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ScienceDirect
Trans. Nonferrous Met. Soc. China 29(2019) 741−753
Transactions of Nonferrous Metals Society of China
www.tnmsc.cn

A forming load analysis for extrusion process of AZ31 magnesium

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Received 18 May 2018; accepted 12 November 2018

Abstract: The effect of extrusion parameters on the extrusion load for AZ31 magnesium alloy was investigated with the support of numerical methods. With this regard, the process temperature, extrusion ratio, friction factor and punch velocity were selected as main parameters for the experiments. Besides, the experimental results were analyzed by using the finite element method (FEM) and artificial neural network (ANN) method to build a numerical model for predicting the forming load. All the experimental and numerical results were compared to each other and it was concluded from the results that the effect of friction factor on the extrusion load is more dominant at lower extrusion temperature for all given extrusion ratios and punch velocities. Besides this, higher extrusion ratios require higher process temperatures to obtain the lower extrusion load. Also, it was observed that the increase in the extrusion speed causes a significant increase in the forming load for all extrusion ratios and extrusion temperatures.

Key words: extrusion; magnesium; AZ31; finite element method; artificial neural network

1 Introduction

Today, different materials are being tested to obtain lighter and more durable products that can meet different needs. Magnesium alloys have been added to this list with offering light weight, high specific strength, and superior damping capacity. It was reported that selecting magnesium material parts instead of aluminum and steel for the same volume of material usage would save the weight around 33% and 77% [1]. It is increasingly used in the automobile industry instead of aluminum and steel. Hence, magnesium has been the center of interest for various applications of automotive and aerospace industry in the last decade [2]. Even though casting products of magnesium are more dominant for various applications, wrought magnesium alloys offer significant advantages in strength and ductility over castings. Extrusion is a suitable process for manufacturing of magnesium wrought alloys providing the desired shapes of products with high specific strength and excellent dimensional accuracy.

Many researchers studied the microstructure and mechanical properties of extrusion products and the relation with extrusion parameters. For example, UEMATSU et al [3] studied on the grain refinement due to the extrusion process and the fatigue behavior of the extruded materials in three magnesium alloys, AZ31B, AZ80 and AZ61A. GALL et al [4] investigated the microstructure and mechanical properties of magnesium AZ31 sheets produced by extrusion. TANG et al [5] carried out various experiments to determine the effect of extrusion parameters on grain size and texture distributions. FATEMI-VARZANEH et al [6] studied the thermomechanical parameters on the microstructure of the AZ31 material and showed that dynamic recrystallization is very dominant with higher strain rates. KANG et al [7] investigated the results of severe plastic deformation on material characteristics. They concluded from tensile tests that the fracture elongation increased with decreasing grain size, while the yield and tensile strength decreased. CHANDRASEKARAN and JOHN [1] used AZ31 and ZK61 magnesium material and carried out experiments for different process temperatures to investigate their extrudability and microstructure. They showed in their study that AZ31 could be formed over 300 °C and Mg alloyed materials can be achieved better formability with higher process temperatures. CHEN et al [2] investigated the effects of extrusion ratio on the microstructure and mechanical properties. They used the AZ31B material for the experimental work and evaluated the results of the effect

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DOI: 10.1016/S1003-6326(19)64984-8

of extrusion ratio on tensile properties and hardness of the material. They proved that there was a critical extrusion ratio for grain refinement and the improvement of mechanical properties.

Besides those studies, some researchers paid attention to analyzing the extrusion process by using numerical methods for shortening the design procedure and eliminating the costly trial-error phase. HAGHIGHAT and MAHDAVI [8] used both upper bound and finite element for bimetal tube extrusion. Some studies reported in the literature focused on the simulations of extrusion of complex profiles and die designs [9−12]. BINGÖL [13] applied FEM method via DEFORM software on extrusion ram speeds for optimization of the process. In another study, BINGÖL and BOZACI [14] investigated the strength of the hollow extrusion profile with seam weld produced at different ram speeds with FEM method both experimentally and numerically. LIANG et al [15] simulated the extrusion process after applying experiments to collect initial data, such as friction factor, heat transfer coefficient and stress-strain curves for the FEM model. Forming load was the output and the comparison criterion for the different temperatures and frictional conditions. They showed that the extrusion load and billet temperature rise could effectively be reduced using oil-based graphite lubricant. Similarly, LI et al [16] investigated hot deformation behavior of extruded AZ80 magnesium alloy at temperatures ranging from 250 to 450 °C with strain rates varying from 0.001 to 10 s^{-1}. LIU et al [17] studied on the X-shaped profile extrusion of AZ31 type magnesium material. They investigated the correlations between the process variables according to the main process parameters (extrusion temperature and peak extrusion pressure) by 3D FEM model and finally compared the calculated results with experiments.

A faster method is getting more popular for metal forming operations as an alternative of finite element method. Artificial neural networks (ANNs) method is preferred because of its robustness and stability. Unlike the FEM, the ANN can predict the results without creating realistic simulations of the metal forming processes depending on many input parameters and could reduce the number of FEM simulations [18,19]. ASHHAB et al [20] applied the ANN method for deep drawing method. TEIMOURI and BASERI [21] used ANN on predictions for friction stir welding process. Moreover, ANN became a useful tool for making predictions for extrusion. HSIANG et al [22] investigated the relationship between the billet temperature and product tensile strength of the hot extrusion of magnesium alloy through ANN analysis. They analyzed the relationship between the temperature range and the tensile strength of a rectangular tube for various extrusion speeds and extrusion ratios. Additionally, some researchers like BINGÖL et al [23] integrated FEM and ANN methods to investigate the effect of gear tooth number, die land length, and extrusion ratio on extrusion load for gear-like profiles.

Extrusion load is the base point of the design study that helps to determine the die design, tool material selection, and press capacity. Nevertheless, so many parameters affect the extrusion load. Therefore, the research in this study aimed to investigate the effect of extrusion ratio, frictional conditions, process temperature and extrusion speed on the extrusion load by using numerical methods for predictions. For this purpose, the establishment of a predictive ANN model for forward extrusion was the focus of this study because of its potential for giving fast and accurate predictions. By achieving this target, firstly, experiments were carried out, and the extrusion load for the condition was saved. Then, FEM results obtained from DEFORM-3D model were compared and validated by experiments. The FEM model was expanded to be used as the initial test and train data for ANN study. Artificial neural network modeling predicted the effects of the parameters on the forming load.

2 Methodology

In order to predict the forming load, the study was divided into three stages. At first, the experiments were carried out to obtain forming load for different extrusion parameters such as extrusion ratio, frictional conditions and the process temperature of the extrusion. After that, the FEM model was built for the same problem to predict the extrusion load, and its results were compared and validated with experiments.

