Simulation of twist extrusion process parameters of AA6061-T6 aluminum alloy by artificial neural network

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Abstract.
Modern fabrication is to a large extent based on deformation processing. Plastic deformation process is a technique capable of producing metal products with high strength and good ductility. Using the parameters of load, temperature and the number of passes in twist extrusion, it is possible to produce an alloy with good properties and characteristics. Plastic deformation of AA6061-T6 aluminum alloy by twist extrusion is an important issue. In this study, we investigated the effect of load, temperature and the number of passes of twist extrusion on AA6061-T6. Using the input and output data, the process was modeled by the neural network method. In order to train the neural network, Neuro Solution software was used and for reducing the mean square error, the gradient descent momentum algorithm was implemented. Results showed that the effect of the number of passes and the load on tensile strength and hardness were maximum and minimum respectively.
Keywords: Twist extrusion, artificial neural network, the number of passes

1. Introduction

Today, the application of severe plastic deformation (SPD) methods has increased widely. These methods are based upon strain accumulation and microstructure formation in nanoscale [1]. Plastic deformation of metals can improve their strength and ductility. Some of the SPD methods investigated broadly include equal channel angular extrusion, cyclic extrusion compression, accumulative roll bonding, multi axial forging and twist extrusion (TE) [1-2]. Extrusion is one of the metal forming processes that has attracted many interests in recent years. This method can be used for manufacturing aircraft engine components, aircraft parts and vehicles [3-4].

In dry powder extrusion, reinforced grains or plastics are heated and passed through a matrix which is the extrusion mold. TE is one of the common plastic deformation methods [5-6]. This is a new technique used as a hydrostatic pressure to make high amount of tension on metals in order to produce refined particles without any significant change in the overall dimensions of the sample [7].

Aluminum alloys are advantageous with regards to light weight and high performance. Among them, AA6061-T6 has proper ductility, good machinability and weldability, low corrosion rate and light weight [8-9].

Optimization of parameters in plastic deformation processes is important. In TE, the effect of parameters like temperature and the number of passes is the main issue for plastic deformation [10]. Ultrafine grain metals have high strength and good flexibility [11]. These properties are very important for developing advance structures. The most effective way to obtain fine grain materials is the simple shear stress [1]. In TE the shape of the mold is similar to that of the equal channel angular extrusion, but in the former there are two shear planes, one perpendicular to and the other parallel with the extrusion axis [12]. TE is capable of extruding hollow parts. Also, it can lead to more homogeneous strains by 90o rotation of the part in each pass, which is a very important issue in magnetic and electronic materials [4].

