EXPERIMENTAL AND NEURAL NETWORK PREDICTION OF ELONGATION AND SPREAD AFTER FIRST STAGE OF FULLERING

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Abstract: Fullering process is a type of open die forging. In this research, elongation and maximum sideways spread in final shape of a billet after the first blow of a fullering process are predicted by designing a back propagation multilayer perceptron neural network. Several experiments are conducted using lead as the model material. Billets with three different square cross-sections are used in these experiments. These fullering physical investigations are performed to simulate the elongation and maximum sideways spread in the final shape of the billet at the end of the first blow of the process. In addition, ring compression tests are undertaken in the quantitative determination of the friction coefficient for three kinds of lubricants. In the training of neural network width of billet, friction coefficient, height of the final shape, and die length are used as the input data. Elongation and maximum sideways spread in the final shape of the billet are the specified outputs. As a result of the specified parameters, the program is able to estimate the elongation and maximum sideways spread for any given input variables instead of time consuming experimental processes or finite element simulations.

Keywords: Artificial Neural Network, Elongation and Spread, Fullering

چکیده فرآیند فولرینگ نوعی از آهنگری قالب باز است. در این تحقیق، با استفاده از یک شبکه عصبی پیشخور چند لایه توزیع عرضی و طولی قطعه بعد از ضربه اول فرآیند فولرینگ پیش‌بینی می‌گردد. چندین آزمایش تجربی با استفاده از ماده مدل سرب انجام می‌شود. بیلت‌ها قطعات منشوری شکل با سه مقطع مربعی متفاوت می‌باشند. این آزمایش به منظور تعیین توزیع عرضی و طولی قطعه در پایان ضربه اول فرآیند فولرینگ صورت می‌پذیرد. علاوه بر آن برای تعیین ضریب اصطکاک سه نوع روانکار استفاده شده، از آزمایش حلقه استفاده می‌شود. برای آموزش شبکه، عرض بیلت، ضریب اصطکاک، ارتفاع نهایی و طول قالب به عنوان پارامترهای ورودی شبکه در نظر گرفته می‌شوند. ازدیاد عرضی و طولی قطعه به عنوان پارامترهای خروجی شبکه می‌باشند. نتایج حاصل از این تحقیق به طراحان کمک می‌کند تا به جای صرف هزینه جهت انجام آزمایش‌های تجربی و یا صرف زمان برای شبیه‌سازی به روش اجزا محدود، ازدیاد طولی و عرضی بیلت را به ازای پارامترهای ورودی متفاوت توسط شبکه عصبی آموزش داده شده پیش‌بینی نمایند.

1. INTRODUCTION

The forging problem can be summarized as the design of a deformation path for the material in order to obtain a prescribed shape with satisfactory properties at the lowest cost [1]. Obtaining a flawless product in forging depends on several parameters such as initial shape (preform) of the billet, initial temperature of material and dies, forming velocity, friction coefficient and the number and shape of intermediate dies [2]. The initial shape of the billet, even for complicated parts is usually simple. Therefore, the material may not flow to its final shape in one press [3]. In such cases the designer must consider using several stages for the deformation. Because of these limitations, we are considering the fullering process which is an important manufacturing step in production of long parts.

One of the main purposes of fullering process is to reduce the cross sectional area of a part of a bar and, at the same time, increase its length to a desired value. This improves the directional strength of the deformed part and also gives a more appropriate mass-length distribution, so that material utilization is improved. During a fullering process the bar is subjected to 2 to 4 blows between shaped anvils [4]. After each blow, the bar is turned 90o about its longitudinal axis. Based on the mass-distribution requirements of the final forging part, several researchers have proposed some empirical rules for fuller die design [5]. Using these rules, CAD/CAM systems have been developed to de-skill the design and manufacturing procedures [6]. Fereshte Saniee et al. simulated a fullering process using 3-D finite element method [4]. Alves et al. [7] have investigated the use of hexahedral elements in metal forming. They used this type of element in the simulation of a fullering process.

Based on the above literature survey, most researchers have used finite element method or empirical formula to predict material flow in fullering processes. The few who have investigated the fullering process have not used neural network analysis to predict process parameters. Since the fullering process is a type of open die forging, metal can flow freely in certain directions. Thus, there is no guarantee that the desired final shape will be obtained [8]. Experimental determination of the final shape after the first stage of a fullering process is very time consuming and expensive. Any empirical or numerical tool capable of predicting the billet shape can reduce the manufacturing process/ control cost.

