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MODELING DEFORMATION FORCE IN OPEN DIES USING NEURAL NETWORKS

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Abstract: *The paper presents a study of deformation in open dies of the aluminum alloy AlMgSi0.5. A part of the research focused on modeling the deformation force during the process is provided. The investigation was conducted according to an experimental plan, adopting a full multi-factorial orthogonal plan with repetition at the central point. The input factors were the geometric parameters of the die and the workpiece, as well as the temperature. Deformation forces were recorded at each point of the plan, and modeling was performed. The modeling was carried out in MATLAB using a Feedforward Neural Network (FNN), with the Deep Learning Toolbox. The obtained model values show a high degree of correlation with the experimentally measured deformation forces.*

Keywords: *Bulk Metal Forming, Open Die, Deformation Force, Neural Networks, Modelling*

1. INTRODUCTION

In the metal processing industry, production conditions have recently changed and become increasingly demanding. This is reflected in the need to produce metal components with minimal consumption of materials, energy, and production time. These requirements are driven by global trends characterized by energy and raw material crises. This is particularly evident in metal forming processes, due to their extensive industrial application. Within metal forming, bulk forming — especially in open-die forging — stands out due to its complexity [1,2].

The main reason for the widespread use of open-die forging lies in its ability to produce workpieces of various shapes with favorable mechanical properties. This is achieved through a favorable stress state within the workpiece during processing, particularly in the final stage, where compressive stress components dominate. On the other hand, the development of materials and tooling technologies, as well as the ability to apply the process at high temperatures and deformation rates, are additional reasons for the broad application of open-die forming [2,3,4].

For the cost-effective design of bulk forming in open dies, it is essential to understand all relevant parameters that influence the forming process, in order to determine the key mechanical process parameters such as forming force. For this purpose, engineering methods are used, as well as numerical modeling techniques, such as the Finite Element Method (FEM), through the use of advanced software packages. In addition, modeling results obtained by other methods can also be utilized. By applying such model-based results to specific forming cases, it is possible to avoid complex numerical simulations or to use them for validation purposes [5,6].

This paper presents a modeling approach based on Artificial Intelligence (AI), using Artificial Neural Networks (ANN), for bulk forming in open dies. This method is well-suited for modeling complex nonlinear relationships, where conventional methods are often insufficiently effective [7].

2. EXPERIMENTAL RESEARCH

The bulk forming process in open dies was investigated for a family of stepped axisymmetric parts. Two height levels were adopted on the upper side and one height level on the lower side of the die parting plane (Figure 1.) [6].

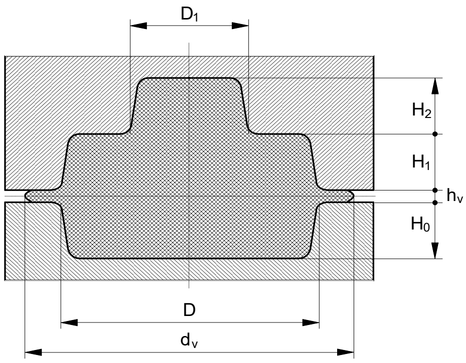

Figure 1. Stepped axisymmetric part

The following zones exist in the meridional cross-section of the workpiece:

1. bottom die zone (H_0),
2. flange zone (hv),
3. first level of the upper die zone (H_1) and
4. second level of the upper die zone (H_2).

The research is conducted under laboratory conditions, adjusted to closely resemble real (production) conditions present in an actual industrial environment. The following conditions for investigating the deformation force are adopted:

1. The tested material is the aluminum alloy AlMgSi0.5, which is very commonly used in bulk forming processes, especially in extrusion and open-die forging. The chemical composition of the experimental material is given in Table 1.

Table 1. Chemical Composition of the Material

AlMgSi0,5	Fe%	Si%	Ti%	Cu%	Zn%
	0.207	0.477	0.01	0.09	0.068
	V%	Cr%	Mn%	Mg%	Ni%
	0.004	0.01	0.1	0.493	0.02

2. The testing is conducted at the hot working temperatures of the mentioned alloy, i.e., within the range t=(420÷460) ^oC.
3. The deformation is performed at a constant deformation rate: v=2 mm/s.
4. The process is carried out with lubrication using graphite grease, which is also applied under production conditions.

2.3 Experimental plan

The experimental plan is based on preliminary research, and the input factors have been adopted according to which the dependence of the working force will be determined.

