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ORIGINAL ARTICLE

Extrusion load prediction of gear-like profile for different die geometries using ANN and FEM with experimental verification

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Abstract This paper deals with the extrusion of gear-like profiles and uses of finite element method (FEM) and artificial neural network (ANN) to predict the extrusion load. In the study, gear-like components has been manufactured by forward extrusion for the AA1070 aluminum alloy and the process was simulated by using a DEFORM-3D software package to establish a database in order to provide the data for ANN modeling. Serious experiments were performed for only one die set and four teeth gear profile to obtain data for comparing with DEFORM-3D results. After verifying a highly appropriate FEM simulation with the experiment at the same conditions, Results were enhanced for different die lengths, extrusion ratios, and two extra teeth number as three and six using FEM simulations. Subsequently, the data from the performed FEM simulations were submitted for the best obtained ANN model. Finally, a good agreement between FE-simulated and ANN-predicted results was obtained. The proposed ANN model is found to be useful in predicting the forming load of the different die set variations based on the reliable test data.

Keywords Gear forming · Finite element method · Artificial neural network · Extrusion · Aluminum

1 Introduction

Extrusion is a commonly used metal forming process in which metal billet is forced into a die that is containing a desired product shape. The direct extrusion of rods and solid shapes is the simplest production method in use. Uniform material flow in the cross-section area is highly important to obtain high quality products in the extrusion process. Besides the type and speed of extrusion, billet material properties at extrusion temperature, frictional conditions, type-layout, and design of die and extrusion ratio (ER) deeply influence the material flow. The die set design is also another decisive factor for the extrusion process. Optimum design would give the product quality and less deformation load. In the past, researchers used conical die because of the ease of the manufacturing. But for the past two decades, CNC machines have provided to manufacture complex die shapes and products like curved dies. Many researchers have performed studies on linearly converging and cosine die profiles because of their advantages in deformation load. Azad-Noorani et al. [1] studied on the optimal die profile by using finite element method (FEM) analysis and experimental results with the comparison of the conical and curved die profiles. They obtained the FEM results and experimental results are found quite familiar but curved dies give 12 % less extrusion load for the same profile. In common with Azad-Noorani, Bakhshi-Jooybari et al. [2] obtained FEM, upper bound method, slab method, and experimental results for conical and curved dies by using lead and aluminum to obtain the optimum die profile. Maity [3] also investigated the three-dimensional extrusion of square section from square billet with a polynomial-shaped curved die using the upper bound method and compared it with the experimental results. Chen and Ling [4, 5] proposed a velocity field for axisymmetric extrusions through cosine, elliptic, and hyperbolic dies. Many of the studies have been performed to investigate the effect of the die profile on the deformation load and the product quality. Reggiani et.al [6] used FEM method to predict the charge weld in hollow sections and validated their results with experiments. Fereshteh-Samiee et al. [7] optimized geometries of the second-order polynomial and

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exponential die profiles in order to minimize the extrusion load by means of experimental, numerical, and analytical approach. Their study showed that the influence of the die geometry was more apparent at lower extrusion ratios. Karami and Abrinia [8] developed a new kinematically admissible velocity field for the forward extrusion of a square section from a round billet and compared the upper bound results with FEM and experimental results. Onuh et al. [9] investigated the effect of the punch velocity and for the different extrusion ratios, extrusion load increases with the increase of the extrusion velocity, respectively. Qamar et al. [10] analyzed the effect of the shape complexity on the dead metal zone and metal flow through the flat-faced dies by experimental and numerical methods using Ansys-LS-Dyna. Zhang et al. [11] applied Taguchi's design to optimize the aluminum extrusion process of hollow sections based on experimental data and the results of numerical simulations.

For the last two decades, there has been an increased interest in the used metal forming methods like forging and extrusion to manufacture gears which are conventionally manufactured by metal cutting methods. Gears are the main machine components that transfer the torque and power and they need high mechanical properties and good surface quality and for this reason, bulk forming methods are convenient for gears to have longer service life and lower manufacturing cost. Jung et al. [12] carried out two different experimental methods to obtain the spur gear form. Song and Im [13] developed a software for the extrusion of the solid and hollow gears. They also proposed empirical equation to have the efficient die design. Altinbalik and Ayer [14, 15] performed a series of studies for the extrusion of clover sections which are used for trochoidal gears of external gear pumps.

