Springer

KSME

Journal of Mechanical Science and Technology 26 (1) (2012) 153~160
www.springerlink.com/content/1738-494x
DOI 10.1007/s12206-011-1020-9

Estimation of flow curve and friction coefficient by means of a one-step ring test using a neural network coupled with FE simulations †

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(Manuscript Received April 6, 2011; Revised August 3, 2011; Accepted September 8, 2011)

Abstract

This paper is concerned with application of artificial neural network (ANN) to the ring compression test for simultaneous determination of the flow curve of the material and the friction factor. The developed ANN model was trained using data from 700 finite-element (FE) simulations of the ring test. The load curve of this test and the final internal diameter of the sample are the inputs for this ANN model and the outputs are the strength coefficient, strain hardening exponent and the friction factor. It was found that the outputs of the developed ANN model were in good agreement with the experimental results.

Keywords: Finite elements; Flow curve; Friction factor; Neural networks; Ring test

1. Introduction

The flow curve and friction coefficient are very important data in metal forming analyses. For this reason, several methods have been proposed for determination of the friction coefficient and flow stress, each having its own advantages and shortcomings. In metal forming investigations, the cylindrical compression test is usually used for specifying the flow curve and the friction coefficient is normally determined by means of the ring compression test [1, 2]. However the latter can be employed for both the purposes [3].

The main objective of the present research work has been identifying the flow curve of the material and the interfacial friction coefficient by means of the ring test and using an artificial neural network (ANN). A deep experimental study on the ring test was carried out by Fereshteh-Saniee et al. [1] in order to model friction when Plasticine and lead were employed as the model materials. By proposing different frictional conditions and lubricants they created an almost full range of friction factors (from nearly zero to sticking frictions) for model tests with Plasticine and lead.

Robinson et al. [4] studied the ring compression test using physical modeling tests and finite element (FE) simulations. They suggested that a combined physical and FE simulations could provide a simple and effective mean in studying the frictional mechanisms for bulk material processing.

In order to determine the deformation pattern at the specimen-tool interface, Noh et al. [5] employed a perfectly-plastic material model for numerical simulation of the ring compression test. They studied various aspects of the ring test, such as surface enlargement, distribution of the interfacial pressure and relative sliding velocity, and concluded that these are significantly affected by the level of friction at the tool-workpiece interface.

ANN technique can be employed for flow stress prediction of different materials. Bahrami et al. employed an ANN model to calculate the flow stress of 304 stainless steel [6]. Strain rate, strain and temperature were considered as input parameters and flow stress was the output parameter. They concluded that ANN could be a practical technique for estimating the flow stress of the material under consideration.

Cavaliere [7] employed artificial neural network technique for prediction of flow curves of a particle–reinforced aluminum alloy. He used a training data set with six inputs (strain ε, temperature T, strain rate $\dot{\varepsilon}$, $\ln\varepsilon$, $\ln\dot{\varepsilon}$ and $1/T$) based on the experimental flow curves and one output, namely flow stress (σ). Employing the ANN-based model for prediction of the new flow curves, not involved in the training data set, showed an excellent capability of the developed predictive model.

For training an ANN, a set of input data are required. Using experimental data for training ANN is very time and cost consuming. The finite-element method is an appropriate approach to provide input data for training ANNs. Finally, the predictions made by the ANN can be verified experimentally. Toparli et al. [8] used FEM results for training an ANN in order to predict temperature distribution and thermal residual

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stresses in cylindrical specimens. Sudarsana Rao et al. [9] also employed a GA-based neural network to simulate stress-strain behavior of ceramic-matrix composites. They used FE simulations for the training process of ANN and the numerical predictions were in good agreement with the FE results.

Shin et al. [10] proposed an inverse method for evaluation of the flow curve and interfacial friction by using the ring compression test. They employed a function for the flow stress and calculated the coefficient of this function by minimizing the differences between the numerical and experimental load-displacement curves, and barreled shapes of the FE model and the test sample.

This paper is concerned with simultaneous determination of the flow curve and friction factor based on the load-displacement curve obtained from a ring test. To achieve these goals a feed-forward back-propagation (FFBP) neural network model was developed. The training data set for this model involved the numerical results obtained from 700 finite element simulations of the ring compression test. After training process, the validation of the ANN model was performed using new FE data not included in the original training data set. Several practical ring compression tests were also conducted under dry and lubricated conditions. Using experimental results as input data for the developed ANN and comparing the outputs of the network with findings obtained from the traditional cylindrical compression test and calibration curves of the ring test, it was concluded that the accuracy of the proposed ANN model was encouragingly very good. The novelty of the present research work is using the load-displacement curve of the ring test and the internal diameter of the deformed ring as input data into the developed ANN model in order to obtain the stress-strain curve of the material and the interfacial shear friction factor.