A full multi-factor orthogonal experimental plan with factors varied at two levels is adopted, including four repetitions at the central point of the plan ($n_0 = 4$).

The input variables (independent variables – factors) include the geometric factors of the die (Figure 1.) and the workpiece, as well as the working temperature. The input factors considered are:

- The geometric factors of the die, expressed as dimensionless ratios of characteristic die dimensions to the base diameter of the die D, to ensure generality of the results:

$$X_1=H_1/D,\ X_2=H_2/D,\ X_3=D_1/D \tag{1}$$

where:
H_1 - height of the first level of the upper die,
H_2 - height of the sec. level of the upper die,
D_1 - diameter of the sec. lev. of the upper die,
D - base diameter of the die.

- The geometric factor of the workpiece is the ratio of the initial diameter of the workpiece to the base diameter of the die:

$$X_4=d_0/D \tag{2}$$

where:
d_0 - workpiece diameter.

- The temperature factor is considered in hot working and represents the working temperature in degrees Celsius:

$$X_5=T\ [°C] \tag{3}$$

The number of points for k factors with n_0 repetitions at the central point is:

$$N=2k+n_0. \tag{4}$$

2.4 Experimental plan matrix

The experimental plan matrix for the full 5-factor plan is given in Table 2.

Table 2. Plan matrix

Plan:	Points	Input factors X_1	X_2	X_3	...	X_5	Output
2^5 ... 2^3 2^2	1	-1	-1	-1	...	-1	Y_1
	2	+1	-1	-1	...	-1	Y_2
	3	-1	+1	-1	...	-1	Y_3
	4	+1	+1	-1	...	-1	Y_4
	5	-1	-1	+1	...	-1	Y_5
	6	+1	-1	+1	...	-1	Y_6
	7	-1	+1	+1	...	-1	Y_7
	8	+1	+1	+1	...	-1	Y_8
	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	$2^5=32$	+1	+1	+1	...	+1	Y_{32}
Central points	$2^k+1=33$	0	0	0	...	0	Y_{33}
	$2^k+2=34$	0	0	0	...	0	Y_{34}
	$2^k+3=35$	0	0	0	...	0	Y_{35}
	$2^k+4=36$	0	0	0	...	0	Y_{36}

The adopted levels of variation of the input factors are given in Table 3.

Table 3. Levels of Variation of Input Factors in the Experimental plan

Input factors	lower level	Middle level	Upper level
X_1	0.175	0.250	0.357
X_2	0.150	0.250	0.417
X_3	0.417	0.500	0.600
X_4	0.757	0.839	0.908
X_5 [°C]	420	440	460

The following values of other dimensions of the workpiece and the die are adopted (Figure 1.):

- Base diameter of the die: D=40 mm;
- Height of the flange: h_v= 1 mm;
- Diameter of the flange: dv=50 mm;
- Height of the bottom die: H_0=10 mm.

The heights of the workpieces are determined based on the dimensions of the die and the diameter of the workpiece, in order to enable variations of the input factors (Table 3.), and the number of workpieces is determined according to the points of the plan matrix (Table 4).

Table 4. Dimensions and Numbers of Workpieces

Workpiece diematar d_0 [mm]	No	Height h_0 [mm]	No of workpieces
30.28	1	34.42	2
	2	36.33	2
	3	37.07	2
	4	42.18	2
	5	46.21	2
	6	48.12	2
	7	48.86	2
	8	53.97	2
33.56	9	33.94	4
36.30	1	23.95	2
	2	25.28	2
	3	25.80	2
	4	29.35	2
	5	32.16	2
	6	33.49	2
	7	34.00	2
	8	37.56	2

2.5 Experimental Equipment

For deformation, a static testing machine with a hydraulic drive, type R100, of Russian manufacture was used, capable of performing tensile and compressive tests (Figure 2.). The maximum load capacity of the press is 1 MN, and the maximum deformation rate is v=2 mm/s.

Measurements during the stated experimental investigations were conducted using the measurement system shown in Figure 3.