At second phase, the FEM model was expanded for extrusion speeds different from experimental values. The developed FEM model results were used as input dataset for ANN study. The ANN method was trained and tested according to FEM study. Finally, ANN results were compared with experiments. The flowchart of this study is given in Fig. 1.

2.1 Experimental study

In the presented study, commercial purity AZ31 was used as workpiece material because of its promising future as a structural engineering material for various industrial applications. The AZ31 chemical composition taken from Shimadzu EDX 720 is given in Table 1.

The physical properties of the AZ31 alloy are listed in Table 2.

The load−displacement data were collected from INSTRON 8501 test machine by tensile tests, and true stress−strain curves were calculated for process temperatures, as shown in Fig. 2. The true stress−strain curve data for punch velocities of 1, 5 and 10 mm/s were then uploaded to DEFORM material library for the FEM simulations.

Experiments were carried out in the PLC-controlled hydraulic press with capacity of 1500 kN. Load−stroke values were recorded and stored by the PLC system. Punch velocity was set to be 5 mm/s. The experimental AZ31 magnesium material was machined to cylindrical samples with a diameter of 30 mm and a height of 60 mm. The die, container and punch materials were selected as AISI H13 alloy hot work tool steel. The die materials were oil quenched and tempered at 500 °C. The hardness value for the die materials was measured as HRC 58. Inner surfaces of the container were polished for preventing the sticking effect. The die setup was heated by circular heating coil system and the temperature was set for specific temperatures (250, 300, 350 and 400 °C). The samples were first covered with aluminum folio to prevent from the oxidation and then put in an oven to be heated to the desired temperature for the experiments. The billet was heated in an external furnace and then swiftly transferred into the container. After that, extrusion started immediately. The die and workpiece were at the same temperature and so there is no heat transfer between die/workpiece interfaces at the beginning of the experiments. The heating coils covered the dies for heating the die for selected temperature levels. Experimental die setup is given in Fig. 3.

The samples were annealed before the experiments at 320 °C for 80 min to eliminate residual stresses and to provide complete recrystallization and homogenous grain distribution. The extrusion experiments were conducted for four different extrusion ratios and five different temperature values, as seen in Table 3. The temperature values were recorded and statistically evaluated and given in Table 3. The ambient temperature of the

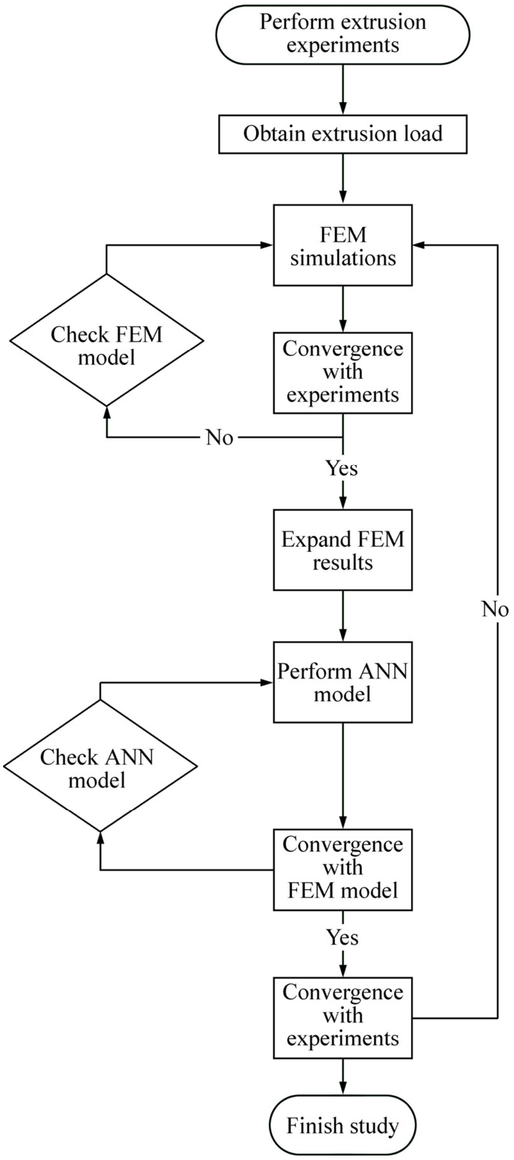

Fig. 1 Flowchart of study method

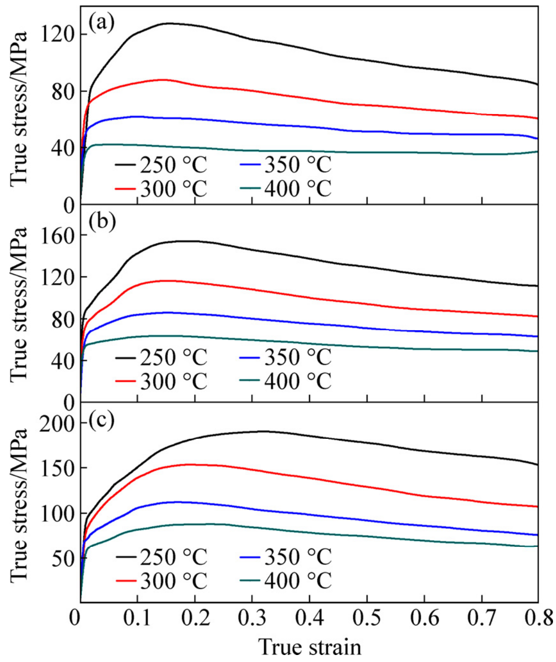

Fig. 2 Experimental true stress−strain curves: (a) v=1 mm/s; (b) v=5 mm/s; (c) v=10 mm/s

Table 1 Chemical composition of AZ31 used in experiments (wt.%)

Al	Zn	Si	Cu	Mn	Ni	Ca	Fe	Mg
3.1	0.94	0.01	≤0.01	0.21	≤0.001	≤0.01	0.004	Bal.

Table 2 Physical properties of AZ31 used in experiments

Poisson ratio	Density/ (kg·m^{-3})	Elastic modulus/ MPa	Emissivity	Coefficient of linear expansion/K^{-1}
0.35	1780	45000	0.12	2.68×10^{-5}

