Prediction of Forging Force and Barreling Behavior in Isothermal Hot Forging of AlCuMgPb Aluminum Alloy Using Artificial Neural Network

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ABSTRACT

In the present investigation, an artificial neural network (ANN) model is developed to predict the isothermal hot forging behavior of AlCuMgPb aluminum alloy. The inputs of the ANN are deformation temperature, frictional factor, ram velocity and displacement whereas the forging force, barreling parameter and final shape are considered as the output variable. The developed feed-forward back-propagation ANN model is trained with Leven berg–Marquardt learning algorithm. Since the finite element (FE) simulation of the process is a time-consuming procedure, the ANN has been designed and the outputs of the FE simulation of the hot forging are used for training the network and then, the network is employed for prediction of the behavior of the output parameters during the isothermal forging process. Experimental data is compared with the FE predictions to verify the model accuracy. The performance of the ANN model is evaluated using a wide variety of standard statistical indices. Results show that the ANN model can efficiently and accurately predict isothermal hot forging behavior of AlCuMgPb alloy. Finally the extrapolation ability and noise sensitivity of the ANN model are also investigated. It is found that the extrapolation ability is very high in the proximity of the training domain, and the noise tolerance ability very robust.

1-Introduction

Aluminum alloys are widely used in many industries such as aerospace and automotive for fabrication of light weight products due to their attractive combination of properties like low weight to strength ratios and good corrosion resistance [1, 2]. The metals and alloys are frequently formed by hot forming processes including hot rolling, forging and extrusion. These processes can be used for processing large size and complex shape of products due to high formability and small deformation resistance; additionally, they can improve the mechanical properties of metals [3, 4].

The design and control of forging process depend on the characteristics of the material, the conditions at the tool/work piece interface, the ram velocity, die shape design and the equipment used [5-7]. However, prediction of the optimum condition for hot forging process is very difficult because all processing parameters change with temperature and deformation history. Various methods have been proposed to analyze the hot forming process optimization, the temperature field, defects of the formed product and the microstructure evolution of metals and alloys. Hot forming processes simulation is a

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powerful tool to predict and control material behavior and process optimization under various deformation conditions. These tools are developed based on numerical simulation techniques such as finite element method (FEM). The FEM can be one of the best methods because it considers all factors, such as thermal properties changes or differing rates of generation of internal heat with time and position [8]. Therefore, many researches have been carried out to predict the material behavior during hot working processes using constitutive equations which these equations are often used to describe the plastic flow behaviors of the materials in a form that is suitable to use in computer code to model the materials response under the indicated loading conditions. So, these equations and simulations can be used for determination of load and power requirements for forming and also microstructure evolution of the metal forming process simulations [9-11]. A number of research groups have made efforts to integrate the developed behavior models into FEM to predict the material evolution during hot metal forming. The effects of thermo-mechanical parameters such as temperature, strain, and strain-rate and deformation history on the strain/stress distribution and microstructural evolution of metals and alloys during hot forming processes have been investigated by integrating the thermo-mechanical coupled finite element (FE) model [12-17]. Also, some researchers have investigated the effects of thermo-mechanical parameters on the defects of hot forged product using FEM [3, 18-19].

There have been many studies dealing with the prediction of parameters such as distributions of strain, temperature and forming load requirements to know the optimum process parameters for the exact quality products. Prabhu [20] simulated a non-isothermal precision forging process of a Ti-6Al-4V first-stage impeller for the gas turbine engine using the FE software and load requirements, damage, velocity field, stress, strain, and temperature distributions investigated in detail. Hot forging process design and parameters determination of magnesium alloy AZ31B spur bevel gear have been investigated by Liu et al. [21] and it has been shown that the finite element results are consistent with the experimental ones and the optimum perform die shape was obtained by FE simulation.

Rao et al. [22] showed that the experimental load–stroke curves correlated well with the simulated ones in hot forging of Magnesium alloy. Chan et al. [23] developed a material constitutive model based on micro-compression test and proposed a modified micro-double cup extrusion test and the corresponding FEM simulation. The effects of friction coefficient on the geometrical changes of cylindrical samples during hot forging processes were studied by Li et al. [24].

In recent years, artificial neural network (ANN) as a more adaptable and rapid method has been developed and used in many engineering applications and is especially suitable for behaving complex and non-linear systems. The ANN has been used in describing and predicting the thermo-viscoplastic deformation behavior of the metal forming processes and has a shorter running time and easier in comparison with the FEM. Also, ANN has been integrated into an FEM to generate learning data of ANN. Microstructural evolution of Ti-6Al-4V alloy under isothermal and non-isothermal hot forging conditions was predicted using ANN and FEM simulation by Kim et al. [25]. Chan et al. [26] developed an integrated methodology based on FEM simulation and ANN to approximate the functions of design parameters and evaluate the performance of designs as the FEM simulation is first used to create training cases for the ANN and the trained ANN is used to predict the performance of the design. Prediction of temperature distribution and required energy in hot non-isothermal forging process of low carbon steel has been done using coupling a thermo-mechanical analysis based on a FEM and ANN by Serajzadeh [27]. Also, in another research, a thermo-mechanical model was developed to predict metal behavior during hot forging process; at first an ANN model was trained to calculate flow stress of deforming metal as a function of temperature, strain and strain rate and then temperature and velocity fields were predicted by coupling the ANN model and a thermo-viscoplastic FE model [28].

In the present research, an ANN model with standard back-propagation learning algorithm is developed and used to predict the thermo-mechanical behavior and forging force, barreling and final shape of AlCuMgPb aluminum alloy samples under different isothermal hot forging conditions including forging temperature, friction, ram velocity and stork. For this purpose a three-dimensional FE model verified with experimental results has been developed to provide a data basis for training and validation of the ANN by DEFORM-3D software. Also, the performances of the ANN model are investigated

with a variety of statistical indices, the extrapolation ability and noise sensitivity of the ANN model in comparison with the FEM results.

