. A Network Model for F_z: Network Algorithm: FFBP
Training: Levenberg Marquardt (LM)
No. of layers: 3
Output: 1
No of neurons : 0 to10
Performance: Mean square error (MSE)
Training function: TRAINLM
Hidden layer transfer function: Tran sigmoid
Output layer transfer function: Pure linear
Adaption of learning rate: LEARNGDM
Figure6 shows the single-layered feed forward (FF) network with one hidden layer. The input to unit x in hidden layer is expressed in Equation (2),

$$net\_hidden = \sum_{j=1}^{j} w_{j,x} i_j + b_x \quad (2)$$

where, $w_{j,x}$ is the weight between the input and hidden neurons and i_j represents the value of the input which considered for SPIF (Table 3). b_x represents the biases on the hidden nodes.

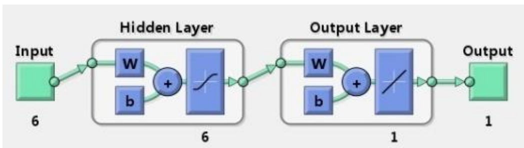

Figure 8. Architecture of two-layer BPNN for surface roughness prediction

The net input to unit z in the output layer is expressed in Equation (3):

$$net\_output = \sum_{x=1}^{x} v_{x,z} h_x + c_z \tag{3}$$

where, $v_{x,z}$is the weight between hidden and output neurons, $h_x$is the value of the output for hidden nodes, and c_z represents the biases on the output nodes.
From the output for hidden nodes (Equation (3)) obtained by resolving Equations (2) and (3):

$$h_k = f(net\_hidden) \tag{4}$$

Finally, the output for output nodes as in Equation (5):

$$o_z = f(net\_output) = R_a \tag{5}$$

where, f is the transfer function.

In the present study, the hyperbolic tangent sigmoid transfer function (Tansig) and linear transfer function (Purelin) are used at hidden layer and output layer respectively. The R_a obtained from each experiment are taken as output whereas different combinations of input parameters (Table 4) are considered as input for predicting surface roughness through ANN. Randomly, the 60% of experimental data are used for training whereas 20% data are used for testing and rest 20% are used for validation of the BP model without normalizing the input data.

6. RESULTS AND DISCUSSION

The output F_z obtained from experiments of various combinations was taken as input for the development of BPNN. The predicted F_z from the NN has been compared with the experimental F_z. The 60% of whole data was used for training. The training stopped after 5 iterations. The result is shown in Figure 9. It indicated that the train data best validated at epoch 5 with a value 360.7869.

Finally, putting the entire data set through the network (training, validation, and test) and performed a linear regression between the network outputs. The outputs are shown in Figure 10. It seems that the input data for NN is to track the targets reasonably well. The training data set of accuracy 0.960, test data set of 0.704 and validation data set of 0.938 achived through ANN. The overall R-value comes as 0.93. It shows that by using LM algorithm performance of the neural network R-value after simulation comes as 0.93%.

The minimum force F_z of each experiment was treated as input data for training, test, and validation in the BPNN. The predicted F_z and corresponding error presented in Table 4. The predicted F_z through ANN is found very close to the experimental data set and found the MAE of -0.215.