Iqbal and Kumar [13] performed experiments on the analysis of mechanical properties and microstructure of AA7075-T6 deformation by TE. They studied TE and deformation of AA7075-T6. Four different temperatures and three passes were used in the experiments. Mechanical properties and microstructure at different temperatures and different number of passes were investigated. Results showed that the TE can change the particles of the structure. With increasing the number of passes, hardness increased and homogeneous structure improved, while tensile strength decreased at high temperatures. It was found that the TE passes reduce particles size and improve mechanical properties. It was reported that the desired temperature range for achieving better mechanical properties of this alloy is 250-350°C. It was also expressed that the microstructure analysis shows that the displacement of particles in three pass TE is less than the one pass, therefore the particles boundary and the particles refinement for this alloy are suitable at the optimum temperature and the more number of passes. Velmanirajan et al. [14] performed the numerical modeling of aluminum sheets ductility and investigated the surface reactions. In their study, tensile properties, tensile limitations in ductility, and flexibility parameters of commercial aluminum alloy sheets were investigated. Sheets with three different thicknesses were selected and tensile test, forming test and flexibility study were performed. The result of modeling showed that the experimental relations for discovering the ductility capability are fully consistent with the experimental results. Therefore, the aforementioned factors for achieving the effective ductility capability are desirable. Kumar and Iqbal [15] investigated the effect of temperature and the number of passes on deformation of AA6082-T6 homogeneous microstructure by TE. Results of their study showed that the change of AA6082-T6 particles after one pass leads to a heterogeneous microstructure. With increasing the number of extrusion passes, the microstructure heterogeneity disappears and the stress induced in the samples is not the same for all passes. With increasing the temperature and the number of passes, both the stress and the heterogeneity in distribution of tension decrease. Tensile strength and hardness of the sample also increase up to 10% with increasing the temperature and the number of passes. Before extrusion, the microstructure of the sample showed particles with an average size of 42 mµ, while with increasing the number of passes and the temperature, the size reduced 20 mµ. As a result, with increasing the number of passes, the particles are refined and the strength and hardness increase, so the temperature and the number of passes are considered as input parameters. Results of this study showed that the model was logically in agreement with the experimental values. The factors investigated on TE of AA6082-T6 show that the lower tension at the beginning of the first pass compared to the third pass, in which the heterogeneity in the distribution of tension is low due to the temperature and the number of twists, leads to work hardening. Iqbal et al. [10] performed experiments on TE of AA6061-T6 to investigate the effect of extrusion load, temperature, the number of passes, hardness distribution and tensile properties. Results showed that the predicted values were consistent with the experimental values. It was also found that the two main factors are temperature and the number of passes which affect the tensile strength and hardness. Using high temperature and the more number of passes, tensile strength and hardness increase 8-10%, and extrusion load has the least effect. Also, the optimal value of variables for TE of AA6061-T6 included: load of 1000 KN, temperature of 500 °C and three extrusion passes. These values are useful in high temperature TE experiment of various aluminum alloys. Zendehdel and Hassani [16] investigated the effect of TE on mechanical properties and microstructure of 6063 aluminum alloy. 6063 aluminum alloy was deformed by TE method and its mechanical properties and microstructure were investigated before and after the experiment. They noticed that the more number of TE passes resulted in finer grain microstructure. Also, with increasing the number of TE passes, yield strength, ultimate tensile strength, and hardness increased, while after a relative reduction of elongation by intermediate of passes, they remained unchanged. Finally when deformed by TE, both the strength and the ductility of material improved. Iqbal and Kumar [8] studied the effect of multi pass TE on AA6061. The effect of three pass TE on AA6061 sample at different temperatures was investigated. Results showed that the normal plastic tension at the end part of the workpiece is higher than the beginning part. It was also found that in the corner areas more tension occurs compared to the center zone. This difference in tensile distribution is reduced by increasing the number of TE passes. Experimental results were also studied. The billet volume decreased in the last phase of the deformation and was minimized by all the TE passes. Asghar et al. [7] investigated the effect of three pass extrusion on an aluminum sample. They found that the end part of the sample, unlike the beginning part, was more affected by the plastic tension. It was also found that in the corner areas more tension occurred compared to the center zone, and by increasing the number of TE passes, the heterogeneity in distribution of tension in both longitudinal and transverse pass regions reduced. Mousavi et al. [17] performed an experiment on successive accumulation of three pass TE of an aluminum sample at room temperature with and without subsequent direct extrusion. They found that direct extrusion after three pass TE increased the hardness and the tensile properties, but reduced the mechanical heterogeneity in the pass region. Asghar et al. [7] investigated the effect of implementation of three pass TE on high purity of an aluminum sample and reported that in the corner areas more tension occurred compared to the central zone. With increasing the number of TE passes, the heterogeneity in tensile distribution decreased.

The purpose of all the aforementioned studies is finding a suitable method for achieving good and homogenous mechanical properties. Researches has been carried out on optimization of TE parameters such as twist angle, friction factor and motor speed. Optimization of experiment conditions makes it possible to achieve good mechanical properties in homogeneous areas. In metal forming processes, normally the trial and error method is used for process design, which is expensive and time consuming. Application of modern hybrid methods such as numerical simulation combined with optimization and modeling techniques makes it possible to achieve the best design without making high expenses.

In this study, optimization of input parameters has been investigated using the artificial neural network (ANN) in order to achieve good strength and hardness.

2. Experimental method

AA6061-T6 plates were cut into rectangular sections by dimensions of 20 × 30 × 100 mm3. The chemical composition of AA6061-T6 is presented in Table 1 and the samples were tested from two to four flat points according to the ASTM standard. Table 2 gives mechanical properties of AA6061-T6. Final specimens were machined in dimensions of 18 × 28 × 100 mm^3 by the milling machine [10].

Table 1. Chemical composition of AA6061-T6 (weight percent) [10].

Al	Fe	Mn	Ti	Si	Cr	Cu	Mg	Zn
balance	0.7	0.2	0.1	0.6	0.35	0.4	1.25	0.25

Table 2. Mechanical properties of AA6061-T6 [10].