2-Experimental procedures and finite element modeling

2-1-Experimental procedures

The chemical composition of the AlCuMgPb aluminum alloy used in this investigation is shown in Table 1. Isothermal hot compression tests were carried out to obtain the AlCuMgPb alloy behavior under different thermo-mechanical conditions during hot deformation described at different levels of strains, strain rates and temperatures in an earlier publication [29]. Specimens (with initial height (h_0) of 12 mm and initial radius (R_0) of 4 mm) for isothermal hot forging were machined from the as-hot extruded aluminum alloy product. To investigate the effects of varying forging temperature, friction, ram velocity and ram displacement (stork) on forging force, barreling and final forged shape, isothermal hot forging were conducted in the temperature range of 350 -500◦C and in the ram velocities range of 25-500 mm/min with ram displacement. The load-stroke used during each deformation was recorded from the dial indicator.

Fig. 1. Cylindrical samples (a) before and (b) after isothermal hot forging

shows a sample cylindrical sample before and after hot forging. As it is clear, h_f is the height of the hot forged and R_b and R_n are the maximum and top radiuses of sample after hot forging, respectively.

Table 1. Chemical composition (wt. %) of AlCuMgPb alloy.

Cu	Mg	Pb	Si	Fe	Mn	Cr	Zn	Ti
3.85	0.92	1.12	0.37	0.58	0.25	0.01	0.37	0.01

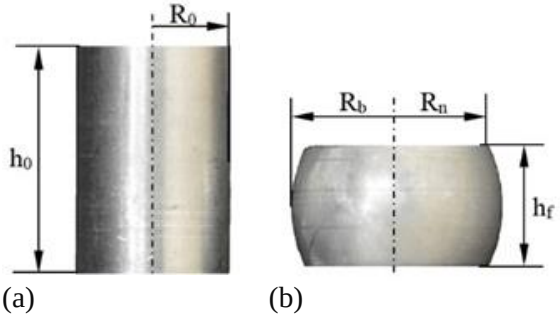


Fig. 1. Cylindrical samples (a) before and (b) after isothermal hot forging

2-2-Finite element modeling

A 3D thermo-mechanical model has been developed to simulate the isothermal hot forging process of AlCuMgPb aluminum alloy using the commercial finite element software package, DEFORM-3D. In this model, the interaction of the mechanical and thermal phenomena is

considered and the AlCuMgPb aluminum alloy is represented deformable with 55332 coupled thermo-mechanical tetrahedral elements whereas the top and bottom dies is assumed as rigid.

The hot forging test is assumed to behave as a thermo-viscoplastic material with temperature independent elastic modulus of 70 GPa and Poisson's ratio of 0.33. The plastic deformation behavior of the work piece is proper to consider uniform or homogeneous deformation conditions. The plastic

behavior of AlCuMgPb modeled as the hyperbolic sine equation, developed from hot compression tests [29] as follows:

$$\dot{\varepsilon} = A[\sinh(\alpha\sigma)]^{n}\exp\left(-\frac{Q}{RT}\right) \quad (1)$$

Where $\dot{\varepsilon}$ is strain rate (s^{-1}), T is the absolute temperature (K), σ is the flow stress (MPa), Q is the deformation activation energy (J mol^{-1}), R is the universal gas constant (8.3144 J $mol^{-1}K^{-1}$); and A, n and α are material constants. The following flow stress parameters have been utilized in the constitutive equation of AlCuMgPb, $A = 1.197 \times 10^{6}$, $Q = 104.2$ kJ/mol,$n = 4.55$and$\alpha = 0.026$ Mpa^{-1}. The thermo-physical properties of AlCuMgPb including thermal conductivity and heat capacity are 130N sec^{-1} K^{-1}(130 W m^{-1} K^{-1}) and 2.28N $mm^{-2}C^{-1}$ (860J $kg^{-1}K^{-1}$), respectively.
Two contact pairs are defined between the work pieces and the top die as well as bottom die, respectively. Interfacial friction based on constant friction law is useful at high pressures and expressed as [30]:

$$\tau = mK \quad (2)$$

Where τ is the frictional shear stress, m is the frictional shear factor and K is the shear yield strength. The frictional shear factor varies in wide ranges due to hot forging condition and different lubricants. It is clear that the interfacial friction between the work piece and dies will affect the non-uniform deformation of the work pieces. The interfacial friction becomes apparent with the increase of deformation. Thus, the deformation is more and more heterogeneous, leading to the barrel shape of the work pieces, as shown in Fig. 1. The barreling parameter (B) has been developed for evaluating the effect of frictional factor, which involves only the geometrical measurement of the work piece shape changes, which is expressed as follows [31]:

$$B = 4\frac{\Delta R}{R}\frac{H}{\Delta H} \quad (3)$$

Where $R = R_0\sqrt{\frac{H_0}{H}}$, $\Delta R = R_b - R_n$ and $\Delta H = H_0 - H$.

In this study, the simulations of isothermal hot forging process has been conducted at 350, 400, 450 and 500 ℃ and ram velocities of 25, 125, 250 and 500 mm/min and also frictional shear factors of 0.1, 0.3, 0.5 and 0.7.

2-3-Finite element model verification

The finite element model developed in this study has been validated by comparing the model predictions including of forging force, barreling parameter and final shapes with experimental results of the isothermal hot compression tests in different temperatures and ram velocity.
The force-stroke curves obtained from the hot compression tests in comparison with the predicted results obtained from finite element method have been shown in

Fig. 2. Comparison between the experimental and FEM results of the forging force at different processing conditions

. As can be seen, the results show that the FEM predictions are in good agreement with the experimental results as the mean absolute percentage error is 12.67% for prediction of forging force.