2. Theory of artificial neural networks

The neural networks are essentially connectionist systems, in which various nodes, called neurons, are linked to each other. A neuron receives one or more input signal and, depending on the processing function involved, provides an output signal. This output is transferred to other neurons with different intensities, based on the weights specified [11].

A feed forward network involves an order of layers, each layer including several neurons. The outputs of neurons of a layer are inputs to the neurons of the next layer. The first layer, namely the input layer, receives the data from the user and the last layer, which is called the output layer, prepares the output data for the user. The middle layers are called hidden layers. The presence of hidden layers provides complexity for the network architecture and this complexity is employed for modeling nonlinear relationships [11].

Depending on the presence or lack of feedback in the architecture of a neural network, there are two separate types of networks, namely with feedback architecture and with feed-forward architecture, respectively. In feed-forward architecture, there is no returning connection from output neurons to the input neurons. A network with feed-forward architecture has been employed in the present study.

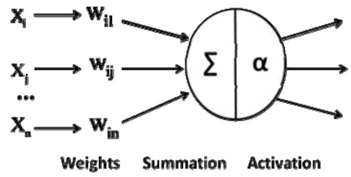


Fig. 1. Data processing in a typical cell of a neural network [11, 12].

In general, there are two different methods for learning the network, namely supervised and unsupervised learning techniques. In supervised learning, an input data is related to a specified output i.e. the learning process is performed with the pairs of data. Unsupervised learning method is used where the output or target values are unspecified [12]. Selection of the best and fastest learning algorithm for solving a problem is very important and difficult. One of common algorithms for adjusting the weights is back-propagation algorithm. This algorithm, which is a sort of supervised learning techniques, is employed in this investigation.

A network starts working with a set of initial weights and then, gradually modifies the weights in a training cycle until the desired weights are achieved. The desired weights perform the input-output mapping with the least error. The training process contains two passes, namely forward and reverse passes. In a forward pass, the input signals are distributed from the input to the output of the network. In the reverse pass, however, the calculated error signals are taken backward in the network in order to adjust the values of the weights. With this regard, an effective optimization method can be used for minimizing the error, when the weights are adjusted. Calculation of the outputs is carried out layer by layer and in the forward direction. The output of a layer is the input for the subsequent layer. In the reverse pass the weights of the output neurons are initially adjusted because the target value of each output neuron is available. Afterwards, the weights of middle layers are changed. Since there is no target value for a middle layer, the errors of previous layers are taken backwards, layer by layer, in the network. This algorithm is called a back-propagation algorithm. The trained network is then validated with a set of data. If the testing error is greater than the training error, it can be claimed that the network possesses excessive overfitting with the data. For a network with good overfitting, the testing and training errors are reasonably close to each other. Now the trained neural network can be employed for estimating the outputs suitable for a new set of data.

Fig. 1 shows the data processing carried out by a typical neuron of a neural network. Each input value is multiplied by the relevant weight. It the simplest case, the inputs and biases are added to each other and then pass through the activation function in order to produce the outputs. Networks including a bias find the relation between the inputs and outputs much more easily, compared with networks without bias. Based on

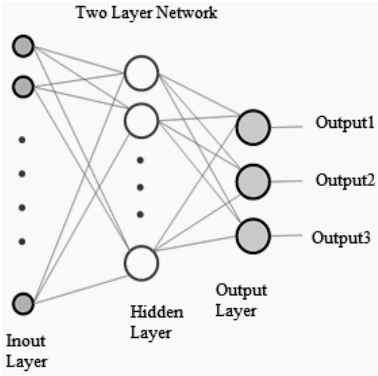


Fig. 2. A schematic diagram of the developed two-layer neural network.

Fig. 1, the output for the ith cell is as follows:

$$\alpha_i = f(\sum_{j=1}^{n} X_j W_{ij}) . \tag{1}$$

The activation functions generally involve linear or nonlinear relationships. The most important step in a neural network is the training stage.