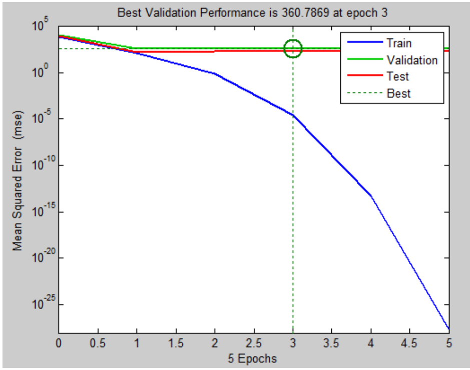

Figure 9. Performance plot of back propagation neural network

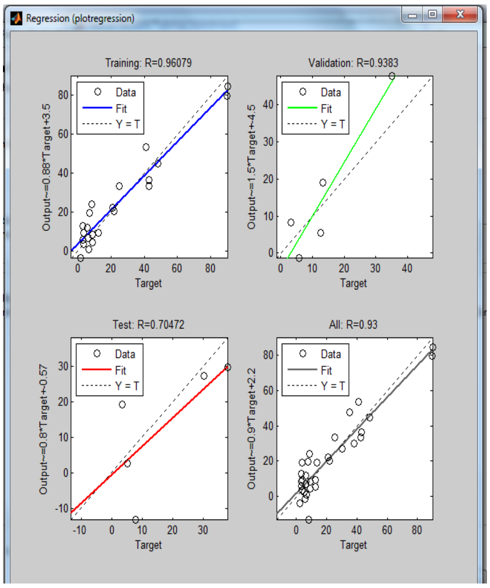

Figure 10. Regression plot of back propagation neural network

7. CONCLUSION

The prediction of process limits in SPIF is very difficult since many variables are involved. Although it is characterized by a localized deformation, the experiments show different process performances, depending on the process parameters. For this reason, during the last decades, several studies, considering this specific process, have been carried out. On the other hand, the achievement of desired surface roughness with SPIF is a major issue.

Optimal designing of the tool and application of suitable input parameters improves the quality of the finished part with low F_z. The selection of desired machine corresponding to the condition of the process also significant during SPIF.

TABLE 4. Comparision of experimental and predicted F_z

Exp. Run	Experiment F_z	ANN F_z	Error	Mean error
1	3.489	3.489	0	-0.215
2	3.723	3.723	0	
3	12.567	12.567	0	
4	30.275	30.275	0	
5	3.324	3.324	0	
6	2.044	2.036	0.007	
7	12.498	15.334	-2.836	
8	13.321	12.289	1.032	
9	3.021	3.021	0	
10	5.286	5.286	0	
11	22.125	14.412	7.704	
12	8.972	8.972	0	
13	8.483	8.421	0.062	
14	6.699	2.059	4.64	
15	6.097	6.097	0	
16	7.934	8.133	-0.199	
17	3.398	3.546	--0.048	
18	9.091	9.090	0.001	
19	40.985	40.732	0.253	
20	42.968	42.281	0.687	
21	7.415	7.415	0	
22	5.848	2.068	3.779	
23	48.364	48.364	0	
24	37.994	37.994	0	
25	89.904	89.904	0.099	
26	3.321	4.322	-1.001	
27	25.128	52.468	-27.34	
28	42.724	42.724	0	
29	89.823	89.823	0	
30	6.353	6.353	0	
31	20.965	20.965	0	
32	35.022	28.754	6.268	

So, initial prediction of F_z in the process will help the designer to select the best materials and processing technique. In such a condition, the ANN can be a great device which reduces both cost and time. The prediction of any output without conducting the experiments can be done with the help of ANN by adopting previuos experimental data set.

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Predicting Force in Single Point Incremental Forming by Using Artificial Neural Network

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چکیده

در این مطالعه، یک شبکه عصبی مصنوعی برای پیش بینی حداقل نیروی مورد نیاز برای تشکیل تک مرحله ای (SPIF) ورق های نازک آلومینیوم AA3003-O و آلیاژ Cu67Zn33 برنج Calamine مورد استفاده قرار گرفت. بر این اساس، پارامترهای پردازش، به عنوان مثال، عمق قدم، سرعت تغذیه ابزار، سرعت واشر، زاویه دیوار، ضخامت ورق های فلزی و نوع مواد انتخاب شده به عنوان ورودی انتخاب شد و حداقل اجزای نیروی عمودی به عنوان خروجی مدل انتخاب شد. برای آموزش مدل، ساختار شبکه عصبی پروپرتن Multilayer و الگوریتم بازگشت عقب به جلو استفاده شده است. پس از آزمایش بسیاری از معماری های شبکه های عصبی مصنوعی (ANN)، ساختار بهینه ای از مدل ۶-۱۴-۱ بدست آمد. نتایج، با یک رابطه همبستگی بین آزمایش ها به نیروی پیش بینی، -۰٫۲۱۵ میانگین خطای مطلق، نشان می دهد که توافق بسیار خوبی است.

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