On the other hand, expert systems such as artificial neural network (ANN), fuzzy logic, and genetic algorithms have been used to predict the material behavior at various conditions [16–19]. Some researchers developed a genetic algorithm to optimize the identified model for optimal shape with minimum force and strain. Among them, the ANNs are very efficient models as an alternative to classical regression models. Artificial neural networks (ANN) are a mathematical system having an interconnected assembly of simple elements, which emulates the ability of biological neural network. ANN models can represent a complex nonlinear relationship between the input and the output of any system. Furthermore, they can solve a diversity of problems because of their speed and capability of learning, robustness, predictive capabilities, generalization properties and ease of working with high dimensional data [20–23]. Regarding the application of ANN modeling to metal forming, Li and Bridgwater [24] studied to forecast the extrusion load. Hsiang et al. [25] studied to investigate the influence of temperature on hot extrusion of AZ61 magnesium alloy using artificial neural networks. It is found that the ANN can accurately analyze the tensile strength distribution for rectangular tube under different parameters. Toros and Ozturk [16] used the ANN modeling to identify the material flow curves of strain hardened 5083-H111 and 5754-O Al–Mg alloys. Qin et al. [26] performed ANN modeling to evaluate and predict the deformation behavior of ZK60 magnesium alloy during hot compression. Zhou et al. [27] used ANN model by taking extrusion ratio, ram speed, shape complexity, and ram displacement as the input variables and the extrusion load and exit temperature as the output parameters for a specific AZ31B magnesium extrusion alloy shape. Jawwad and Barghash [28] studied the effects of industrial extrusion process parameters and their interactions on the resulting maximum extrusion pressure by using a newly devised ANN-based partial modeling technique. They found that their ANN-based model has shown superior prediction capabilities compared to the linear model with a marginal overall prediction error value of ±2.5 %.

Extrusion load is one of the most important parameters to obtain the suitable die design. However, there are so many parameters that affect the extrusion load. Herein, it should be noticed that, to the authors' best knowledge, a predictive ANN model for gear profiles having different teeth number has not been studied in the literature and is the subject of current study. Therefore, the research presented in this study focused to investigate the nonlinear effect of tooth number of gear, extrusion ratio, die land length, and the die displacement on the extrusion load. For this purpose, FEM result obtained from DEFORM-3D software are validated by extrusion experiments and then changes of the mentioned parameters were successfully predicted by using artificial neural network modeling.

2 Methodology

In the first stage of the study, gear-like profiles were formed by forward extrusion, and experimental data was obtained for the selected process parameters. Then, FEM simulations were performed and their results were compared and validated with experimental results. In the next stage of study, 27 FEM simulations totally were applied for the parameters which were selected with the different levels. Finally, the best developed ANN model was selected for prediction of the FEM results. The flowchart of the study was given in Fig. 1.

2.1 Experimental study and die layout

AA1070 billet material was used in the experiment to obtain the gear formed products because of having cold formability properties. Stress–strain relationship of the material was obtained from compression test and the equation was determined