Some statistical methods such as root mean square (RMS) error or mean square error (MSE) are usually employed for validation of the results. During the training stage, the error is specified by root mean square error or mean square error. In the latter case, MSE is calculated by the following equation:

$$MSE = \frac{1}{n}\sum_{j=1}^{n}(t_j - O_j)^2 \tag{2}$$

in which t_j is the target value for the jth output data, O_j is the corresponding output value and *n* is the number of data.

In the present research, an FFBP neural network model with two layers (Fig. 2) is used for estimation of the flow curve of the material and the friction factor by using the load curve of the ring compression test and the final inner diameter of the ring sample as the input data.

3. Application of neural network to the ring test

3.1 The ring test

The ring test is a widely used friction test for evaluation of friction factor for bulk metal forming processes, such as forging, extrusion and rolling operations. As shown in Fig. 3, this test is a friction sensitive experiment [3]. At low levels of friction, both internal and external diameters of the deformed ring increase. But at high frictions the internal diameter decreases, whereas the external diameter increases with a certain reduction in height. For a practical evaluation of friction related to a lubricant, the experimental data points which include the percentages of reductions in height and internal diameter

(a) Low friction (b) High friction

Fig. 3. Flow of material during a ring test with different levels of friction [3].

of the sample are overlaid onto the calibration curves obtained from analytical or numerical methods [1-4]. Comparing the situations of experimental data points with respect to each curve relevant to a specific level of friction, one can determine the friction factor corresponding to a special lubricant or frictional condition.

3.2. Development of a neural network model

Every neural network needs data for learning. For this reason, many finite element (FE) simulations of the ring test have been carried out by means of Deform 2D FE code. In this way, the initial data for learning the neural network were produced. For each numerical analysis of the test a specific Hollomon's equation was employed as the stress-strain relation of the material:

$$\sigma = K\varepsilon^n \tag{3}$$

in which *K* and *n* are the strength coefficient and strain hardening exponent of the material, respectively. Each FE simulation was performed with specified values of *K*, *n* and shear friction factor (*m*) until 60% reduction in height of the ring. After finishing the FE analysis, the load-displacement curve together with the final internal diameter of the ring was selected for training the neural network model.

It is worthy to mention that, based on the similarity laws [1], both the values of *n* and *m* for a model material and a lubricant should respectively be the same as those of the real material and frictional conditions. Since the model materials for physical simulation of hot and warm metal forming processes were concerned, different values of *K*, ranging from 1 to 50 MPa were chosen for the simulations conducted in this research work. The strain hardening exponent (*n*) was selected from 0.01 to 0.18. In order to cover a quite full range of frictional conditions, FE analyses were performed for various values of *m*, ranging from 0.05 to 0.99. Theoretically *m* can vary between 0 and 1.

The main objective of developing the ANN model was deriving the stress-strain curve of the material and interfacial friction factor by using the load-displacement curve of the ring compression test and the internal diameter of the specimen after 60% reduction in height. Only rings with an outer diameter/inner diameter/height ratio of 6/3/2 were considered here.

For training the network, a sixth order polynomial ($y = a_1 + a_2x + a_3x^2 + a_4x^3 + a_5x^4 + a_6x^5 + a_7x^6$ where *x* was the reduction in height) was fitted on the load-displacement

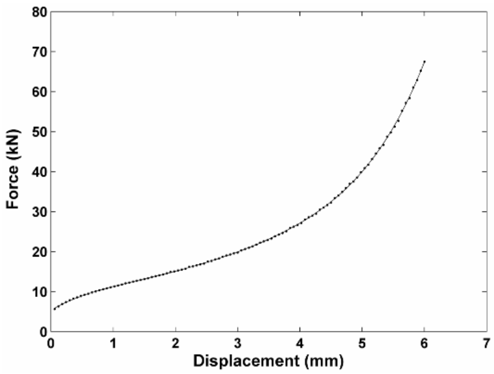
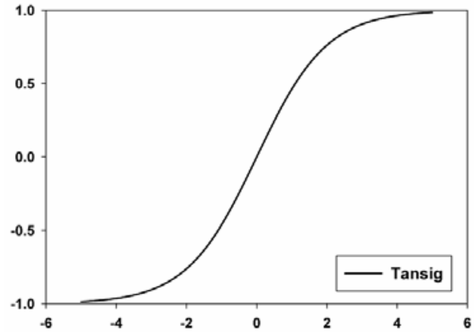
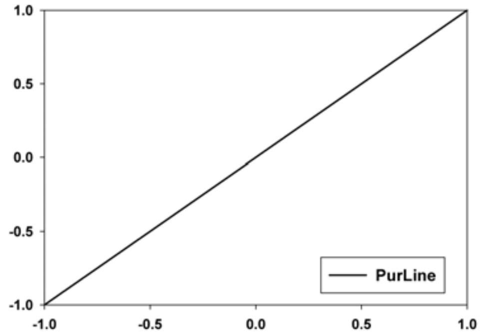


Fig. 4. A typical load-displacement curve of the ring test with the fitted sixth-order polynomial curve.