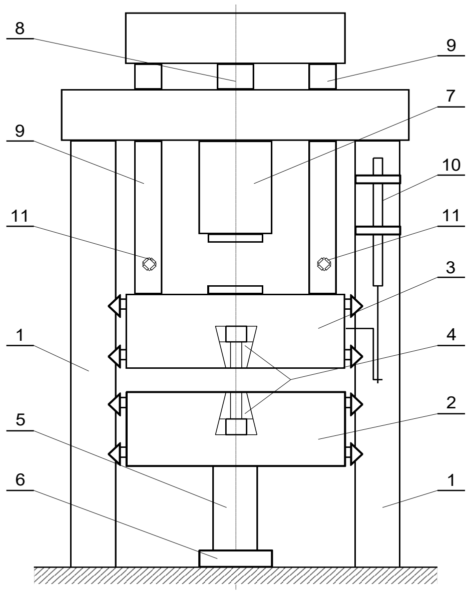

Figure 2. Hydraulic press: 10 – inductive displacement sensor, 11 – force sensors.

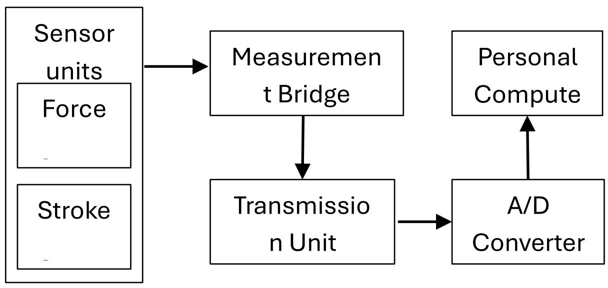

Figure 3. Information measurement system

Strain gauge sensors of type HBM 6/120LY11, connected in a full Wheatstone bridge, were used as force sensors, while an inductive displacement sensor of type HBM W 200K was used for displacement measurement. The signals from the sensor units were amplified using a digital six-channel measuring bridge of type HBM KWS.637.D4. The analog output signal from the bridge was transmitted via a transmission unit to an AD/DA card of type DT 2801-A, converted to digital form, and stored on a personal computer with installed GLOBAL-LAB data acquisition software. Temperature control was performed using a digital thermometer for measuring the temperature on the surface of hard materials, type DT IM Dalmacija. The thermometer uses a tactile probe based on a thermocouple.

2.6 Measurement of deformation force during the deformation process

As part of the experimental research, measurements of the deformation force during bulk deformation in open dies were performed according to the experimental plan. The order of execution of the experimental points from the plan matrix was randomized. Lubrication was done by manually applying a layer of graphite grease onto the working surfaces of the tools. To achieve isothermal deformation, the deformation tools were heated together with the workpieces.

After heating in the furnace, the deformation tool assembly, together with the workpiece, was placed on the press. After starting the information measurement system for force measurement as a function of displacement, the press was put into operation. The deformation of the workpieces was carried out in a single stroke, and the process was stopped upon reaching the final dimensions. The final dimensions were ensured by a steel ring whose thickness corresponds to the required flange height.

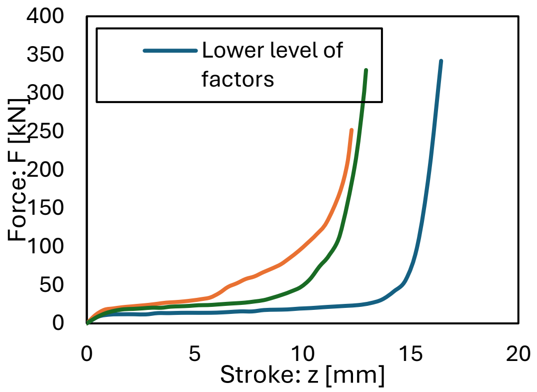

Figure 4. Forces for the lower, middle, and upper factor levels

Upon stopping the press stroke, the measurement process with the information measurement system was also stopped, and the force signals from the strain gauge sensors on both supporting columns of the upper press table, as well as from the inductive displacement sensor, were recorded on the computer's hard drive.

In this way, the force variations as a function of displacement were obtained at all points of the experimental plan. Figure 4. shows the deformation forces for the lower, middle, and upper levels of variation of the input factors.

3. MODELING OF DEFORMATION FORCE USING NEURAL NETWORKS

The modeling of the deformation process in open dies was carried out in Matlab version 24.2.0. The Deep Learning Toolbox was used for fitting via a Feedforward Neural Network (FNN), which represents a standard multilayer network. Launching this application activates a very efficient GUI where modeling can be performed in a relatively simple way.