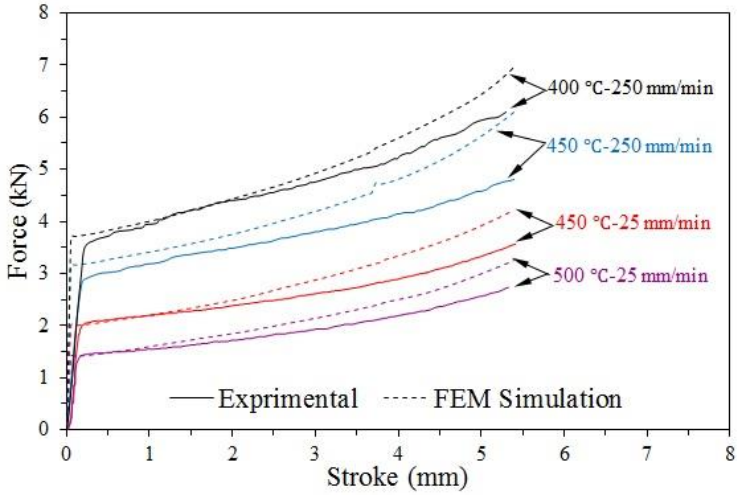


Fig. 2. Comparison between the experimental and FEM results of the forging force at different processing conditions

Fig. 3. The comparison between experimental results and FEM prediction of final shapes under different conditions

shows comparisons between the experimental and finite element simulation barreling parameters and final specimens shapes under different hot forging conditions. It can be seen that the simulated samples have similar shapes with the experimental ones after isothermal hot forging process. The finite element and experimental geometry dimensions are almost the same under different deformation conditions. Table 2 shows the shape errors between experimental and simulated specimens. The relative errors of R_n and R_b change between 0.62 to 3.14% and 0.18 to 2.08%, respectively.

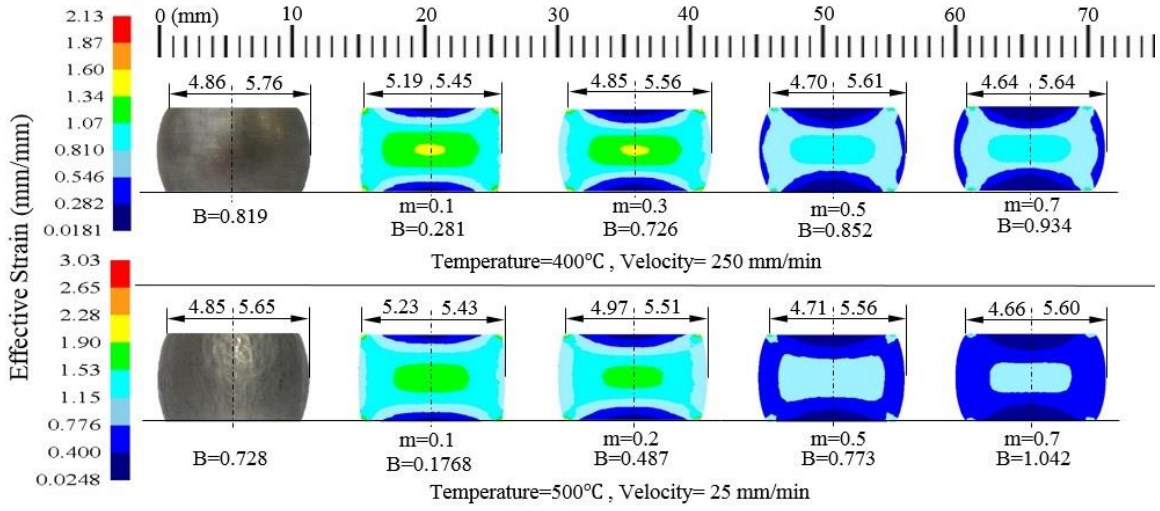


Fig. 3. The comparison between experimental results and FEM prediction of final shapes under different conditions

Table 2. Shape errors between experimental (Exp) and simulated (Sim) specimens under different processing conditions

(Temperature℃-velocity mm/min)	Exp(R_n)	Sim(R_n)	Error (%)	Exp(R_b)	Sim(R_b)	Error (%)
350-25	10.10	9.92	1.78	11.28	11.24	0.35
350-250	10.04	9.82	2.19	11.22	11.16	0.53
400-25	9.90	9.80	1.01	11.20	11.18	0.18
400-250	9.72	9.86	3.14	11.52	11.28	2.08
450-25	9.98	9.82	1.60	11.24	11.21	0.26
450-250	9.86	9.70	2.64	11.28	11.24	0.35
500-25	9.70	9.66	2.42	11.30	11.22	0.71
500-250	9.64	9.58	0.62	11.36	11.21	1.32

Therefore, the comparison of the results obtained by simulation tests with the experimental results allowed verifying the precision of the proposed FEM model for the forging process under investigation, and can reliably be used as a surrogate resource to data for artificial neural network modeling.

3-Artificial neural network model development

Artificial neural network (ANN) is a non-linear statistical data modeling tool that can be used to model complex relationships between inputs and outputs or to supply patterns in data [32]. A typical neural network consists of an input layer, one or more hidden layers and an output layer, which are connected by the processing units called neurons. The development of an ANN model is generally consisted of the following steps: (i) to collect the signs, symptoms and experimental data; (ii) to determine the input/output parameters; (iii) to analysis and pre-process the collected data; (iv) to train the network; (v) to test the trained network and (vi) to evaluate the performance of the developed ANN [33]. Among various kinds of ANN approaches that have been, the multilayer perceptions (MLP) based feed forward with back-propagation algorithm (BP) is the most popular in materials processing control and engineering applications [34]. In the feed-forward BP network, the final predicted outputs are compared with the target data outputs, and the errors are calculated. These errors are used for adjusting the weights of each of the neurons. The process of using the target data outputs to minimize the mean square error iteratively is called as training the network. The iterations are repeated until a specified convergence is reached. The weights of the trained network are stored, and can be used later for predicting outputs given a different set of inputs. The convergence of the network is determined by the mean square error (MSE) between the target and predicted output data [35].