(a)



(b)

Fig. 5. Activation functions employed in the network of this research: (a) Tansig function; (b) Purline function.

curve derived from the numerical analysis (Fig. 4). Then factors a_1 to a_7 of the polynomial fitted to the specified curve for each simulation were selected as input parameters for training the network. Considering the internal diameter at 60% reduction in height, there was a total number of 8 parameters as input data for the proposed ANN model. After preparation of the training data, a two-layer neural network was chosen in *Matlab* software. The first layer involved 21 neurons and a tansig activation function, whereas the second layer included three neurons and a purline activation function. The tansig and purline functions are expressed by the following equations, respectively:

$$y = \frac{1-\exp(-x)}{1+\exp(-x)}, \tag{4}$$

$$y = x. \tag{5}$$

These activation functions are illustrated in Fig. 5. There is no specific rule or regulation for selection of numbers of the layers and neurons in a network. This has usually been carried out by trial and error.

First of all, factors a_1 to a_7 of the load-displacement polynomial together with the final internal diameter of the ring were considered as input data for the network. The outputs were strain hardening exponent, strength coefficient and the friction factor. However with these inputs and outputs, there was a problem in the training process. In this situation, because of low values of n and m, the neural network could not establish a suitable correlation between its weights. Hence the strain hardening exponent and friction factor were multiplied by 100 and 10, respectively, and the training of the network was carried out again. With these new conditions, the network was successfully trained and found a proper relation between the outputs and inputs.

After gaining a reasonable error, it was possible to obtain values of K, n and m based on the load-displacement curve of the ring test and the final internal diameter. As the final step, to ensure the validity of the trained neural network, several new data not included in the data set for the training process, were input to the network. After comparing the outputs of the network with those obtained from actual FE simulations, it was found that the agreement between them was encouragingly good.

4. Experimental procedure

As a widely used model material, lead was employed for conducting several experiments in the present investigation. The main objective of performing the experiments was validation of the developed neural network with the results obtained from practical tests. When a model material such as lead is used for a metal forming experimentation, the required load and energy together with the costs involved reduce considerably [1, 2]. On the other hand, the observations can also be made much more easily.

Ten rings with outer diameter, inner diameter and height of 30, 15 and 10 mm, respectively, were prepared and compressed under two different frictional conditions and with various reduction percentages. The maximum reduction in height of the ring samples was about 60% for both the frictional conditions.

Several compression tests were also conducted in order to obtain the stress-strain curve of the model material. This was necessary for performing precise FE simulations of the ring test and calculation of values of K and n for material under consideration. The nominal height and diameter of the cylindrical samples were 30 and 20 mm, respectively. The compression tests were also conducted with grease as lubricant

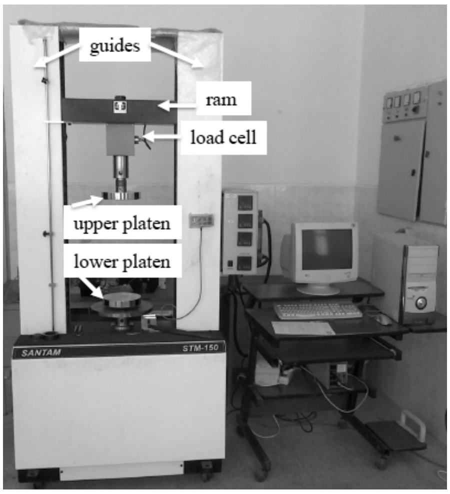


Fig. 6. The servo-electrical universal testing machine used for conducting the experiments.