In this paper, elongation and maximum sideways spread in final shape of the billet after the first stage of a fullering process are predicted using a back propagation artificial neural network (BPANN). This prediction can be helpful for the designer to easily select the number of fullering stages. In addition, prediction of maximum sideways spread is an important manufacturing consideration, since it determines the width of the fuller dies instead of expensive and time consuming experimental measurements or finite element simulations.

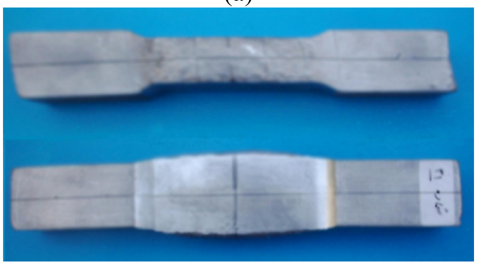
2. EXPERIMENTAL

Artificial neural networks (ANN) have the ability to analyze non-linear processes due to the learning ability using previously obtained data [9]. So, fullering experiments were performed to determine the elongation and maximum sideways spread in the final shape of the billet at the end of the first stage of the process. Measured elongation and maximum sideways spread data were used to train the neural network. The experimental procedures will be explained in the following section.

2.1. Fullering Experiments A series of fullering experiments were designed to simulate the material flow and measure the elongation and maximum sideways spread of the final shape of the billet at the end of the first stage of the process. The experimental setup is shown in Figure 1. The press which was used in this research was Instron8503. The capacity of the press is 60 tons [10]. The equipment can be programmed to apply successive blows on the specimen at the desired load or ram speed. In our experiments, the ram speed was set at 0.1 mm/sec. The workpieces were prismatic bars with different dimensions. The billets were 10x10, 20x20, and 30x30mm. The length of each side of the billet is designated with letter b as shown in figure 2.

Figures 3(a) and 3(b) show the dies and workpiece before and after deformation. As can be seen in this figure the upper and lower dies are flat. The geometry of dies is specified by length of the dies, L, and radius of the dies, R. Three sets of dies with different lengths of 20, 40 and 60mm were used in the experiments. The radius of the dies is constant and equal to 25 mm. The material of dies is St37.

(a)



(b)

Figure 1. Open die forging experimental setup. (a) Dies (b) Final specimen shape in two views.

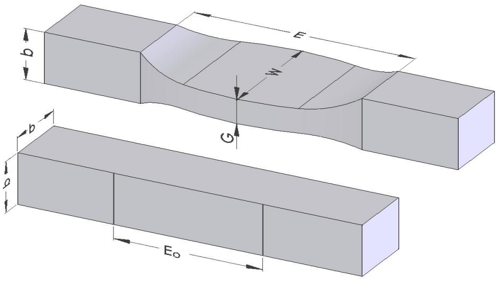
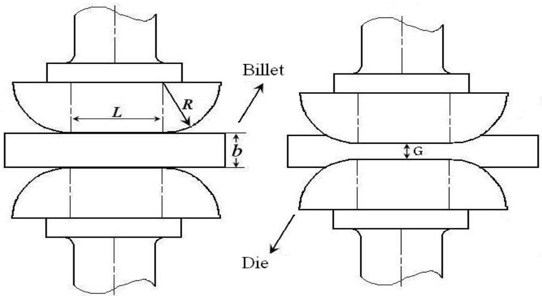


Figure 2. Workpiece before and after deformation.



(a) (b)

Figure 3. Dies and workpiece before (a) and after (b) deformation.

As can be seen in Figures 2 and 3(b), letter G defines the final height of billet after the first blow of the fullering process. In some articles letter G has been called fuller gap. The model material used in experiments was lead. Using this model material has several advantages, namely: reducing the required load, possibility of using less expensive dies, and reducing material cost.

As can be seen in figure 2, the elongation and maximum sideways spread are shown in final shape of the billet with letters E and W, respectively. In Figure 2, E_o is the original test length.