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{M}_i - \mathrm{P}_\mathrm{i})^2 \tag{4}$$

Where M_i is the measured finding, P_i is the predicted data from ANN model, and N is the total number of employed data pairs in the investigation. Problems with the gradient descent approach are slow convergence speed and existence of local minimum for target function, therefore several high performance algorithms have also been proposed like variable learning rate algorithm, resilient algorithm, conjugate gradient algorithm, quasi-Newton algorithm, and Leven berg–Marquardt algorithm [32].

In this study, a three-layer feed forward back-propagation ANN has been employed to describe the hot forging process in which the inputs consist of deformation temperature, ram velocity, stroke and frictional factor, while the forging force, barreling parameter and final shape are considered as the output variable. One hidden layer was employed to test the present BP network. The schematic representation of the ANN architecture is shown in

Fig. 4. The schematic of the ANN architecture with one hidden layer

. The architecture of the neural network relates to the number of the neurons in the hidden layer. The effect of the number of neurons in the hidden layer on the convergence criterion was studied numerously. It is very complicated to choose the number of neurons in hidden layer, which is usually determined according to the experiments or researchers' trial. If the architecture of neural network is too simple, the trained network might not have enough ability to learn the process correctly. Conversely, if the architecture is too complex, it may not converge during training [36-37]. In order to determine the suitable number of neurons in the hidden layer, the trial and error method was started with two neurons in the hidden layer and further carried out with more neurons. It was found that a network with one hidden layer containing 14 hidden neurons gave a minimum MSE and was therefore considered as the optimal structure for the prediction of hot forging process at various conditions. The effect of the number of neurons in hidden layer on the network performance is shown in

Fig. 5. The influence of number of neurons in the hidden layer .

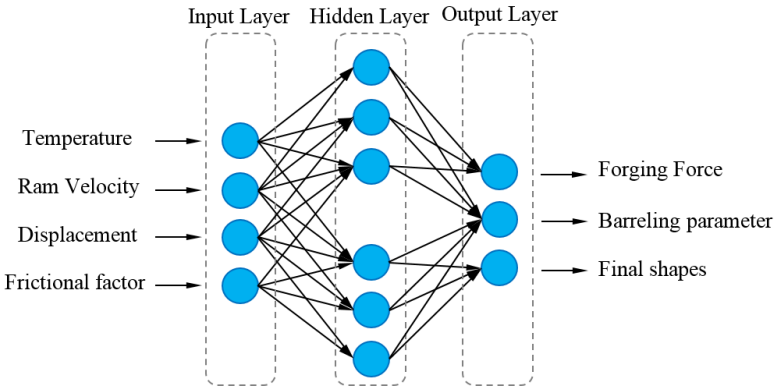


Fig. 4. The schematic of the ANN architecture with one hidden layer

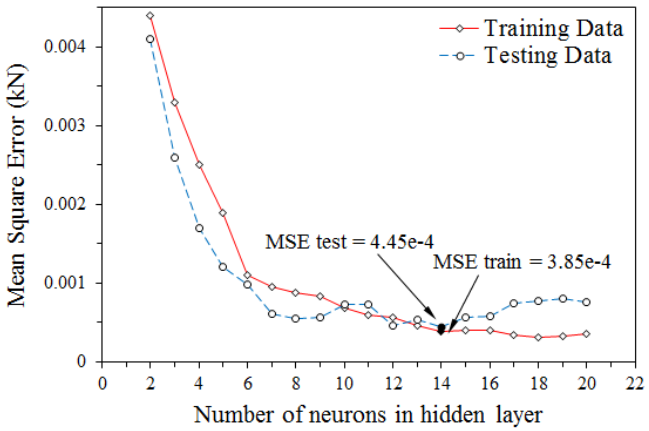


Fig. 5. The influence of number of neurons in the hidden layer

Before the training of the network begins, it is necessary to normalize the input and output data within the range from 0-1 in order to obtain a same form for the network to read. The pre-processing procedure, which can make the neural network training more efficient, has been used the following normalization equation [38]:

$$X_n = 0.1 + 0.8 \times \left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) \quad (5)$$

Where X is the original data and X_n the unified data corresponding to X, X_{min} and X_{max} are the minimum and maximum value of X, respectively.

In the present ANN, 448 data sets selected from the FEM results were divided into two subsets: a training dataset (75%) and a test dataset (25%). During establishing the ANN, 336 data sets were used to train the network model, and the other 112 data sets at displacement between 0.8 and 5.4 mm were applied to test the performance of the ANN. The training function was Leven berg–Marquardt because it is fast convergence in training [34]. Meanwhile, a hyperbolic tangent sigmoid transfer function is used for neurons in the hidden layers and the output layer. The ANN architecture and functions used in the resulted model have been summarized in Table 3.

Table 3. The ANN architecture and functions

AAN	**Parameters**
Learning function	Feed-forward back-propagation
Training function	Levenberg–Marquardt (trainlm)
Transfer function	Tangent sigmoid (tansig)
Performance function	MSE
Number of input layer unit	4
Number of output layer units	3
Number of hidden layers	1
Number of hidden layer units	14
Iteration	10000

4-Results and discussion

In this study, the developed ANN is used to predict the forging force, barreling parameter and final shapes of the hot forging process data. The wide kinds of standard statistical performance evaluation measures have been applied to evaluate the model performance. The predictability of the neural network is expressed in terms of correlation coefficient (R), average absolute relative error (AARE), and root mean square error (RMSE) , expressed as:

$$R = \frac{\sum_{i=1}^{N}(M_i - \bar{M})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N}(M_i - \bar{M})^2 \sum_{i=1}^{N}(P_i - \bar{P})^2}} \quad (6)$$

$$AARE\ (\%) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{M_i - P_i}{M_i}\right| \times 100 \quad (7)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(M_i - P_i)^2} \quad (8)$$

Where M_i is the measured finding, P_i is the predicted data from ANN model, $\bar{M}$ and $\bar{P}$ are the mean values of all the measured and predicted results, respectively, and N is the total number of employed data pairs in the investigation

4-1-Forging force

The performance of the developed ANN has been plotted in

a and b for the forging force, on training and testing data, respectively. As can be seen, the proposed ANN model can predict the forging force with a reasonable accuracy. The developed ANN model for forging force prediction have correlation coefficients of 0.9989 and 0.9984 for the training and testing data set, respectively, and have AARE of 1.489% and 2.10% for the training and testing data set of ANN model, respectively.