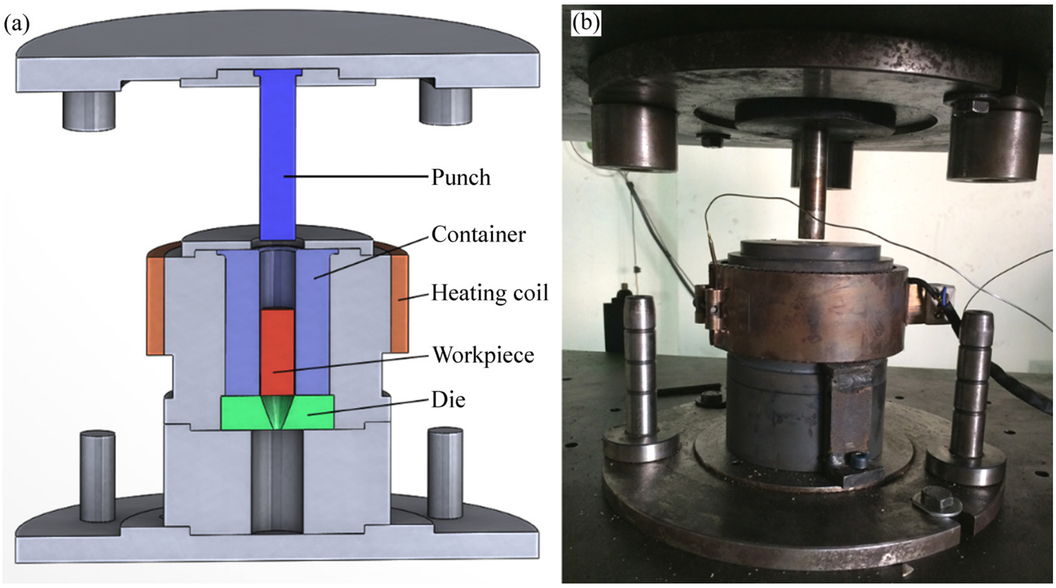

Fig. 3 CAD model (a) and experimental die setup (b)

Table 3 Measured temperature values of container and workpiece

Extrusion ratio	Billet temperature/°C	Container temperature/°C	Outlet temperature/°C
2, 4, 6, 8	250, 300, 350, 400	250, 300, 350, 400	Avg. 25

experiments was measured as 25 °C. Four different temperature values were selected (250, 300, 350 and 400 °C) for the experiments. Temperature values were measured for each experiment by TESTO infrared thermometer with K type probe.

The friction type was considered as shear and the friction factor (*m*) at workpiece/die interfaces was calculated as constant. The friction factor (*m*) is defined as 0.4 for dry conditions with well-cleaned samples obtained from the ring compression test and the friction factor was defined as 0.052 when MoS_2 lubricant was used and friction factor was 0.2 for the graphite-based lubricant in lubricated conditions [15].

2.2 FEM modeling

Finite element method is one of the most efficient method for complex engineering problems. FE method is based on dividing the whole geometry into the finite elements and then calculations were performed for every single element. Final result for general geometry is the sum of every elemental result. There are a number of FEM based softwares for specialized research areas and DEFORM 3D is a commercial software specialized for metal forming problems [24]. Lagrangian finite element code was used in the simulations. The geometric model was first built and assembled in CAD software and then imported to DEFORM 3D as STL file format. The FEM model is given in Fig. 4. The billet was selected as plastic material and die components were defined as rigid bodies. The AZ31 type material was generated in the software library according to test data taken from tensile tests. The die component materials were selected from the software library as H13 die steel material. Mesh distribution is essential for the accuracy of the FEM result and also affects the calculation time and data storage space, so the optimum mesh should be selected to balance the simulation time and the sensitivity. Element number was determined as 110000 elements for workpiece material and 45000 elements for die components. It was decided that the convergence error limits for velocity and load are 0.005 and 0.05, respectively. The global remeshing was chosen, and the

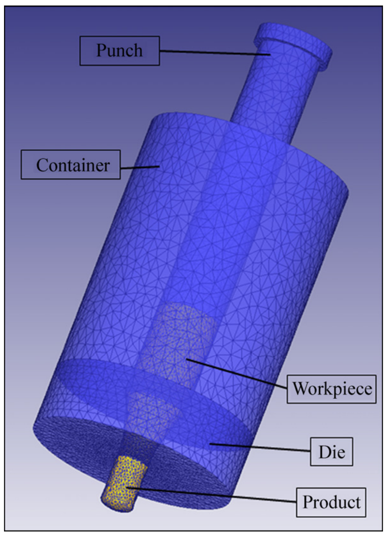

Fig. 4 FEM model and mesh distribution

type of interference depth was selected as relative one and its value was considered as 0.7. The Conjugate−Gradient solver has been used to solve the problem because of its capability for complex geometries. The constant friction factor was used by several researchers like FERESHTEH-SANIEE et al [24]. So, in this study, it was selected as 0.052, 0.2 and 0.4 as it was defined in the experiments. The die and workpiece temperatures for each sample were measured before the experiment starts. Heat transfer coefficient between die and workpiece was set to be 11 $N\cdot s^{-1}\cdot mm^{-1}\cdot °C^{-1}$.

The mesh distribution was selected to be as possible as homogenized on the flow region of the workpiece. The initial temperatures of billet, container and the die were taken to be as same as measured in the experiments as seen in Table 3 for FEM simulations.

2.3 ANN study

Expert systems such as fuzzy logic, artificial neural network (ANN) and the genetic algorithm can be used to predict the material behavior under different conditions. Among them, artificial neural networks are powerful than other traditional methods for the solutions of complex problems where mathematical models are challenging to build and for problems, especially where the boundary conditions are not well defined, or the solution are complicated to calculate. The fact remains that, finite element method also can make predictions for the same conditions of the problem but, when the parameters were changed, it requires renewing the simulations. Conversely, ANN does not need a new model for the same situation, unlike others. That is the most crucial advantage of the ANN method. Hence, many researchers paid attention to applying ANN solutions for complicated engineering problems, particularly in the last decade [25].

An ANN structure is built on three main layers which are defined as a set of input, one or more layers of hidden nodes, and a set of output nodes aiming to establish a connection with input and output data sets. Some neurons in each layer operate as independent elements and are intimately related together. The learning method is critical stage of the study and different learning rules can be used so, proposed ANN model is trained by a back-propagation algorithm which is the typical learning method, and then subjected to testing and verification using a new data set.

Learning rule [26] is generally given as

$$(W_{kj})_{\text{new}} = (W_{kj})_{\text{old}} + \Delta W_{kj} \tag{1}$$

where W is the weight of the layer, ΔW represents the change in weight, k is the kth node of the output layer and j represents the jth node of the hidden layer.

Best weight increment is computed by updating the values in each step with Eq. (2). The momentum is combined for fast convergence of the back-propagation algorithm:

$$\Delta W_{kj}(K) = \eta\delta_{ok} y_i + \alpha\Delta W_{kj}(K-1) \tag{2}$$

where $\Delta W_{kj}(K)$ is the change in the weight for the Kth iteration, $\alpha\Delta W_{kj}(K-1)$ is named as momentum term, η is the learning rate parameter, δ_{ok} is an error term for node i, α is the forgetting factor in the interval (0,1) and $\delta_{ok}y_i$ is the partial derivative of the error signal. The momentum is combined for fast convergence of the back-propagation algorithm.