Materials	Elongation	Shear strength	Ultimate tensile strength	Performance power	Hardness
AA6061-T6	12	207	243	214	84

After cleaning, the samples were placed in a furnace and heated to the required temperature. Figure 1 shows the two parts of the TE mold. The cross section of the two channels has the characteristics of 18 × 28 × 100 mm3 and the angle between them is β= 36°. TE experiments were performed by a 1500 KN Yukon hydraulic press, as is shown in Figure 2. The back pressure of the machine press was 200 MPa and the extrusion displacement velocity was 5 mm/s. Figure 3 shows the specimens before and after TE [10].

3. Experiment based ANN

The extrusion process has an effective role in manufactering of products due to its changeability, efficiency and high production rate. In order to improve the quality of products or manufacturing of products with new shapes, the process design and analyze

Fig. 1. The two parts of the TE mold [10].

Fig. 2. Experiment set up [10].

through experiments is costly and time consuming. One of the methods that can predict the relations between process parameters and results is the ANN model. This model has attracted many interests in recent years and has been used to predict the behavior of various forming processes in many cases [18-19].

b a

Fig. 3. AA6061-T6 specimens (a) before TE and (b) after TE [10].

The neural network theory is derived from the structure of human brain and can process large amounts of information. ANNs are adaptive models that can learn from the data and can generalize to the trained data. The multilayer neural network consists of input, hidden and output layers. The hidden layer can have one layer or more. The input layer is the first layer of multilayer neural networks. The layers placed between the input and output layers are called hidden. The hidden layer processes the data received from the input layer and sends the response to the output layer. The output layer receives all the responses and generates the output vector [20]. An ANN has been designed in order to achieve the desired results in TE. For a perfect extrusion operation, the extrusion pressure is a critical factor. The extrusion load difference is mainly due to the temperature of primary specimen which interacts with factors such as engine speed. The quality of extruders is estimated by two factors which limit manufacturing, i.e. the output temperature and the extrusion maximum load. In this study, the initial temperature and the initial load were adjusted by the operators based on experience and parameters like the number of passes. Considering the above factors, experiments were performed on different load ranges, temperatures and the number of passes. In low levels of parameters (lower than load 1000 KN and 300 °C) the work was difficult because the ductility was impressed and the compounds were faulty due to insufficient load. In high levels of parameters (higher than 500 °C and load 1200 KN), no compound was stored, which is in contrary to the principle of TE. According to the experiments results, the parameters range was selected based on the macrostructure of electrodes twisting and the defects observable for each specimen. The working limitations of TE parameters selected based on the above criteria are presented in Table 3. In this experiment, the purpose is achieving the maximum tensile strength, hardness and properties like better and larger types

Table 3. Chemical composition of AA6061-T6 (weight percent) [10].

parameters	Levels		
	(-1)	(0)	(+1)
Load (KN)	1000	1100	1200
Temperature ($°C$)	350	425	500
Number of passes	1	2	3

3.1. Design of experiment matrix

Due to a wide range of factors, the application of three factors, three levels and a complete design of factor matrix was decided in order to establish the desired conditions of experiments. The factorial section is essentially the design of a full factorial with all the factors in two levels (high, +1 and low, 1-) formed from eight star points and six central points (coded with level zero). The full factorial is the midpoint of high and low levels and corresponds to value α. All of coefficients were determined using the full factorial pattern designed by a statistical software. After the coefficients estimation (at the probability level of 95%), all of relationships were extended and only these coefficients were used in them. Thus, the effect of nonlinear, quadratic and two interaction factors on the strength of twist extruders compounds were estimated by twenty experiments. For ease of the experimental data record and process, the factors upper and lower levels were coded +1 and -1, respectively. The design of experiment matrix is shown in Table 4 [10].

3.2. Experimental tests

As shown in the design of experiment in table 4, twenty tests were performed and in each compound the samples were polished with chlorine solution. Then the samples were etched and observed under a microscope, and the microstructures were analyzed using a photo analysis software. Surface scan was performed by Hitachi S-3400N model electron microscope. AA6061-T6 tensile specimens were prepared by spark cutting according to ASTM B557M-10 standard. Tensile test was performed by a Hansfield machine with capacity of 50 KN. Hardness test was performed using Akashi MVK-E3 hardness tester with 2.5 g material and time of 15 s. Hardness test was performed at the distance of 0.5 mm. In each experiment, three samples were tested and the mean values are given in Table 4.