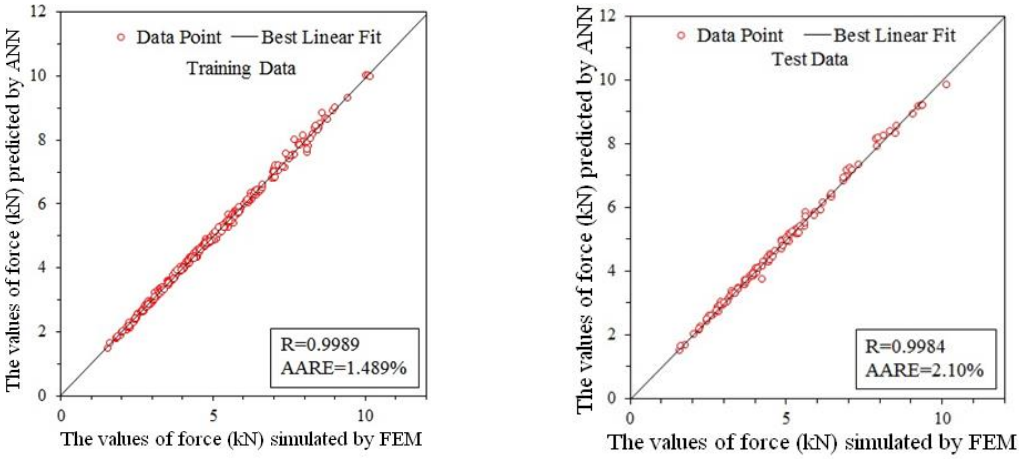


Fig. 6. Correlation between the simulated and ANN predicted forging force for the (a) training and (b) testing data set

Fig. 7 compares the force–displacement curves predicted by the FEM and ANN with different temperatures, frictional factor and ram velocity during isothermal hot forging.

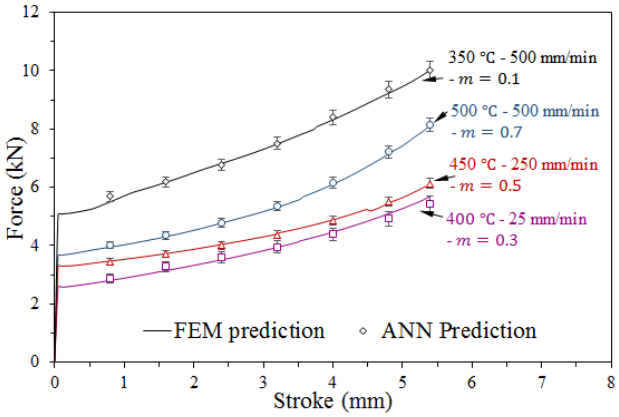


Fig. 7. Force–displacement curves predicted by FEM and ANN under different conditions

The comparison between the FEM results and ANN predications on the forging forces at different temperatures has been shown in
. As it is obvious, the forging force will decrease and the accuracy of ANN model prediction clearly increase with increasing the forging temperature. Fig. 9 shows the effect of ram velocity on the forging force. As it is clear, the forging force increases with increasing of the ram velocity, and the developed ANN model can estimate forging force with a reasonable accuracy as the maximum errors of approximations is almost 0.65% at velocity of 250 mm/min. The comparison between the FEM results and ANN predications on the forging forces at different friction factor has been shown in

. It can be seen that the forging force increases with increasing of the values of friction factors and the absolute percentage error between the FEM and ANN prediction of the force changes between 0.031% and 1.107% for the different friction factors. The RMSE, R and AARE values obtained from the developed ANN at different temperature levels have been listed in Table 4. It can be seen that the maximum values of R, AARE and RMSE obtained for training and testing data of the developed ANN model are 0.9991, 1.691% and 0.092 MPa, and 0.9989, 2.043% and 0.125 MPa, respectively.

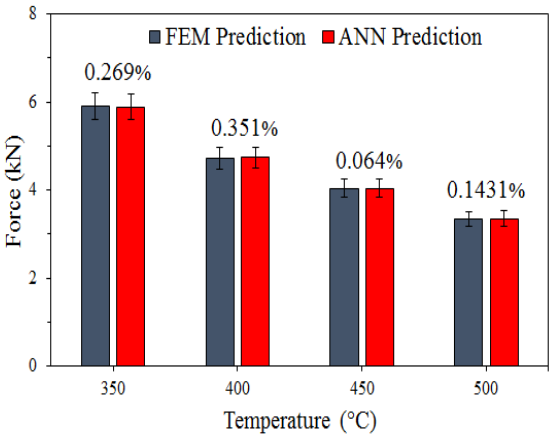


Fig. 8. Effects of temperature on the forging force for ram velocity of 250 mm/min and friction factor of 0.5, in displacement of 2.4 mm

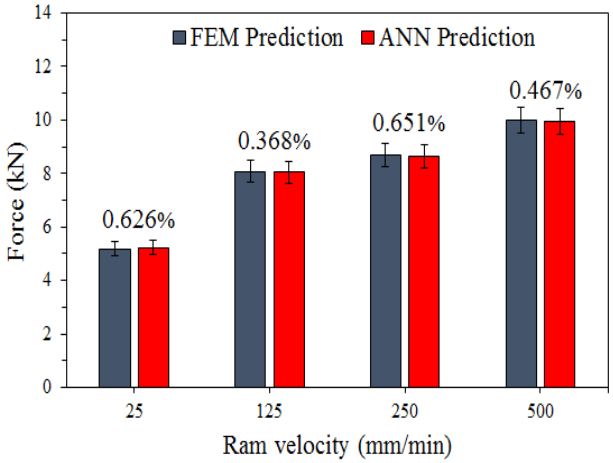


Fig. 9. Effects of ram velocity on the forging force at temperature of 350℃, friction factor of 0.1 and displacement of 5.4 mm