The network is continuously run and updated to an acceptable error criterion value by a training function. The back-propagation artificial neural network with a Levenberg–Marquardt and momentum algorithm is employed to predict the forming load. The algorithm was coded in the MATLAB software to train the neural network model. The number of hidden layers and the number of neurons in each hidden layer were calculated based on trial and error and the mean squared error. Necessary input and target data for ANN study were obtained from FEM study. Following iterations for the ANN model was simulated and the training procedure was stopped when the mean error was 0.99955 between output and target. The new outputs of the ANN model were compared with FEM and finally experimental results. ANN made predictions according to training data obtained from FEM study. This model used the extrusion ratio, process temperature, friction factor and extrusion speed for input data and the extrusion forming load is the output layer with different process parameters. The structure of the ANN method is given in Fig. 5.

The levels of ANN study based on the FEM results are given in Table 4 in detail.

3 Results

3.1 Experimental and FEM results

For the extrusion researches, extrusion load prediction is the crucial point to determine the optimum press capacity. Besides, it is essential to understand the effects of extrusion parameters on the extrusion load. In traditional approaches, many researchers do many experiments and solve complicated equations. However, numerical methods promise significant advantage instead of expensive and long-continued trial and error. The current study was performed for this purpose including three phases. The first stage starts with experimentation with direct extrusion of AZ31 magnesium alloy material under different initial conditions to provide a database for numerical analysis of both FEM and ANN.

Figure 6 shows the variation of the extrusion load with the change of extrusion ratio for different process

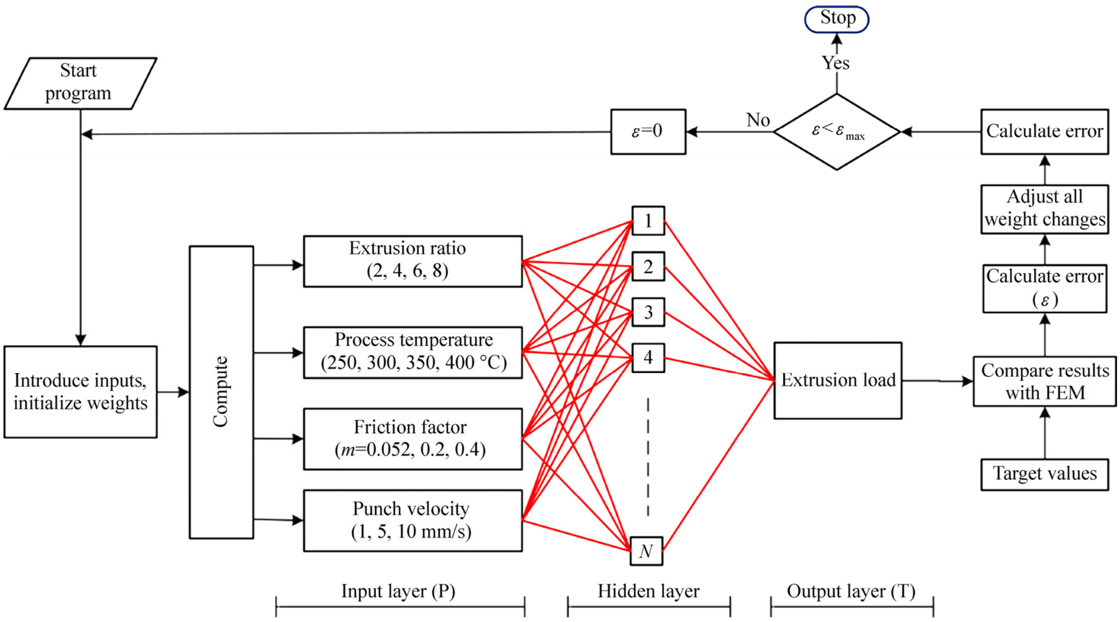

Fig. 5 Flowchart of ANN study

Table 4 Levels of parameters used in simulations

Input parameter	Level 1	Level 2	Level 3	Level 4
Process temperature, T/°C	250	300	350	400
Extrusion ratio, R_E	2	4	6	8
Friction factor, m	0.052	0.2	0.4	−
Punch velocity, v/(mm·s^{-1})	1	5	10	−

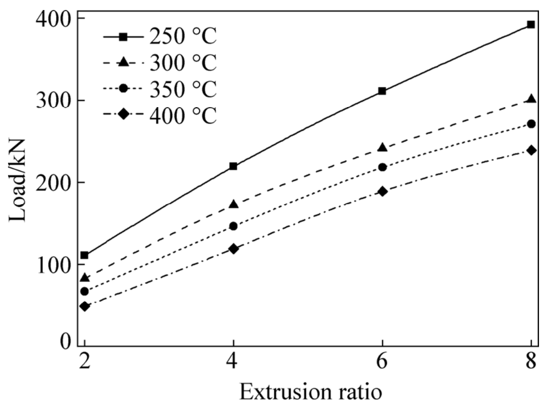

Fig. 6 Experimental load comparison for different process parameters at m=0.052

temperatures of friction factor m=0.052. The highest forming load was obtained at 250 °C process temperature for all given extrusion ratios. A significant decline in the forming load could be observed after increasing the temperature, and all of the extrusion loads decrease. That is the result of the crystal lattice structure of magnesium that the temperature starts the deformation mechanisms and activates dislocations at the same time. The effect of temperature rise has different responses for different extrusion ratios, but significantly, higher extrusion ratios require higher process temperatures for lower extrusion load. For the samples with the extrusion ratio of 2, forming load was measured as 110 kN for 250 °C; when it was 54 kN for 400 °C, the forming load decreased by about 50%, in return for the rise of temperature from 250 to 400 °C. However, that change in the load was observed differently for higher extrusion ratios. Especially, for the temperature of 400 °C, the decrease of the forming load was measured at about 144 kN which equals 36% decrease in the load.

Figure 7 gives the load comparison for different extrusion ratios when the friction factor was m=0.2. It was observed an increase in process temperature from 250 to 300 °C caused load decrease for extrusion ratio of 2 by about a range of 20%. The forming load decreases considerably by increasing the process temperature. For the extrusion ratio of 4, the extrusion load decreases in the range of 24% for the 50 °C temperature rise. At

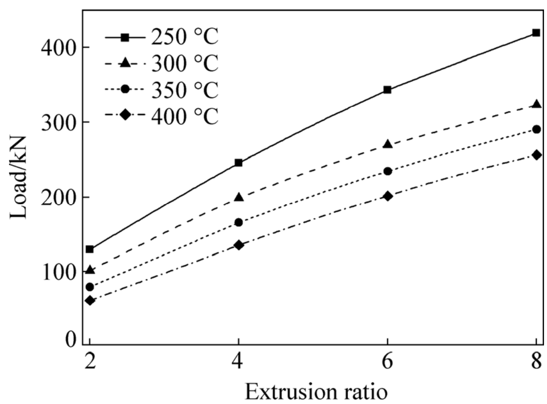

Fig. 7 Experimental load comparison for different process parameters at m=0.2

300 °C process temperature, the decrease in the forming load is proportional and shows linear tendency conversely. The load change curve shows exponential character for 250 °C process temperature. Additionally, the forming load increases with the increase of the extrusion ratio. For the higher extrusion ratio, the forming load is sensitive to the rise of the process temperature compared to the lower extrusion ratio values. This effect is more apparent for the extrusion ratio of 8. The extrusion load could be reduced by about 40% by increasing the temperature to 400 °C compared to measured load value of 250 °C process temperature.