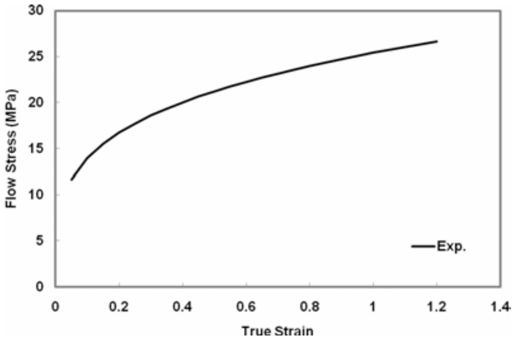


Fig. 7. The experimental flow curve of the lead.

and reductions about 60%. Nevertheless the cylindrical specimens barreled slightly because grease did not remove the friction completely. Hence, it was necessary to apply appropriate correction factors to the calculated stresses.

All of the experiments were carried out with a 150 KN servo-electrical press equipped with computer. This press, which can work in position or load control modes, is illustrated in Fig. 6. The average strain rates of all experiments were almost the same, namely about 0.01 s^{-1}.

5. Results and discussions

As mentioned in the previous section, because of non-zero frictional condition, the specimens barreled during the compression tests. Therefore, it was essential to employ appropriate correction factors for modifying the calculated stresses. In this way, the force and stress needed for redundant deformation of the specimen can be eliminated and a corrected flow stress corresponding to a homogeneous deformation can be determined [2].

Using the numerical correction factors obtained from FE simulations for the experimental data, the stress-strain curve of the material was attained. Fig. 7 shows this flow curve and the relevant Hollomon's equation is:

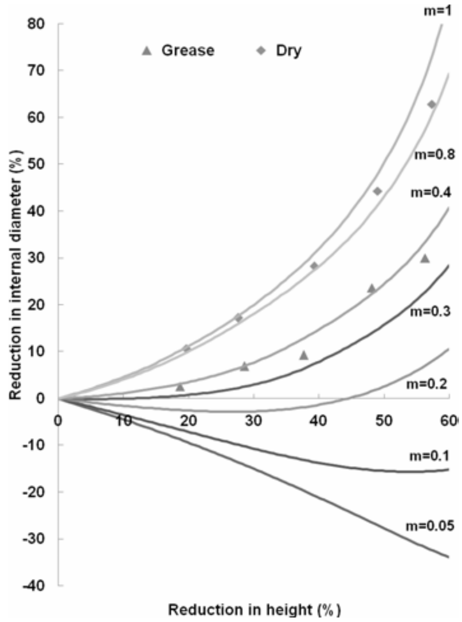


Fig. 8. The numerical calibration curves with the experimental results superimposed.

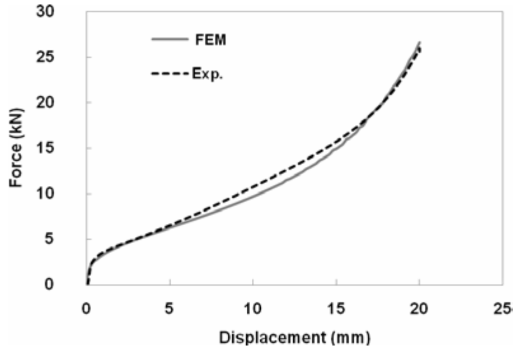


Fig. 9. The experimental and FE load-displacement curves obtained for the compression test.

$$\sigma = 25.4\varepsilon^{0.26} \text{ (MPa)} . \quad (6)$$

In order to determine the friction factor for a special interfacial condition, the FE simulations of the ring test were conducted using the above-obtained stress-strain curve for various values of *m*. The calibration curves obtained with this technique are illustrated in Fig. 8 with experimental sampling points obtained from the ring tests. Fig. 8 implies that the shear friction factor corresponding to dry condition and grease lubricant are, respectively, 0.85 and 0.4.

When the flow curve of the material and the shear friction factor of grease were employed for the finite element simulation of the compression test, the load-displacement curve shown in Fig. 9 was obtained.

The experimental curve is also overlaid in this figure. The agreement between numerical and experimental curves is encouragingly good. This implies that the FE simulation of the

Table 1. Final results obtained from the developed ANN for the ring tests performed with two friction conditions.