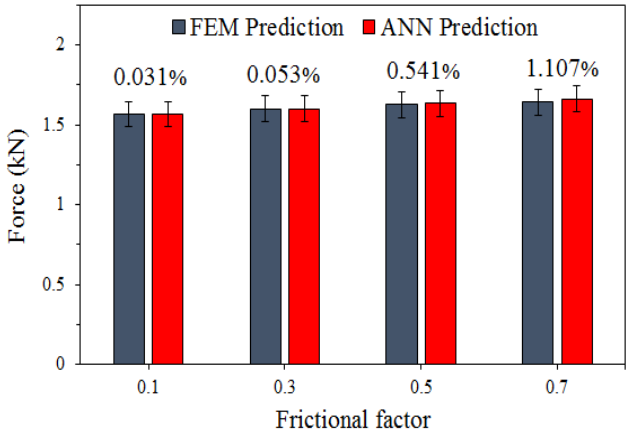
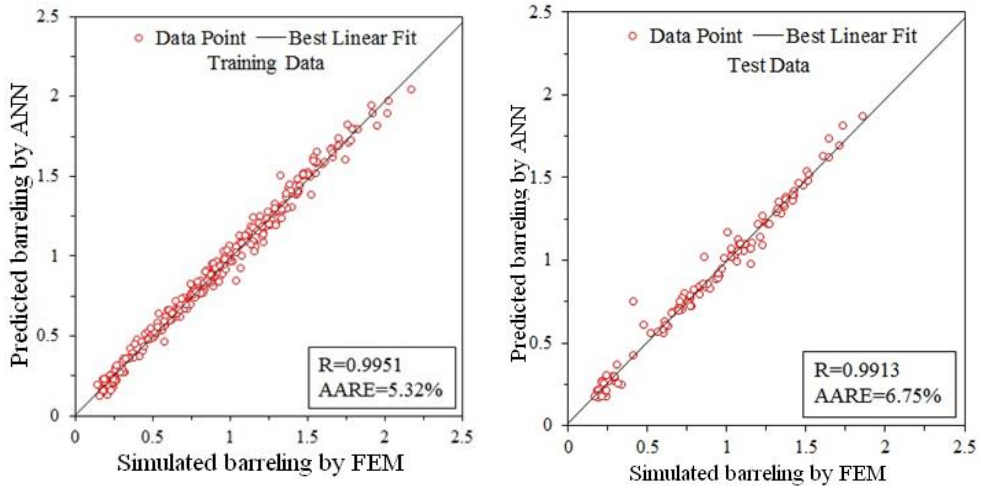


Fig. 10. Effects of frictional factor on the forging force for ram velocity of 25 mm/min, temperature of 500℃ at displacement of

4-2-Barreling parameter

The barreling parameter (B) has been calculated by Eq. (3) for each ram displacement under different deformation conditions. The comparison between the FEM results and ANN predications of barreling parameter for training and testing data has been presented in Fig. 11a and b, respectively. As it is clear, the results of ANN model and FEM are extremely similar hence the training and testing stages of the developed ANN have been successfully constructed and the developed ANN model can predict the barreling of specimen with a reasonable accuracy. Also, it can be seen that R and AARE values are 0.9951 and 5.32%, respectively in the training stage of the ANN. Whereas, the values of R and AARE are 0.9951 and 6.75% respectively for the testing stage of the ANN.



(a) (b)

Fig. 11. Performance of proposed ANN model in prediction of barreling parameter for the (a) training and (b) testing data set

The influences of the processing parameters consist of friction, temperature and ram velocity on the barreling parameter were investigated using FEM and ANN model. The variations of the barreling parameter with ram displacement or stroke in the different friction factor (m) have been shown in Fig. 12. The investigations of barreling results show that the frictional shear factor has the main effect on the barreling parameter during hot forging as the magnitude of barreling increases with increasing of friction.

Fig. 13 shows the effects of temperature on barreling. As it is clear, the barreling parameter decreases with the increasing of temperature at constant velocity and friction coefficient. This behavior occurs due to the increase in the plastic flow and the softening behavior of the material at elevated temperatures. The effects of ram velocity on the barreling parameter have been shown in Fig. 14. As can be seen, at constant friction factor and temperature, the effects of ram velocity on the barreling is irregular due to strain hardening.

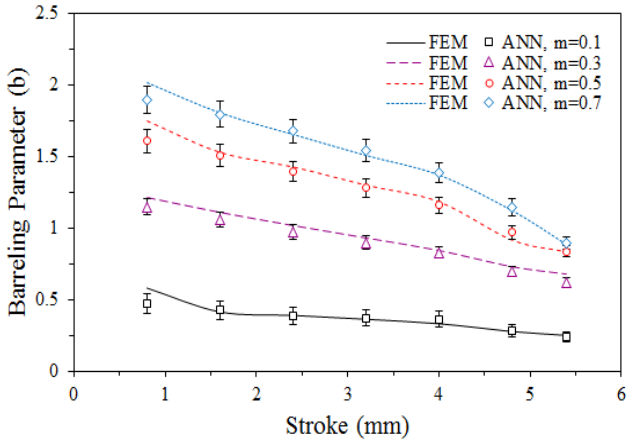


Fig. 12. Comparison between the FEM and ANN prediction of the barreling parameter for different friction factor at temperature of 350℃ and ram velocity of 250 mm/min