It can be concluded from the Fig. 8 that, when the extrusion ratio increases from 2 to 8, the load value increases by 2.96 times for 300 °C process temperature, but, this increase becomes 3.74 times whereas process temperature was 400 °C. This result can be explained as a positive effect of the process temperature on the formability of the AZ31 type magnesium material.

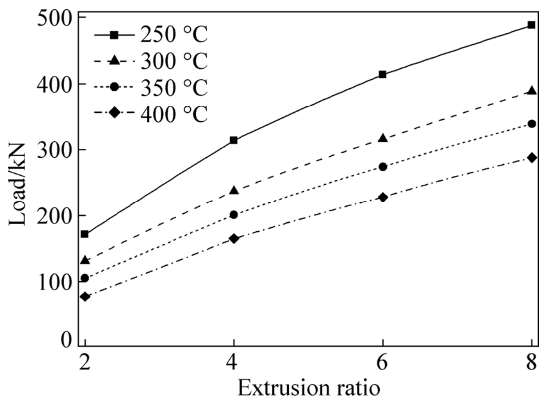

Fig. 8 Experimental load comparison for different process parameters at m=0.4

When the diagrams were evaluated together, both frictional forces and extrusion ratio are useful parameters on forming load but notably, the higher extrusion ratios lead to increased extrusion load. Addition to this, the point which temperature changes from 250 to 300 °C, is noteworthy. After that point, increasing the process temperature gives rise to a reduction in the forming load. This positive effect on forming load is related with forming behavior of magnesium and it is specially essential when higher extrusion ratios are concerned, because magnesium and its alloys have limited formability at room temperature due to their hexagonal crystal structure. There are three slip systems in HCP metals: basal, prismatic and pyramidal, and only basal slip system is active. For this reason, magnesium and its alloys are difficult to be formed at room temperature. However, raising temperature activates other slip systems by generating local stress concentrations and leading to accumulating the dislocations on the grain boundaries and enhances the ductility of magnesium. The effect of process temperature on the extrusion load shows similarity with results obtained from CHANDRASEKERA and JOHN [1].

After the experimental study, actual experimental results were compared with DEFORM-3D software FEM results. DEFORM 3D simulations were used to put foresights about real forming problems without any experiment. The main purpose using DEFORM 3D aided FEM study is to determine the forming load for different process temperatures, extrusion ratios, frictional conditions and punch velocities. A satisfactory convenience can be clearly seen between calculated FEM results and the experiments. The maximum forming load was determined to be the comparison criterion for the prediction of forming load for different process conditions because of its importance for the selection of press capacity and optimum die design. Figures 9−11 suggest the comparative diagrams for all extrusion ratios under different frictional conditions.

Figure 9 gives the load comparison for m=0.052. The regression value was used to measure statistically how FEM data are close to the experiments. It is seen that the estimated forming load decreases with the increase of the process temperature, same as experiments. The measured and calculated load values are very close to each other, as seen from the regression values of each diagram. The regression values are of 99.99% accuracy, which proves the validity of the proposed FEM model.

The prediction of the maximum extrusion load is vital to decide all forming parameters such as die design, press capacity, and tool material selection, so the proposed FEM model shows reasonably good prediction results when being compared with the experimental study, as seen in Figs. 9−11. The maximum load error is less than 9% for all predictions, which shows that the FEM estimations are in good agreement with the actual extrusion experiments. The regression (R^2) values, which validates that the FEM model fits with the experimental data and the differences between the measured and predicted values are acceptable and unbiased for all experimental conditions. The regression value for friction factor of m=0.052 is calculated as 0.9997−0.9999. The regression value is observed as <0.9994 when friction factor is 0.2. The FEM model gives a suitable prediction for given process parameters. For the friction factor of m=0.4, the regression values were obtained between 0.9987 and 0.9999. The more accurate results regarding regression value were taken from the lower process temperatures. However, in general, the obtained regression values which identify the applicability and validity of FEM model could be acceptable for future predictions. This also reveals the robustness of the proposed FEM model for giving accurate predictions.