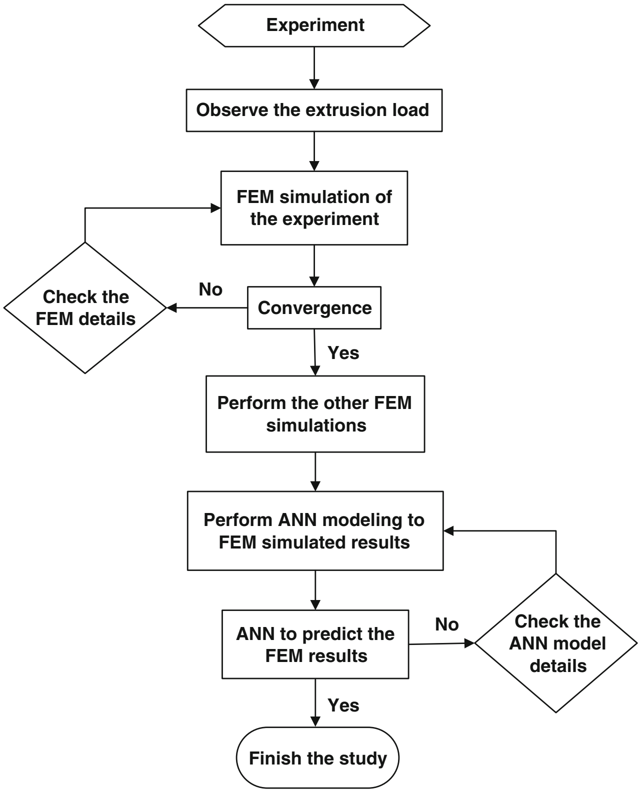

Fig. 1 The flow chart of this study

as follows:

$$\sigma = 144\varepsilon^{0.162}\mathrm{MPa} \tag{1}$$

Gear-like profile of the dies was defined mathematically and the inlet and exit geometries of the die were expressed as;

$$R_{\mathrm{inlet}}(\theta, z) = 14 \tag{2}$$

$$R_{\mathrm{outlet}}(\theta, z) = 8.7 + 3.5\cos(4\theta) \tag{3}$$

In this study, transition profile of forward extrusion die was selected as straight tapered which is given Eq. 4.:

$$R_{\mathrm{tap}}(\theta, z) = R_{\mathrm{outlet}} + (R_{\mathrm{inlet}} - R_{\mathrm{outlet}})\left(\frac{L-z}{L}\right) \tag{4}$$

The die land length was determined to be L=15 for the produced experimental die. Photographical view of the die assembly with each part with experimental set-up and schematic illustrations of profiles of dies for forward extrusion are shown in Fig. 2.

Experimental billet specimens have been cut from the bar and machined to 28-mm diameter and 45 mm in length. An extrusion container with internal diameter of 28.2 mm having 60-mm