2.2. Friction Coefficient Measurement In this paper, ring compression tests were used in the quantitative determination of the friction coefficient for three kinds of lubricants. When a short ring specimen is compressed between two flat dies, parallel platens, the diameter of inner surface either increases or decreases as the height of the specimen is reduced, depending on the friction condition at the interface. The inner diameter of the ring is increased if the interface friction is low and it is decreased if this friction is high. Because the change in internal diameter of the compressed ring is sensitive to friction at the die-workpiece interface, ring compression has been widely used as a test to evaluate the friction condition in forging processes [11].

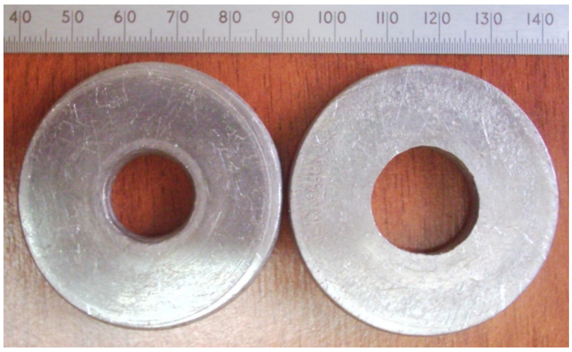


Figure 4. The specimens after ring tests using different lubricants. (Left): Emery powder. (Right): Grease

Three lubrication conditions were studied in this work: dry, grease and emery powder. Height, inner diameter and outer diameter of rings which were used in these tests were 13, 19.5 and 39mm, respectively. Figure 4 shows two of the specimens after ring test with different lubricants. In this figure the right specimen was deformed using grease and emery powder was used on the left one. As can be seen in this figure the inner diameter of the left specimen has decreased while the inner diameter of the right hand specimen has increased. The outer diameter of both specimens has increased. By fitting the results of ring tests on calibration curves, friction coefficients were found to be 0.25, 0.068 and 0.557 for dry condition, grease and emery powder, respectively.

2.3. Fullering Experimental Results More than 120 model experimental tests were performed with various dimensions of dies and workpieces. Several experiments were performed twice to check the repeatability of the results and satisfactory correlation was observed. From these experiments 97 were selected for results presentation.

The selection was based on how well the specimen behaved in the experiment. Test conditions, measured percent elongation, and percent maximum sideways spread are shown in Figure 5 for the selected experiments. The grey bars indicate the percent maximum sideways spread and the black bars are percent elongation. These experiments are grouped according to test conditions marked with right hand brackets. Note that in each group of experiments the fuller gap, G, was different but the rest of the experimental parameters were kept the same. Figure 6 shows the ratio of fuller gap and initial height of billet, G/b, for the 97 experiments.

Figure 7 shows the percent maximum side ways spread and percent elongation with percent reduction in height for different lubricants.

Figure 7(a) shows the percent maximum side ways spread and Figure 7(b) shows the percent elongation. The results show that, figure 7, with increasing friction coefficient, the percent elongation decreases and the maximum sideways spread increases.

In addition, the percent elongation and percent maximum sideways spread were found to increase with decreasing final height of the workpiece. Finally, with increasing work-piece aspect ratio, L/b, the elongation decreases and sideways spread increases. The effects of other parameters such as: fuller gap, width of billet, and length of die have also been considered as shown in Figure 5. Due to the limited space, we did not present these results separately in this paper.