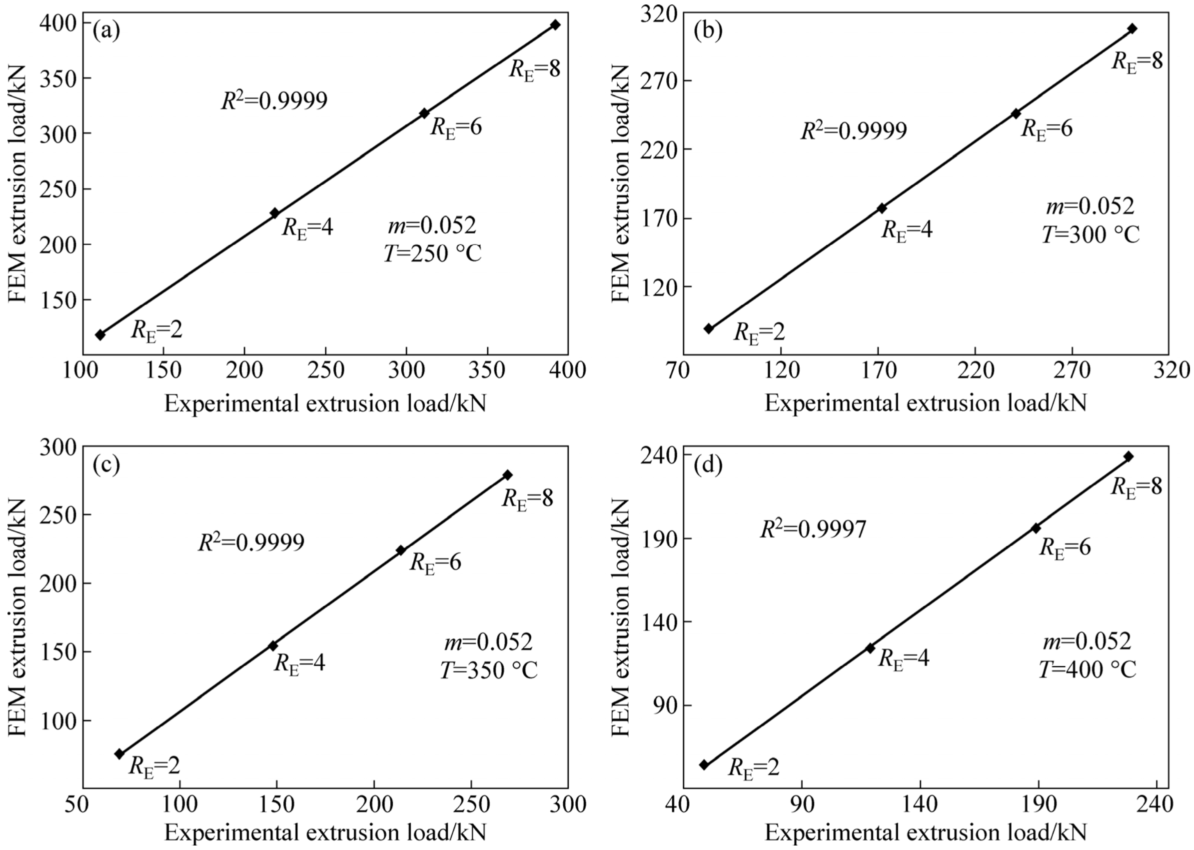

Fig. 9 Comparison between FEM and experimental load values for m=0.052

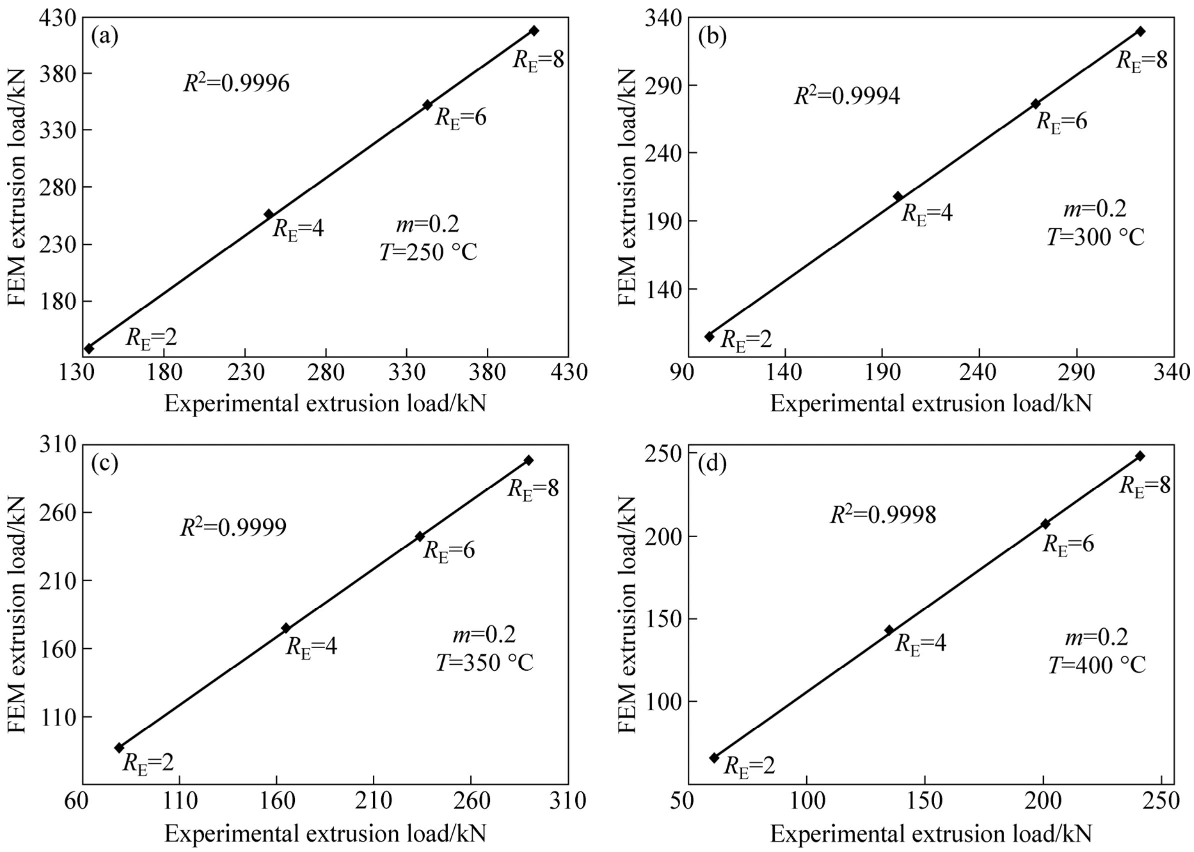

Fig. 10 Comparison between FEM and experimental load values for m=0.2

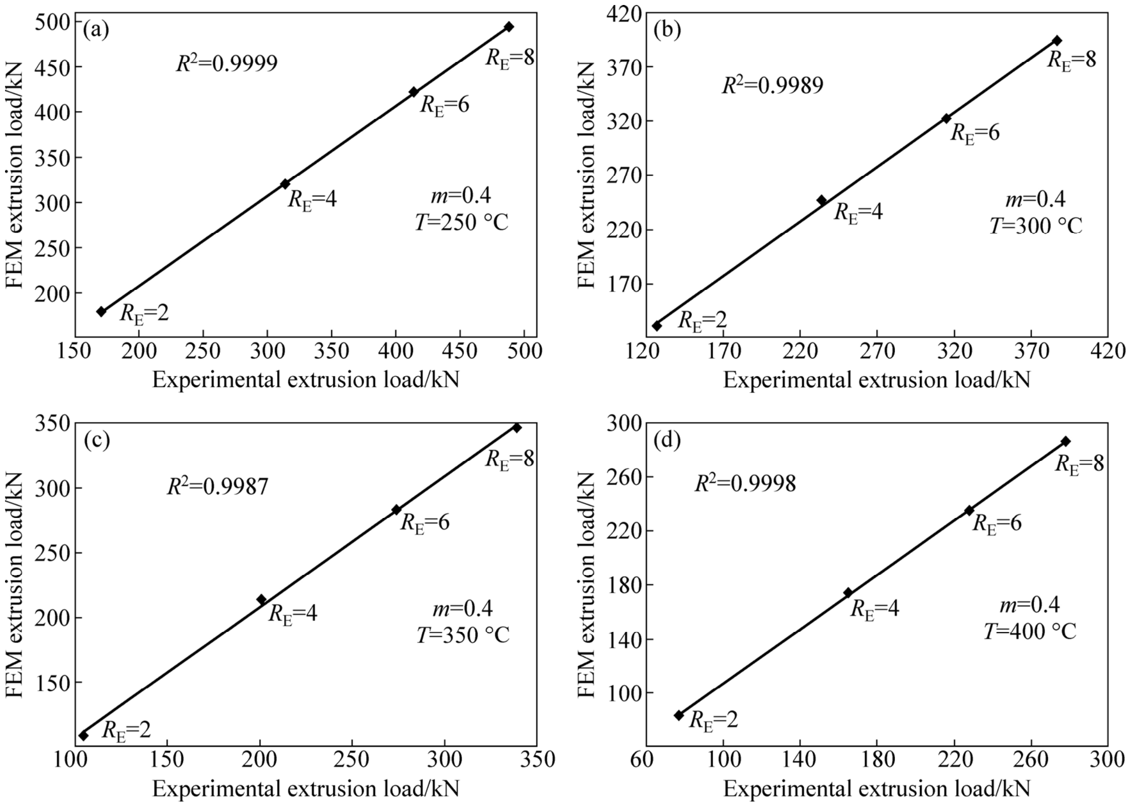

Fig. 11 Comparison between FEM and experimental load values for m=0.4

After approving the reliability of FEM results with experiments, the FEM model was extended to obtain results according to different process parameters in addition to experiments. For this purpose, the effect of the extrusion velocity change was investigated additionally. The simulations were performed with new extrusion parameters. Extrusion load values were used as test and validation of ANN study.