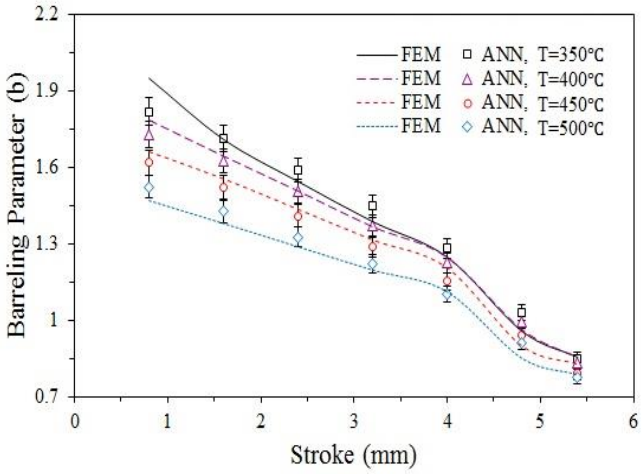


Fig. 13. Comparison between the FEM and ANN prediction of the barreling parameter for different temperature, at ram velocity of 125 mm/min and friction factor of 0.5

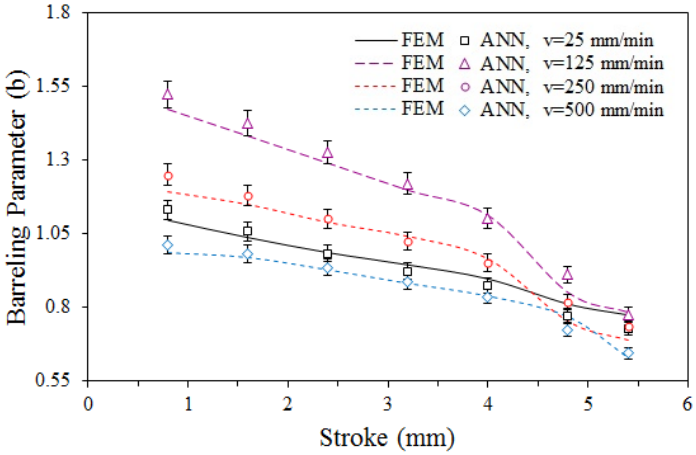


Fig. 14. Comparison between the FEM and ANN prediction of the barreling parameter for different ram velocity, at temperature of 500℃ and friction factor of 0.5

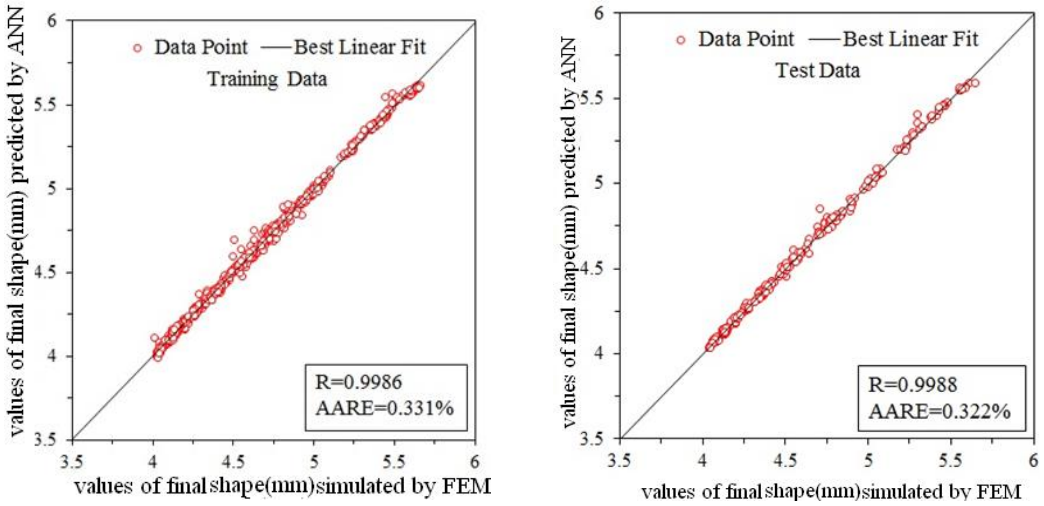
The standard statistical values of the barreling parameter predicted by the developed ANN model at different temperature levels have been listed in Table 5. It can be seen that the maximum values of R, AARE and RMSE are 0.9968, 6.172% and 0.042 MPa, respectively in training stage of the ANN R and AARE values are 0.9951 and 5.32%, respectively, in the training stage of the ANN, whereas, the values of R, AARE and RMSE are 0.9967, 7.778% and 0.041 MPa respectively for the testing stage of the ANN.

Table 5. Statistical values of barreling parameter predicted by ANN

Temperature (℃)	**R**		**AARE (%)**		**RMSE (MPa)**	
	Training	testing	Training	testing	Training	testing
350	0.9935	0.9967	6.172	4.074	0.042	0.034
400	0.9964	0.9941	4.607	7.117	0.032	0.038
450	0.9968	0.9862	4.997	7.778	0.031	0.041
500	0.9947	0.9920	5.629	6.889	0.032	0.039

4-3-Final shapes

As it was mentioned earlier, the final shapes of hot forged specimen are indicated by R_b and R_n which are the maximum and top surface radiuses of the hot forged specimen, respectively (see Fig. 1). Fig. 15a and b shows the comparison of the FEM and ANN results of the final shapes (R_n and R_b) of the forged specimen on training and testing data, respectively. It indicates that the R values are 0.9986 and 0.9988 for the training and testing stages of ANN, respectively. Moreover, AARE values are 0.331% and 0.322% for the training and testing stages of ANN, respectively. As it is clear, the developed ANN model can predict the final shape of the forged specimen with a reasonable accuracy.