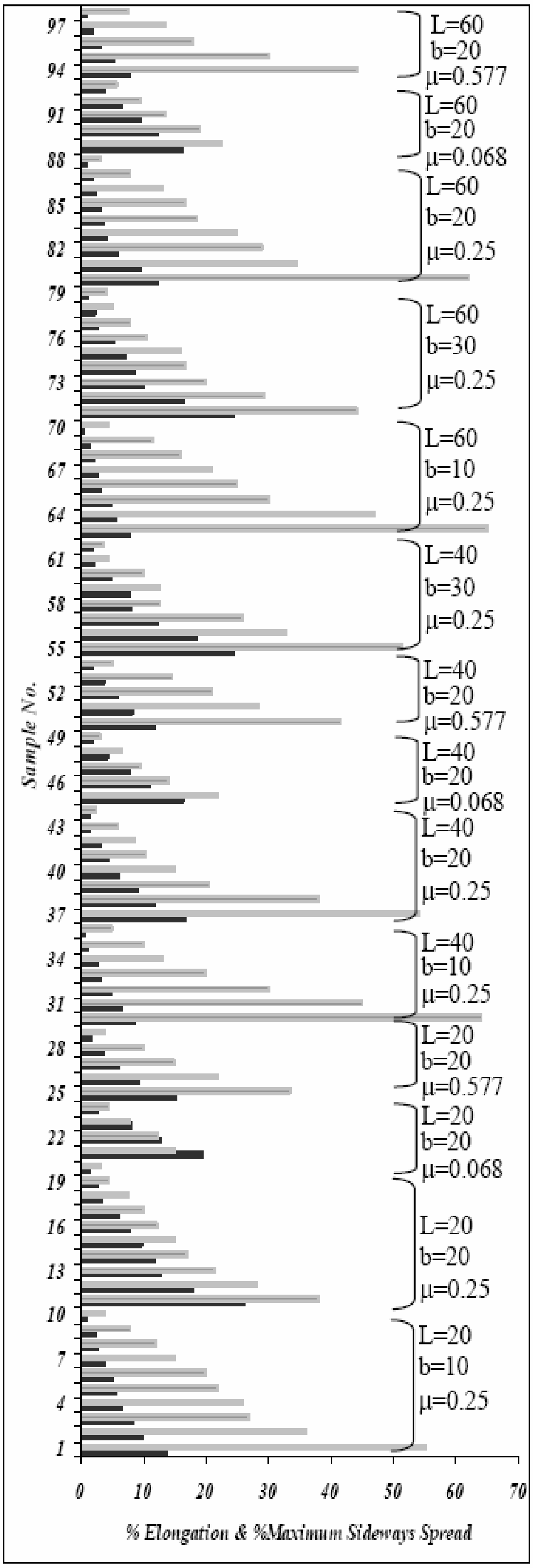
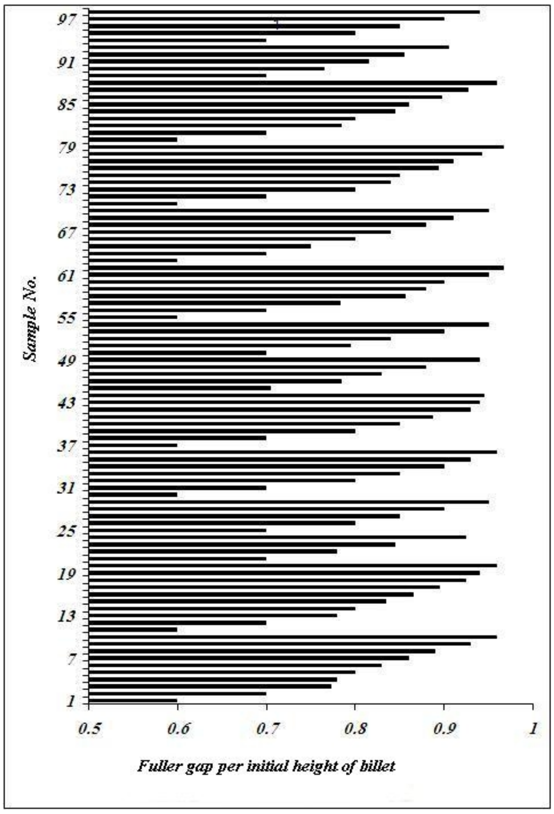


Figure 5. The measured percent elongation and percent maximum sideways spread for the selected experiments.

3. NEURAL NETWORK APPROACH

The problem addressed in this paper is how to estimate elongation, E, and maximum sideways spread, W, in final shape of a workpiece as a function of known parameters; namely width of billet, b, friction, μ, fuller gap, G, and die length, L. The known and the unknown sets of variables will be called the input and output variables, respectively.