3.2 Application of ANN method

Applying a stronger prediction method gives an ability to neural network to generalize new data. For this aim, the obtained data set is divided into two categories which can be called as training and test subsets. Levels of the parameters are listed in Table 4. Then, testing subset data are used to measure the generalization of the network. Among 144 data patterns which are given in detail in Table 5, 108 data are categorized to training representing 75% proportion, and 36 data pattern which represents the proportion of 25% is selected to test the built ANN model. In this study, the testing data patterns were used at the final stage of the calculation as a test instrument for the accuracy of the network. Levenberg–Marquardt and Momentum were selected to obtain the best fitting back propagation algorithm for the proposed model. The coefficient of multiple determinations (R^2) value was compared with the predicted ANN results and simulated FEM data set. Back-propagation algorithm is the most used learning algorithm for the ANN method. Moreover, the performance of the BP algorithm was measured with average absolute error (%). The results of this comparison for the proposed model are given in Table 6 with the maximum R^2 and the minimum average absolute error for the Levenberg–Marquardt (LM) algorithm and transfer function of TanhAxon.

Hidden layer of the ANN algorithm needed a transfer function to define the nonlinearity into the network. A TanhAxon transfer function was selected as a transfer function. FEM simulation was applied as the feed-forward neural network for the forming load prediction of ANN model.

In the hidden layer, the optimum number of neurons should be determined according to comparison values by using trial and error. Four neurons in the hidden layer were used for initial guess value as a starting point for the optimization of the trial process. Subsequently, the number of neurons to achieve the optimum multiple determination coefficients (R^2) was increased until it reaches 28 neurons for Momentum while the Levenberg−Marquardt back-propagation algorithm with a TanhAxon transfer function at the hidden layer was given more accurate R^2 value with 12 neurons. So, it was selected as a fast and accurate function for ANN calculations.

Table 5 Design of extended FEM simulations for training and testing ANN model

Punch velocity/ $(mm \cdot s^{-1})$	Process temperature/ °C	Forming load/kN											
		R_E=2			R_E=4			R_E=6			R_E=8		
		m=0.052	m=0.2	m=0.4	m=0.052	m=0.2	m=0.4	m=0.052	m=0.2	m=0.4	m=0.052	m=0.2	m=0.4
10	250	305	378	412	408	511	563	585	661	736	674	741	873
	300	225	286	331	326	405	492	475	514	621	598	662	751
	350	192	224	265	281	324	401	387	422	512	462	503	663
	400	144	174	201	213	279	263	301	376	443	341	419	546
5	250	118	134	179	228	271	320	318	352	422	398	427	494
	300	89	105	126	177	208	248	246	276	311	308	329	394
	350	76	92	109	154	187	225	227	239	283	279	298	346
	400	54	67	83	124	143	179	196	198	235	248	263	296
1	250	81	108	141	121	152	195	236	269	338	287	314	375
	300	64	78	92	81	98	150	161	187	226	221	235	281
	350	51	61	84	64	75	129	129	152	176	192	187	228
	400	39	49	58	42	51	92	91	104	148	165	171	168

Table 6 Comparison of different neural network modeling results

Algorithm	Function	Neuron No.	R^2	Average absolute error/%
LM	TanhAxon	12	0.9997	1.25
Momentum	TanhAxon	12	0.9965	6.75
Momentum	TanhAxon	20	0.9978	4.36
Momentum	TanhAxon	28	0.9986	2.34

Although trained ANN does not fit 100% with the simulation results which were taken from FE model, it approaches suitably to the FEM solution results. Predicted values are necessary to be validated for ensuring that the proposed model is applicable for various process parameters. Similarly, KIM and KIM [26] applied the neural network method to metal forming processes with the support of FEM also. It can be clearly seen that the input data set is admissible with small errors for the problem. It is important to note that errors are connected directly to the deviations of the ANN training results from the FEM train data. The ANN training which contributes to minimize the errors in the optimal inputs minimizes the deviations of the ANN outputs from the FEM model outputs. In addition to that, the Jacobian matrix should be calculated numerically and requires FE simulation data in small increments as inputs for each calculation cycle. The available data indicate that the outputs are sensitive enough for all the inputs over the given range providing satisfactory confidence that the Jacobian matrix does not become singular. Moreover, the obtained errors should be identified to be acceptable or not. If necessary, optimal inputs in the time-consuming FE simulation can be verified by a single study.

A feed-forward ANN model was used for prediction of extrusion load with one input, one hidden and one output layer. The proposed model is capable of predicting the extrusion load satisfactorily when the results were compared with the experimental one. This outcome shows that the ANN model is more successful than the finite element method over the range of the training data. Apart from the training data, the theoretical model is generally more sophisticated and it captures many essential features of the existing theory.

As it is seen from Fig. 12, the ANN model for prediction of forming load can not only perform well in training/validation but also accurately predict the test sets

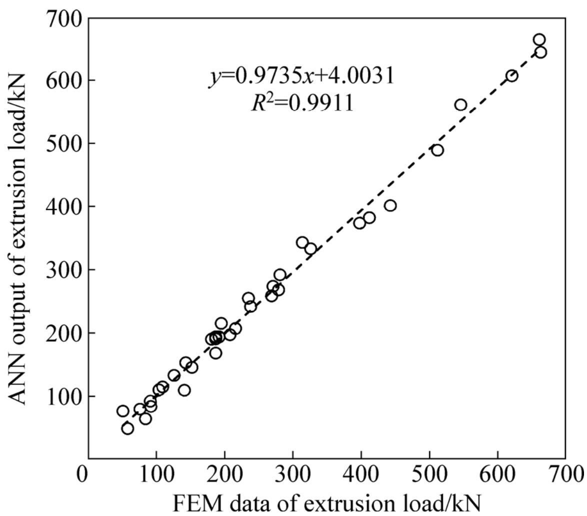

Fig. 12 FEM simulation and ANN predicted extrusion load in test period

with a linear correlation coefficient (R^2) of 0.9911. For the prediction of forming load, this is an excellent correlation.