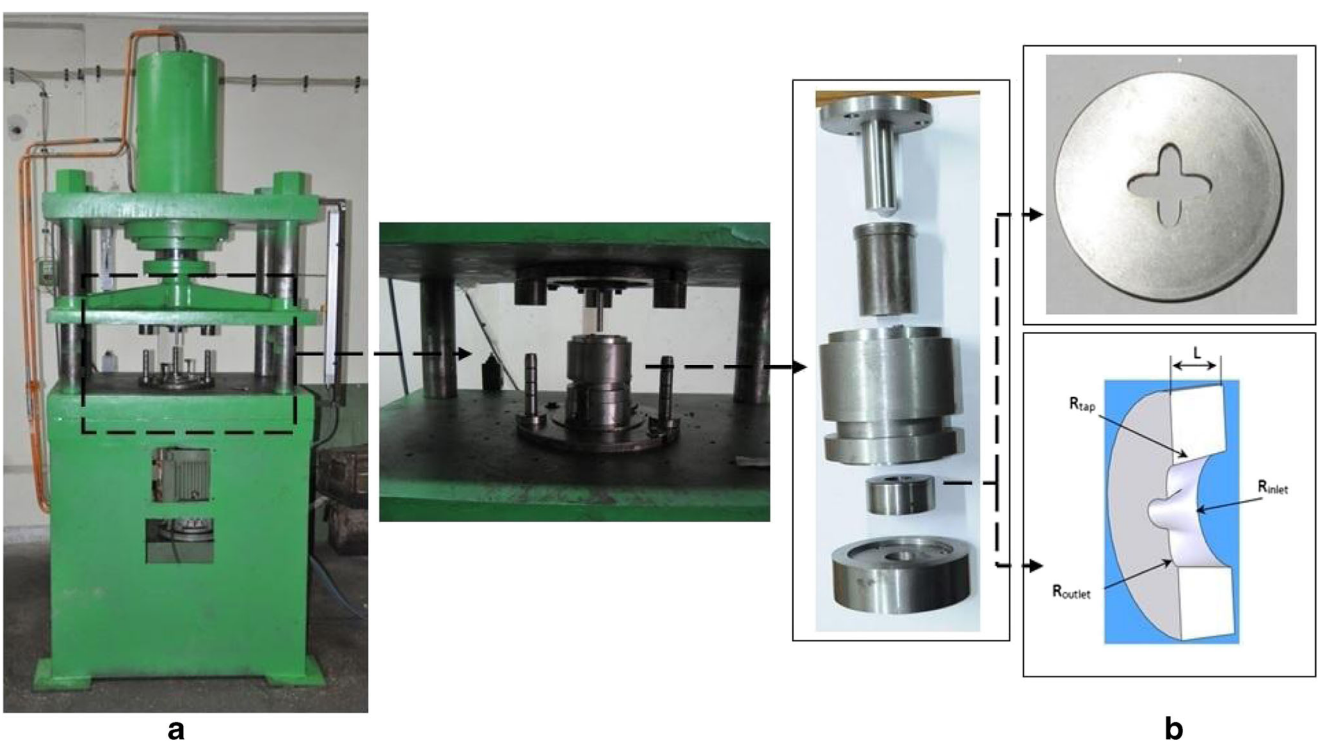

Fig. 2 Photographic view of die assembly and schematic view of the dies **a** experimental set-up of die assembly; **b** straight tapered-four teeth die

Table 1 Levels of the parameters used in simulations

Input parameters	Level 1	Level 2	Level 3
Teeth number (T)	3	4	6
Extrusion ratio (R)	2.07	2.39	3.08
Die bearing length (mm) (L)	10	15	20

outer diameter and a punch having 28.2-mm diameter were machined. The die transition geometry chosen was straight-tapered die. The extrusion ratio is given by $R = (A_{inlet}/A_{outlet})$ and it is obtained as R=2.39. The die was manufactured by W-EDM machine because of their geometrical complexity and the other die components were machined at CNC. Container and the punch were made from 1.2344 DIN hot worked tool steel materials and hardened to 54 HR_C.

Forward extrusion experiments were carried out on the 150-ton hydraulic press with constant ram speed of 5 mm/s. The specimens were cleaned with acetone before deformation in order to ensure the similar friction conditions. The load values were obtained by transforming the pressure signal that was received from the programmable logic controller (PLC) system that is formed and the pressure transmitter that is located on the hydraulic press by the PLC system. The movement and the position of the press were determined in accordance with the information taken from the digital linear ruler. The PLC system computes the load-stroke values by combining the load values that are read with the signals which come from the pressure valve that corresponds to the position information that is coming from the digital linear ruler. In this way, when the upper plate of the press reached the adjusted position of 28-mm ram travel, the experiment was stopped by means of the software. Data files of the extrusion load versus the stroke were stored in the software.

2.2 Finite element modeling of the extrusion

DEFORM-3D was specialized as finite element-based software for metal-forming simulations and it was used in this study to simulate the extrusion trials by the dies having a different number of gears, extrusion ratios, and die land lengths (L) combinations. Calculation of the plastic deformation behavior of the workpiece can be simulated by DEFORM-3D. The die and the other extrusion tooling equipments, like punch and container, were assigned to be rigid and made from H13 tool steel. Temperature of the die components and billet materials were defined as cold extrusion condition due to the fact that the experiment was performed at room temperature. Ram speed was also adjusted as 5 mm/s constant value same as punch velocity and friction factor is determined by compression tests as 0.4 to be compatible with the experimental conditions.

In the present simulation, the complete models of the experiments were modeled to obtain more intensive simulation results. Three extrusion dies having different teeth number of gears (T), three different extrusion ratios (R) and three die land lengths (L) were designed with CAD software while the geometry and dimensions of the billet and stem were kept unchanged. Thus, totally 27 simulations were performed using all combination of T, R and L. Levels of the parameters used in the simulations can be seen in Table 1.