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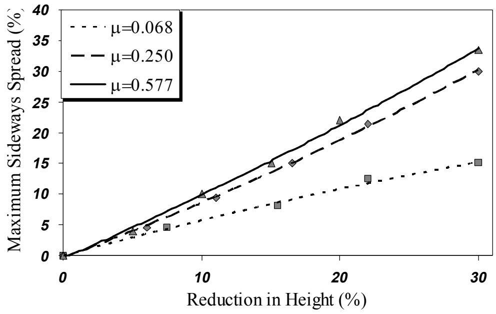

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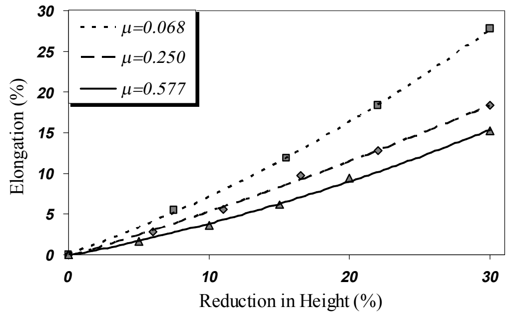

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Figure 7. Variation of the measured (a) percent maximum sideways spread and (b) percent elongation with lubricant type.

3.1. Artificial Neuron Model The Basic idea of the ANN is to imitate the human brain functioning. An artificial neural network is a parallel-distributed information processing system. It stores the samples with distributed coding, thus forming a trainable nonlinear system. Given the inputs and the desired outputs, it is also self-adaptive to the environment so as to respond to different inputs rationally [12].

Among various neural network models the back-propagation neural network BPANN, a kind of supervised network, has been used widely. This theory came from the learning algorithm of the hidden layer, which was proposed by Werbos in 1974 [13]. Parker [14] proposed the application of BPANN, which received much attention in 1985. The network topology used for the back propagation algorithm is a fully connected, layered and feed forward network. The network is divided into an input layer, several hidden layers and an output layer. The number of hidden layers in the architecture of neural network is very important. Too many hidden layers not only lead to slow learning, but results in overfitting and poor generalization of the network. Usually a three-layer feed forward BP network can approximate any arbitrary continuous nonlinear function to any degree of accuracy, so a three-layer network including only one hidden layer is sufficient to meet the demand of the actual problem [15].

In this study, the transfer function is the basic tangent hyperbolic, which possesses the distinctive properties of nonlinearity, continuity and differentiability on $(-\infty, +\infty)$. The tangent hyperbolic function is expressed as:

$$f(x) = \frac{1+e^{x}}{1-e^{-x}} \tag{1}$$

We can have different number of neurons in different layers. The number of neurons in the input layer is determined according to the problem to be solved. According to the experimental situation, elongation and maximum sideways spread depend mainly on four variables, including die length, friction coefficient, fuller gap, and width of the billet. As a result, the network chooses these four parameters as the input variables so that the number of neurons in the input layer is 4. Each neuron in the input layer is fully connected in the forward direction to all the neurons in the hidden layer through a set of weights. Similarly, each neuron in the hidden layer is fully connected in the forward direction to all the neurons in the output layer through another set of weights.

The elongation and maximum sideways spread were selected as the output variables of the network, thus the number of nodes in the output layer is 2. A network with too few hidden nodes is incapable of differentiating between complex patterns leading to only a linear estimate of the actual trend. In contrast, if the network has too many hidden nodes, it will follow the noise in the data due to over parameterization leading to poor generalization for untrained data [16]. On the other hand, with increasing number of hidden nodes, training becomes excessively time-consuming. It is shown generally that when the number of nodes in the hidden layer is two times or so as the number of nodes in the input layer, the network can be more compatible in terms of the capacity and training time [17]. According to this rule, the number of nodes in the hidden layer must be between 4 and 8. In this work the 4-8-2 structure is more suitable. The structure of the network is shown in Figure 8.

The number of training example data has a great effect on computational property of the network. Data to be used for training BPANN should be large enough to cover the possible variation in the problem domain. Too few example data lead to the instability of the computing result of the network. In contrast, too many example data result in no convergence as well as overfitting of the network. Currently, there are no mathematical rules for the determination of the required size of the example data [11].

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where t(k), a(k) and Q are target value, the output value and the number of target data.

Due to the characteristic of tangent hyperbolic activation function, the training set is scaled between -1 and 1. Figure 9 shows the change in the mean squared error (MSE) with the number of iterations. At the end of the 120,000 iterations, MSE reached the value of 0.003, where convergence was assumed.