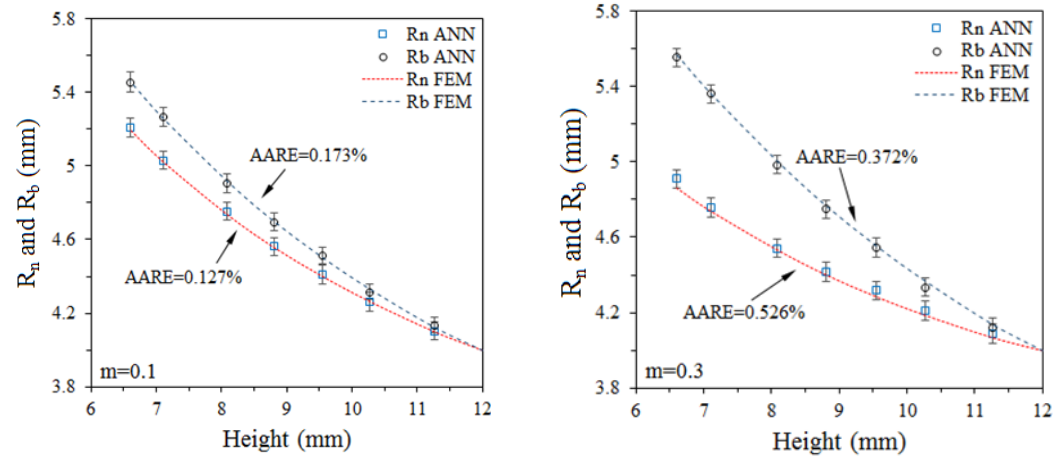


(a) (b)

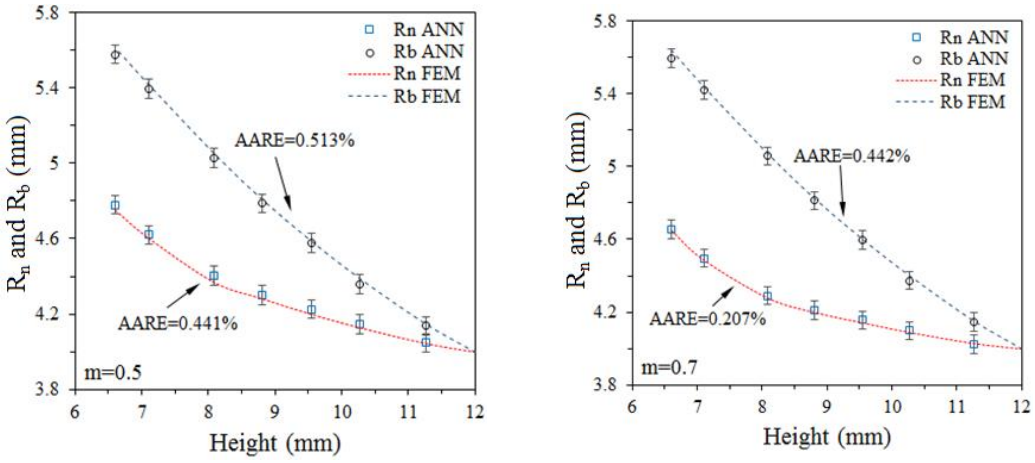
Fig. 15. Performance of proposed ANN in prediction of final shapes (a) training and (b) testing

The variations of R_n and R_b values with height of the forged specimen predicted by ANN and FEM have been shown in Fig. 16. As it is seen, the final shape sensitively increases with increasing of the friction coefficient in a same height of the forged specimen. Comparison of the FEM and ANN results indicates the predicted final shapes at different condition are in good agreement during hot forging. Also it is obvious that the distance between of the R_n and R_b values increases with increasing friction and decreasing height of the forged specimen at the constant temperature and ram velocity.

The predictability of the final shapes by the developed ANN model at various temperatures has been summarized in Table 6. It can be seen that the maximum values of R, AARE and RMSE are 0.9989, 0.356% and 0.018 MPa, respectively in the training stage of the ANN, whereas, the values of R, AARE and RMSE are 0.9993, 0.378% and 0.017 MPa respectively for the testing stage of the ANN.



(a) (b)



(c) (d)

Fig. 16. Comparison between the FEM and ANN results of final shapes at temperature of 400℃, ram velocity of 25 mm/min and frictional factor of (a) 0.1, (b) 0.3, (c) 0.5 and (d) 0.7

Table 6. Statistical values of final shapes predicted by ANN

Temperature (℃)	**R**		**AARE (%)**		**RMSE (MPa)**	
	Training	testing	Training	testing	Training	testing
350	0.9989	0.9988	0.324	0.378	0.015	0.017
400	0.9988	0.9991	0.321	0.313	0.015	0.014
450	0.9968	0.9993	0.342	0.278	0.016	0.012
500	0.9984	0.9982	0.356	0.330	0.018	0.015

5-Conclusions

In this work, an artificial neural network model was developed for the accurate prediction of isothermal hot forging process behavior of AlCuMgPb aluminum alloy under different processing conditions using experimental data

and a thermo–viscoplastic analysis based on a thermo-mechanical three-dimensional finite elements. The FE model was developed and verified to provide a data base for training and validation of the neural network. The developed ANN was used for prediction of the forging force, barreling and final shapes of metal being deformed. Noting the results of the FEM simulation and the developed ANN predictions, the following conclusions can be drawn:

- By comparison between the measured data and simulation results, the developed finite element model can describe well the hot forging behavior of AlCuMgPb aluminum alloy under different process conditions.
- The developed ANN predictions are found to be in extremely good agreement with the simulation results which indicates the capability of the developed model for predicting the effects of various parameters on the hot forging process.
- The ANN model is capable of considering the effects of important parameters such as temperature, height reduction, ram velocity and friction coefficient.
- Ram velocity and temperature have the maximum effects on the forging force, as the forging force increases with increasing of the ram velocity and decreasing of the forging temperature.
- The friction factor has the main effect on the barreling parameter and final shape during hot forging as the barreling parameter increases with increase of the friction values.
- Using ANN which has been learned properly, the time of process analysis

can be clearly reduced in comparison with FEM.

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