In finite element simulations, it is important to balance the calculation of the simulation time and the sensitivity of the simulation. The more mesh density in an object provides more

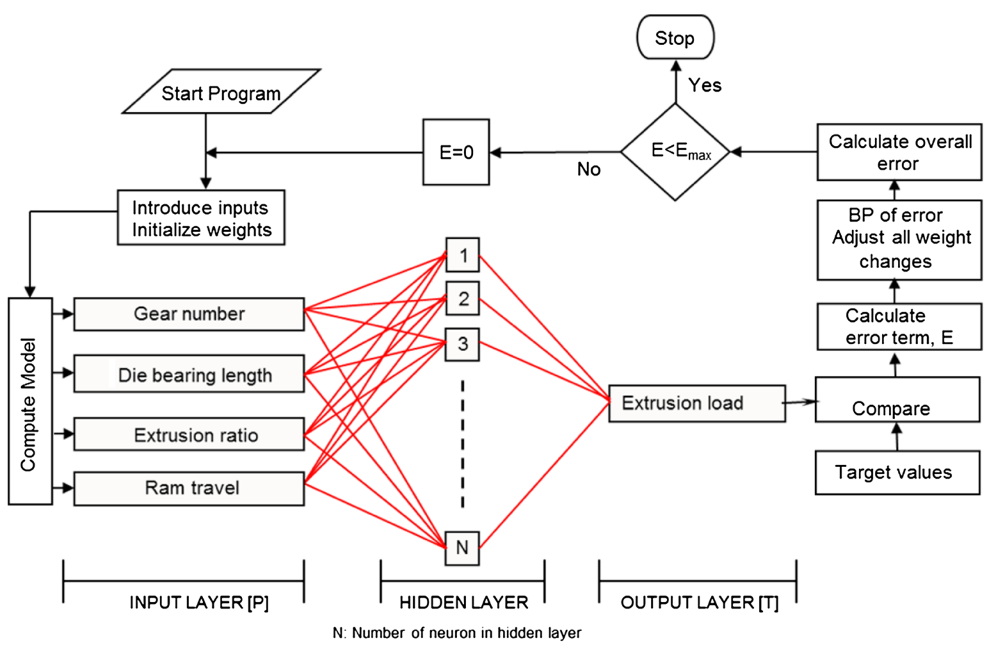

Fig. 3 Neural network structure with a flowchart of BP algorithm for extrusion load prediction

Table 2 Comparison of the different NN modeling results

Algorithm	Function	Neuron number	R^2	Average absolute error (%)
LM	TanhAxon	12	0.998	1.96
Momentum	TanhAxon	12	0.906	13.72
Momentum	TanhAxon	20	0.908	13.81
Momentum	TanhAxon	28	0.933	11.91

correct simulation results. However, it needs a longer simulation time. The different mesh density distributions were used to save the calculation time and data storage space for the simulations performed in the present work. Finer meshes were generated in the areas around the gears cavity of the dies, while coarser meshes were generated in the other areas of the workpieces that are close to the punch.

2.3 Application of ANN to FEM simulations of extrusion

2.3.1 View of the artificial neural network

An artificial neural network is a flexible mathematical structure which is capable of learning from past experiences and then forecasting new results on the basis of the experiences. ANN models are useful and efficient to predict the results of processes related to the input parameters, particularly in problems for which the characteristics of the processes are difficult to describe by using physical equations. Therefore, researchers paid attention to investigate on ANN due to difficulties in solutions for some of the complex engineering systems in the past decade. An ANN structure has three main layers: a set of input nodes, one or more layers of hidden nodes, and a set of output nodes. A number of neurons in each layer work as an independent processing element and densely interconnected with each other. The methodology of ANNs is based on learning the relationship between input and output data sets. After training, the ANN using a special learning function and learning rule, a data set which has not been trained are used for the test and validation of networks. The network is continuously worked and updated by a training function till a desired error criterion is obtained [29, 22].

Different learning rules can be used for the self-organization of the ANN structure. The most widely used learning algorithm is the back propagation algorithm since it works by sending inputs forward and then propagating errors calculated using a certain error criteria backwards. In this algorithm, the learning procedure is continued till the minimal error is obtained.