First, it is necessary to prepare the input and output data. The output data must be in the form of a matrix with a certain number of rows and columns equal to the number of points in the experimental plan. It was chosen to be a matrix of dimension Y[101,36]. Since the displacement differs for individual points of the plan, displacement normalization must be performed. This is achieved using the expression:

$$Z_{norm}=(z-z_{min})/(z_{max}-z_{min}) \tag{5}$$

This ensures that the value of the normalized displacement ranges from 0 at the start of deformation to 1, which corresponds to the maximum displacement value at the end of the deformation process. For each value of the normalized displacement, the corresponding force values for individual points of the plan are entered, thus obtaining a normalized matrix of output values.

The input data are prepared to have 5 rows, corresponding to the number of input factors, and 36 columns, corresponding to the number of points in the plan matrix, so the matrix has dimensions X[5,36]. Each column contains the values of the input factors for a specific point of the plan.

After entering the data, the structure of the neural network is selected (Figure 5.).

The structure of the neural network for modeling the deformation force consists of:

1. Input layer with 5 input features, corresponding to the input factors,
2. Hidden layer with 10 neurons, using a sigmoid activation function (wave-like symbol),
3. Output layer with 100 neurons, using a linear activation function (straight-line symbol).

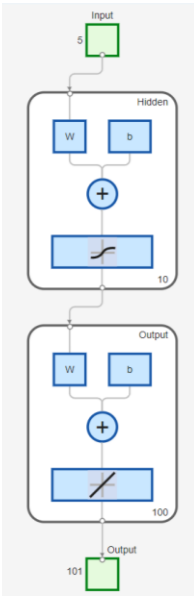

Figure 5. Neural network structure

So, this is a classic "function fitting" regression network, which is used to learn the relationship between multiple inputs and a complex vector output. The neural network is created using the command:

net = fitnet(hiddenLayerSize,trainFcn); (6)

and trained using the command:

[net,tr] = train(net,x,t); (7)

This yields a function that models the deformation force in all points of the experimental plan of the form:

y = net(x); (8)

This applies throughout the entire hypercube space, and likely within a certain domain outside of that space as well.

Figure 6. shows the modeled values of the deformation force for the lower, middle, and upper levels of the input factors. Figures 7. through 9. present comparative values of the experimentally obtained deformation force and those modeled using neural networks.