Computer training is performed on specific epoch numbers. An epoch is a cycle that the algorithm sees all samples in the dataset. Thus, the obtained results are the number of epochs which are determined by comparison with a minimum tolerance. Different functions can be used for Epoch. In the proposed ANN model, epoch number when the training error was at its minimum is 733. The minimum calculated error is 0.000275696. Training error was calculated as 0.000282799 at the last Epoch. The general view of epoch course can be seen in Fig. 13.

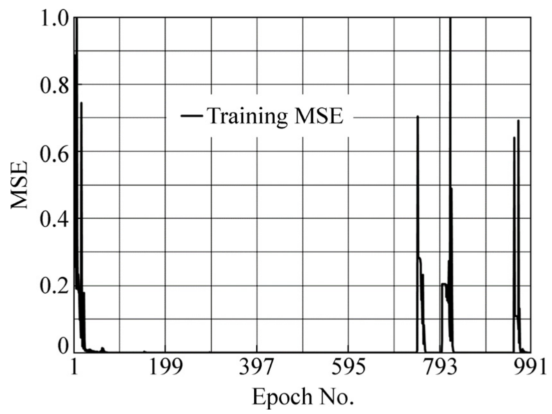

Fig. 13 Mean square error values for epoch

Figure 14 gives the desired output values of the ANN method and actually measured forming load from experiments. The figure reveals that the proposed ANN model predicts the experimental forming load. The courses of the curves are so similar, which represents the validity of the ANN model. The obtained results show the high compatibility of ANN and experiments, which means that ANN model is capable of identifying the variables dominating the extrusion load with high accuracy.

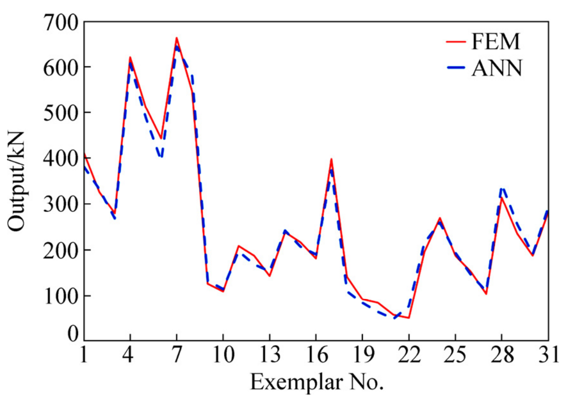

Fig. 14 FEM simulation and ANN predicted extrusion load in test period

The correlation of ANN prediction results versus experimental ones is given in Fig. 15. Regression coefficient (R^2) value was obtained as 0.9939, and such a high regression coefficient value expresses a good agreement between experimental results and validity of the ANN model. It can also be seen in Fig. 16 that the ANN model results are very close to the experimental ones according to the error values.

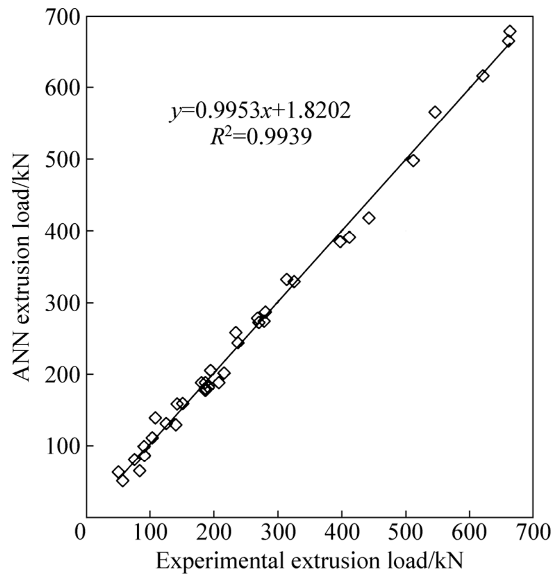

Fig. 15 ANN predicted extrusion load versus experimental results

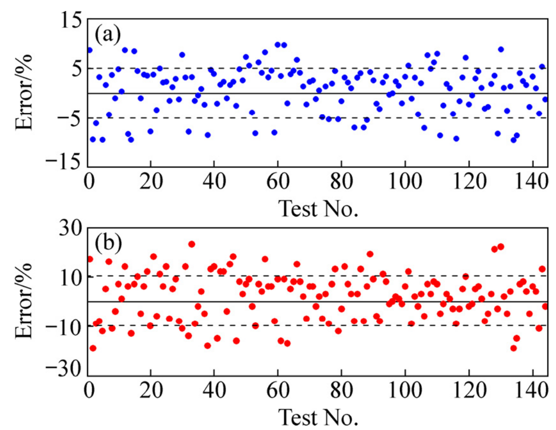

Fig. 16 Relative error (a) and absolute error (b) of ANN compared with experiments

It is obvious from Fig. 16 that the differences between ANN and experimental results are in the range from −19.81 to 23.71 kN but most are in ±10 kN. The relative error results are in the range from −9.39597% to 9.78261%, but mainly error values are cumulated in ±5%. It is observed that there is no favorable proportion for most points because of the change of the forming load. Consequently, using relative error values would give a more realistic approach for the prediction performance of the ANN model.

4 Conclusions

(1) Regarding the statistical measurements, comparisons show that the ANN method can be used as a fast and accurate prediction tool instead of long-running and uneconomic experiments in the process-planning phase for metal forming operations. Also, it can be supported by FEM study to obtain more accurate prediction results.

(2) It is found that the effect of friction factor on the extrusion load is more dominant at lower extrusion temperatures compared to all given extrusion ratios and punch velocities.

(3) According to the comparative results, higher extrusion ratios require higher process temperatures in order to achieve a lower extrusion load.

(4) The increase in the extrusion speed causes a significant increase in the forming load for all extrusion ratios and extrusion temperatures.

(5) Raising the process temperature causes to decrease forming load till 350°C, but from that point, the increase in the temperature does not lead to a significant decrease for AZ31 magnesium.

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镁合金挤压成形过程中的成形载荷分析

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摘　要：采用数值模拟方法研究挤压成形过程中工艺参数对 AZ31 镁合金挤压载荷的影响，选取挤压温度、挤出比、摩擦因数和冲压速度作为主要参数。采用有限元法(FEM)和人工神经网络(ANN)方法对试验结果进行分析，建立可预测成形载荷的数值模型。将实验结果和数值分析结果进行比较，结果表明，对于所有给定的挤压比和冲压速度，在较低的挤压温度下，摩擦因数对挤压载荷的影响最大。此外，当挤压比较高时，需要较高的加工温度以便获得较低的挤压载荷。结果还表明，在所有的挤压比和挤压温度下，提高挤压速度会导致成形载荷显著增加。

关键词：挤压；镁；AZ31；有限元法；人工神经网络

(Edited by Bing YANG)