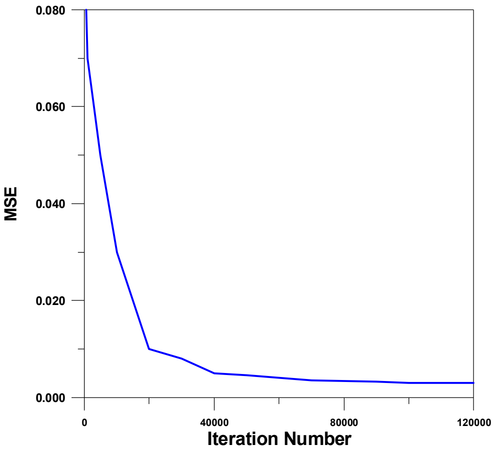

Figure 9. Schematic diagram of network convergence.

3.2. Artificial Neuron Model Using a least-square curve-fitting technique we can determine a mathematical relationship between the dependent variables, elongation and maximum sideways spread, and experimental independent variables. These relationships are determined using EVIEWS software on 97 experimental measurements. Equations (3) and (4) give the relationships between elongation and maximum sideways spread with b, L, μ, R and G/b, respectively.

$$E = \left| \begin{array}{l} -0.26R^{0.92} - 0.83L^{0.67} + 6.49b^{0.46} \\ +115.73\mu^{-0.03} + 176.08\left(\frac{G}{b}\right)^{-0.23} - 306.908 \end{array} \right| \qquad (3)$$

$R^2 = 0.91$

$$W = \left| \begin{array}{l} -964.20r^{-0.002} - 1093.25L^{-0.008} + 863.84b^{-0.013} \\ +1805.64\mu^{0.005} + 290.19\left(\frac{G}{b}\right)^{-0.29} - 896.73 \end{array} \right| \qquad (4)$$

$R^2 = 0.90$

4. RESULTS AND DISCUSSION

The percent elongation predictions of the ANN model and equation (3) with experimental measurements are compared in Table 2 for the test sets. As can be seen in this table ANN and equation (3) predictions are in good agreement with the experimental results. Note that ANN predictions are more accurate.

TABLE 2. Comparison of percent elongation between the ANN and equation (3) predictions with experimental measurements.

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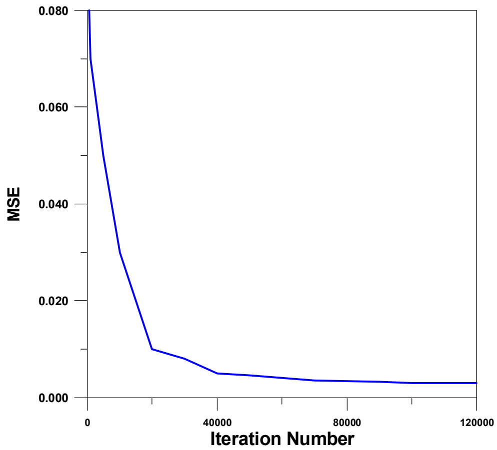

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although in some cases the errors are more than twenty percent. The percent maximum sideways spread predictions of the ANN and equation (4) with experimental measurements are compared in Table 3 for the test sets. The results indicate that the developed ANN model has good interpolation capability and can be used as an efficient predictive tool for the maximum sideways spread in final shape of workpiece after the first blow of fullering.

5. CONCLUDING REMARKS

Fullering experiments were performed to determine variation of elongation and maximum sideways spread with fuller gap, friction coefficient, length of die, and width of billet. Prediction of maximum sideways spread is an important manufacturing consideration since it determines the width of the fuller dies. In addition, this information can be used to decide on the number of required blows in advance.

According to our experimental results:

1. With increasing friction coefficient, the elongation decreases and the maximum sideways spread increases.
2. The elongation and maximum sideways spread are found to increase with decreasing final height of product.
3. Finally with increasing the billet aspect ratio, L/b, the elongation decreases and maximum sideways spread increases.
4. By a proper selection of the billet aspect ratio, L/b, and type of lubricant one can reduce a four-stage fullering to a two-stage process.

In the second part of this investigation, a neural network was designed to predict preform elongation and maximum sideways spread at any desired condition of fuller gap, friction coefficient, length of die, and width of billet. Also the mathematical relationships between output variables and input variables were determined. The generalization ability of the neural network was the basic consideration in this paper. The developed neural network and mathematical relationships were found to predict elongation and maximum sideways spread with a good accuracy. However, ANN perditions were more accurate. ANN approach can be used to predict elongation and maximum sideways spread easily instead of expensive and time consuming experimental measurements.

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