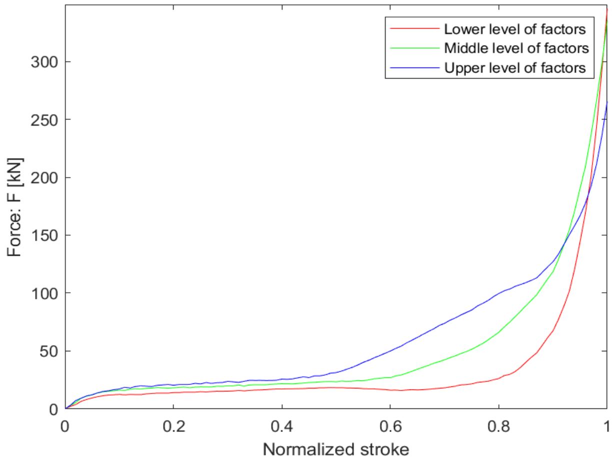

Figure 6. Modeled force values for the lower, middle, and upper factor levels

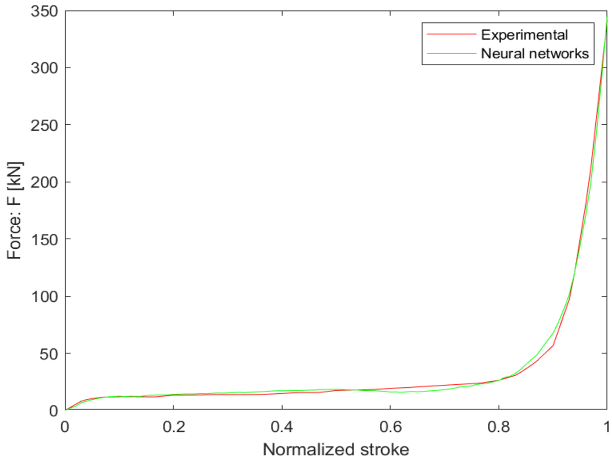

Figure 7. Experimental and modeled force values for the lower factor level

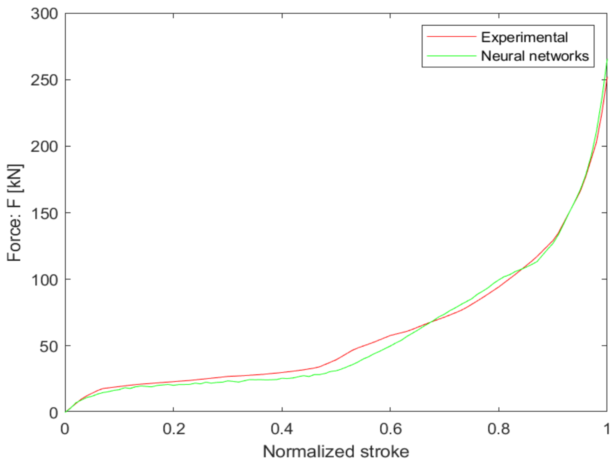

Figure 8. Experimental and modeled force values for the upper factor level

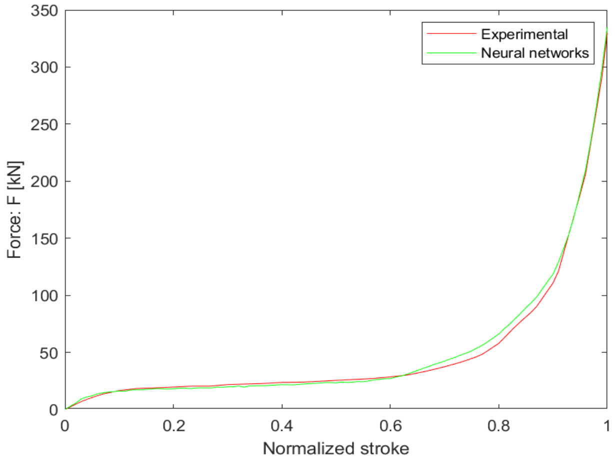

Figure 9. Experimental and modeled force values for the middle factor level

4. ANALYSIS OF RESULTS

From the figures, a good match between the experimental and modeled values can be concluded. The Deep Learning Toolbox enables analysis of modeling performance.

Figure 10. shows the results of training the neural network in MATLAB for modeling the deformation force in open dies in the form of the standard plotregression graph that MATLAB generates for assessing the quality of the network. The figure shows a high degree of model correlation (>95), which means the model closely follows the training data, generalizes the problem well, and is not overfitted.

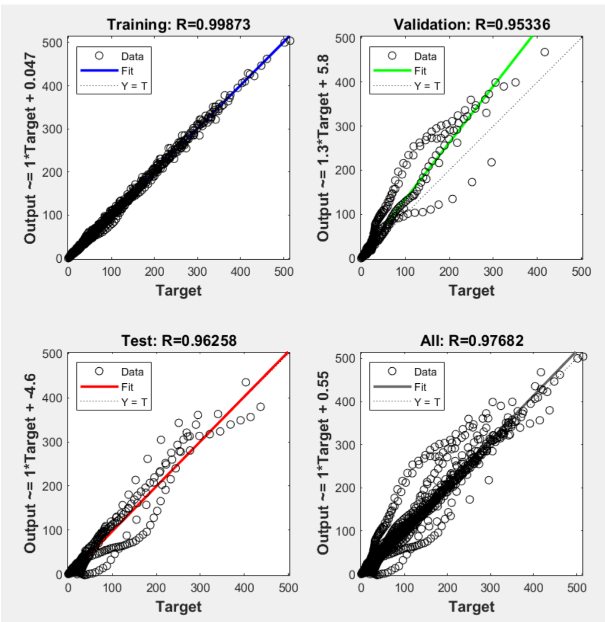

Figure 10. Neural network training results

It can be stated that a very successful model was obtained using a neural network for the compression deformation force in open dies. The network can be successfully used to predict compression results without the need for complex simulations, such as the finite element method.

5. CONCLUSION

Neural networks can be successfully used for modeling the deformation force during bulk deformation in open dies. This is demonstrated in the paper through the example of modeling the deformation force in the deformation of the aluminum alloy AlMgSi0.5 in open dies.

Deformation forces were recorded at each point of the full multi-factor orthogonal plan with repetition at the central point. The input factors adopted were geometric factors of the die and billet, given as relative ratios, and the hot working temperature. The modeling of the dependence of the deformation force on the working stroke was performed using a Feedforward Neural Network (FNN) in Matlab, utilizing the Deep Learning Toolbox.

A good agreement between experimental and modeled values was obtained, with a high degree of model correlation (>95), indicating that the modeled values are adequate. Thus, it can be concluded that the network can be successfully used to predict compression results under given conditions, without the need for complex numerical simulations.

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