4. Conclusions

One advantage of using an ANN is that the network model is easily constructed and trained based on the input and output data to accurately predict dynamic processes. Neural networks are capable of approximating a multi-input/output process with any level of complexity based on the accuracy required by the network designer, an if the selected neural network fits with the data and the nature of process, then it will lead to proper learning and accurate prediction [21]. The nonlinear nature of the problem studied here from one side, and the number of parameters affecting the process from the other side, led to the application of an ANN for modeling the process. The mentioned network is capable of processing any kind of data properly and is one of the strongest networks for simulating nonlinear problems. This network is trained through the change of middle layers' weight and these changes are stored as the network assumptions [22]. The network structure used is designed with three inputs and two outputs. The input parameters include temperature, load and the number of passes while the outputs include tensile strength and hardness.

Table 4. Design of experiment matrix and reactions of AA6061-T6 [10].

Number	Coded values			Original values			Tensile strength (MPa)	Hardness $(HV@0.5)$
	A	B	C	Load (KN)	Temperature $(°C)$	Number of passes		
1	-1	٠	0	1000	425	2	295	100
2	+1	+١	-1	1200	500	1	301	107
3	+1	-١	+1	1200	350	3	256	96
4	0	0	0	1100	425	2	290	99
5	+1	0	0	1200	425	2	294	98
6	+1	+1	+1	1200	500	3	309	111
7	-1	+1	+1	1000	500	3	312	110
8	0	+1	0	1100	500	2	301	107
9	0	-1	0	1100	350	2	251	91
10	0	0	0	1100	425	2	294	99
11	0	0	+1	1100	425	3	304	101
12	0	0	0	1100	425	2	293	98
13	0	0	0	1100	425	2	293	94
14	-1	-1	+1	1000	350	3	255	95
15	0	0	-1	1100	425	1	284	93
16	0	0	0	1100	425	2	291	99
17	0	0	0	1100	425	2	294	98
18	-1	-1	-1	1200	350	1	249	90
19	-1	-1	-1	1000	350	1	248	89
20	+1	+1	-1	1000	500	1	299	106

The Tansig transfer function is considered for the hidden layers and the pureline transfer function for the output layer. The method of training and the way of learning include Lunberg-Marquardt and Gradient descent momentum, respectively. In training the simulation of mechanical processes, Lunberg-Marquardt method is often used. In order to optimally design the neural network, by trial and error, the network with different structures has been evaluated based on the mean squared errors criterion. This criterion is equation (1) defined as:

$$MSE = \frac{1}{2n}\sum_{i=1}^{n}\sum_{i=1}^{m}\left(T_{ij} - O_{jj}\right)^2 \quad (1)$$

where m is the number of neural network output neurons, n is the number of data used for network training, T is the target data for each output neuron, and O is the predicted value per output neuron.

5. Results and discussion

In order to train the neural network, Neuro Solution software was used while for reducing the root mean square error, the Lunberg-Marquardt algorithm was implemented. Out of the 20 laboratory data, 60% of them were used for training, 15% for validation, and 25% for network testing. Table 5 shows the neural network model characterization used for network training.

Table 5. The developed neural network characterization.

Network type	Forward with the error propagation algorithm
Network architecture	$2-1-12-3$
Learning algorithm	Gradient descent momentum
Hidden layers transfer functions	Tansig
Output layer transfer function	Linear
The number of iterations	1000
The number of runs	3

The network with 2-1-12-3 architecture means that in the first layer (the input) there are 3 neurons which are equal to the number of variable parameters investigated. Layers 2 and 3 are hidden layers which have 12 and 1 neurons, respectively. The last layer (the output) has two neurons which are equal to the number of outputs investigated in this network.
In order to train the neural network, the gradient descent momentum algorithm, which is one of the fastest network training methods, was implemented. The duty of this algorithm is reduction of root mean square error during network training. Sigmoid transfer function was considered for hidden layers in which case the data outputs were placed inside the range of +1 and -1. For the output layer, a linear function was used. The linear output allows the network to have outputs outside the range of +1 and -1.
Table 6 shows the mean error obtained after network training with 1000 iterations and a total of three runs. Table 7 gives the best network obtained during training. As is shown in Figure 4, the best network is obtained in the third run and the convergence of the root mean square error is occurred in iteration 1000.
In order to investigate the effect of each parameter, the Neuro Solution method was used. As is shown in Figure 5, the number of passes has the maximum effect and the load has the minimum effect on tensile strength and hardness.