Lubrication condition	K	n	m
Grease	24.5	0.29	0.34
Dry	26.8	0.29	0.76

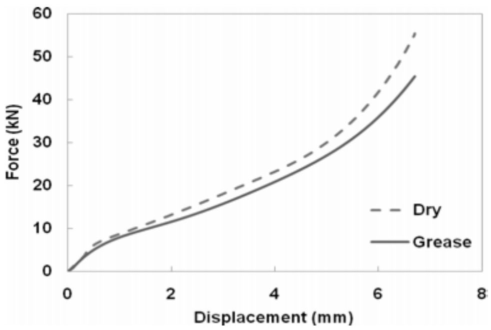


Fig. 10. Experimental load-displacement curves obtained from the ring tests with two different frictional conditions.

compression test was carried out with quite accurate flow curve and friction factor. It is notable that, although the n value of the material selected for experimentation is out of the initial range of n employed for training the network, the agreement between the predictions of ANN and the experimental results is reasonably good. This is due to iterative nature of the method and use of each new set of data for retraining the ANN under consideration.

Fig. 10 illustrates the experimental load-displacement curves achieved from the ring tests with two previously mentioned frictional conditions. It is obvious that the greater the friction factor, the larger is the required forming load. Two sixth-order polynomials were fitted to these curves. For each curve, factors a_1 to a_7 together with the final internal diameter of the ring were input to the trained neural network to obtain values of K, n and m for the corresponding ring test. To improve the accuracy of the ANN under consideration, the finite element analysis of the ring test was carried out with the first series of outputs. Then the results of this simulation together with the previous data were employed for training the ANN. This process was repeated until the desired accuracy was achieved. The iterated FE simulation of the ring test and training stage of the network increase the capability of the proposed ANN for processing the new data. The final results obtained from the ANN for both the frictional conditions are listed in Table 1.

Fig. 11 shows the flow curves predicted by the developed ANN technique superimposed with the experimental stress-strain curve obtained from the compression test. It can be seen in Table 1 and Fig. 11 that the estimations made by the developed ANN are quite reasonable, especially when the slight differences between the material properties of the ring and compression test samples are kept in mind. These differences might be due to casting and/or machining conditions or other operations for the preparation of the specimens. It is worthy to mention that depending on how a new data set is close to the initial inputs used for training of the network; the number of iteration may differ from 1 to 3.

The load-displacement curves are illustrated in Fig. 12. The predicted and actual loads for three different displacements, namely 2, 4 and 6 mm are also summarized in Table 2. The differences between the estimated and real values are generally smaller for grease lubricant, compared with dry condi-

Table 2. FE load predictions based on the ANN results, compared with the relevant experimental loads for various frictional conditions and ram displacements.

Disp. (mm)	Force (kN)					
	Grease			Dry		
	Exp.	Predicted	Error (%)	Exp.	Predicted	Error (%)
2	13.3	12.5	6.2	15.6	14.3	8.6
4	23.6	22.1	6.4	27.0	26.7	1.1
6	43.6	45.4	4.0	55.6	67.7	21.8

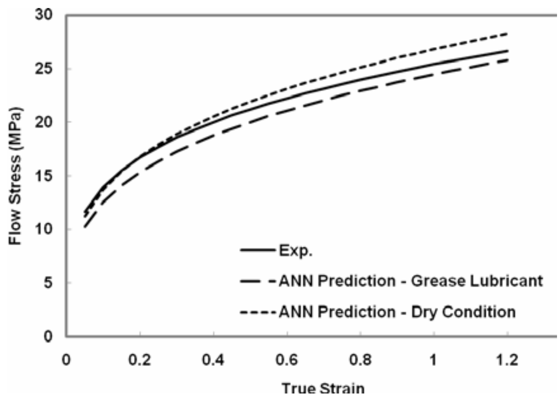


Fig. 11. Flow curves predicted by the developed ANN with superimposed experimental stress-strain curve of the lead.

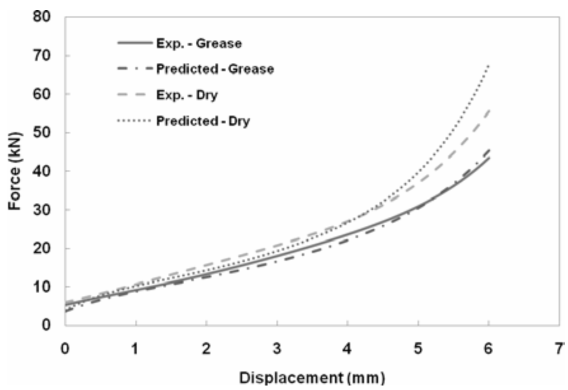


Fig. 12. Correlations between the FE load curves, obtained based on the ANN predictions, and the corresponding experimental ones for ring tests with various frictional conditions.

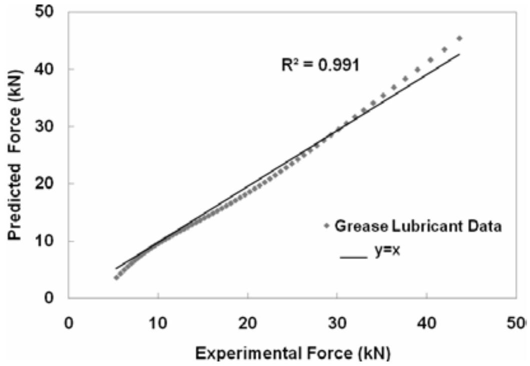


Fig. 13. A comparison between the predicted and experimental loads for the ring test with grease lubricant.

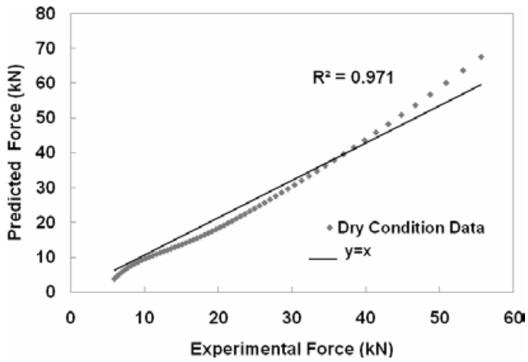


Fig. 14. Predicted force versus experimental force for the ring test performed under dry conditions.

tions. The deviations could be due to greater changes in the value of friction factor for the dry condition, as can be observed in Fig. 8. It is worthy to mention that despite the test conditions, the friction factor was constant during each FE simulation of the ring test. The developed ANN was also trained based on this situation. Therefore, considering this point, one can conclude that the agreement between actual and predicted forces is reasonably good.

The sixth order polynomials determined for the experimental load-displacement curves, which coefficients were employed as input to the ANN, were as follows:

$$F_{dry} = -5.574x^6 + 106.5x^5 - 708.3x^4 + 2187x^3 - 3133x^2 + 6661x + 5560 \quad (7)$$

$$F_{grease} = 0.382x^6 + 5.499x^5 - 98.46x^4 + 507.9x^3 - 846x^2 + 4328x + 5337. \quad (8)$$

To obtain more accurate results, the network should be trained with more experimental findings. R-square (root mean square) values together with the predicted forces versus the experimental loads are plotted in Figs. 13 and 14. R-square is an index showing how successful the fit is in describing the variation of the data. The values of this parameter are 0.99 and 0.97 for the grease lubricant and dry conditions, respectively. The comparisons made in the last three figures, implies that there is an encouraging agreement between the actual forming loads with those predicted by the proposed ANN.

6. Conclusion

In the present research work, a two-layer feed-forward back-propagation (FFBP) artificial neural network was employed and trained in order to predict the flow curve of the material and the interfacial friction factor based on the load-displacement curve of a ring test and the final internal diameter of the specimen. In a feed-forward architecture, there is no returning connection from output neurons to the input ones. On the other hand, one of common algorithms for adjusting the weights is back-propagation algorithm, which is a sort of supervised learning techniques. The procedure, proposed in this paper, is a novel technique and the results presented and discussed in the previous sections proved its accuracy and appropriate capability. One of important advantages of the proposed method is that it is not necessary to interrupt the ring test to measure various geometrical dimensions of the sample. In other words, the whole experiment can be performed in just one step. This benefit is very helpful in doing the tests at elevated temperatures.

It was found that the precision of the network was higher for low frictions compared with high frictions. This could be due to higher variation of the actual friction factor at the end stage of the ring test for higher levels of friction. It seems that training the network with more experimental results obtained from the ring tests at high frictions could improve the accuracy of the network at this level of friction.

Finally, it should be claimed that during each FE analysis, the friction factor is constant, whereas in a practical ring test it may vary. This variation could due to any change in the roughness of the test sample and/or die surfaces or variations of the contact pressure at the tool-workpiece interface. Therefore, FE modeling of the ring test with variable friction factor and/or training the network with more experimental findings could provide an excellent accuracy for the developed ANN.

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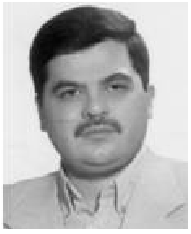

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