Table 6. Neural network mean error.

Total runs	Minimum training	Standard deviation training
Mean errors	0.0538	0.0879
Final mean errors	0.0538	0.0879

Table 7. Results of the best neural network run.

The best network	Training
Run	3
Iteration	1000
The least error	0.0030
Final error	0.0030

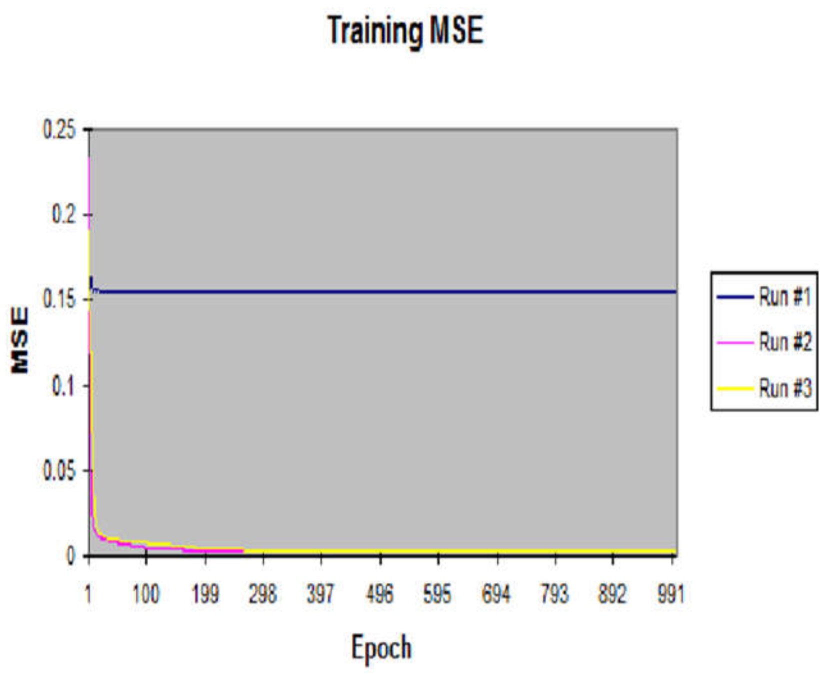

Fig. 4. Convergence plot of the root mean square error based on the number of iterations.

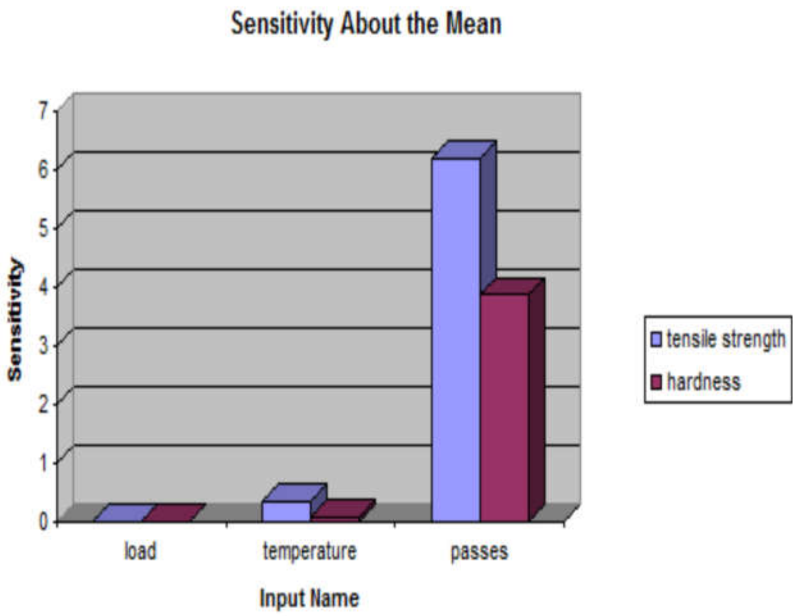

Fig. 5. The effect of the number of passes, temperature and load on tensile strength and hardness.

6. Conclusions

In this study, experimental investigations and optimization of TE of AA6061-T6 were performed in order to explore the effect of extrusion load, temperature, and the number of passes on hardness and tensile strength. The results of neural network showed that the two main effective parameters including temperature and the number of passes had the maximum effect and the extrusion load had the minimum effect on tensile strength and stiffness.

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