2.3.2 Parameter setting for ANN (development of neural network model structure)

The neural network was built to predict the results of the extrusion load obtained from FEM simulation results and its structure is given in Fig. 3. This study takes into consideration for input parameters such as gear number, die bearing length (L path), extrusion ratio, and ram travel (taken into account with 28 mm). The aim of using the ram travel as an input neuron is that the determining of the extrusion load at prescribed ram travel path at various gear number, die bearing length and extrusion ratio. The output layer consists of one neuron representing extrusion load occurring at different die design parameters.

A transfer function for the hidden layer is required to acquaint the nonlinearity into the network. A TanhAxon transfer function was used. The proposed ANN model for predicting extrusion load of different die designs in FEM simulations was employed as the feed-forward neural

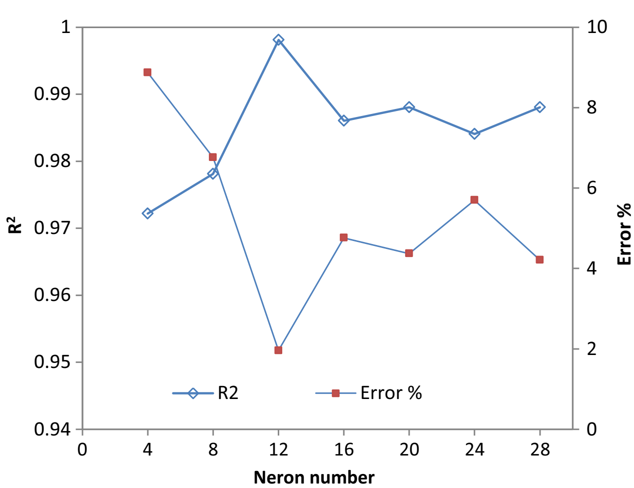

Fig. 4 Performance of the network for different neuron numbers for LM learning algorithm and TanhAxon transfer function

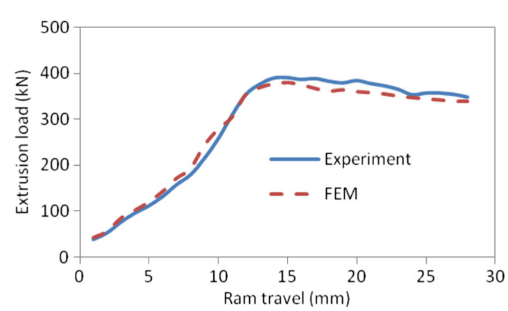

Fig. 5 Experimental and FEM-simulated extrusion load

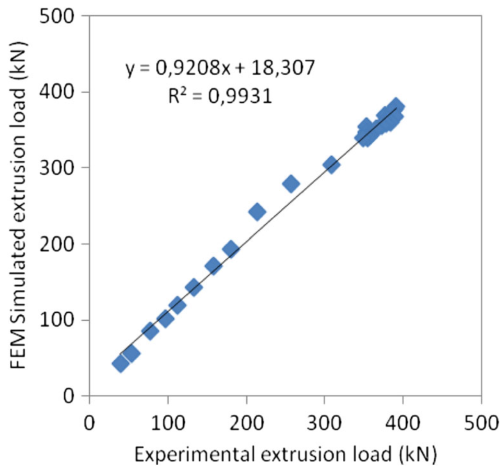

Fig. 6 Comparisons between the experimental and FE simulated extrusion load

networks which consist of multilayer perceptions trained back-propagation algorithms.

The predicted results should be validated to assure that the proposed model is robust and generalizable to different conditions. When a robust prediction method is implemented, the neural network can be capable of generalizing new data. For this purpose, the available data set is split into two categories named training and test subsets. For this study, 756 data patterns were randomly divided into 604 training data patterns (80 %) and 152 test data patterns (20 %). Then, measuring the generalization of the network is performed by the testing subset data. In this study, testing data sets were not used during training of the network and therefore, they could form a good indicator to test the accuracy of the developed network.

2.3.3 Selection of back-propagation algorithm (Levenberg–Marquardt algorithm)

Two back-propagation algorithms, Levenberg–Marquardt (LM) and momentum, are compared to select the best fitting back propagation algorithm for the present study. In the selection, coefficient of multiple determinations (R^2) between the ANN-predicted and FEM-simulated data set were compared. In addition, the performance of the back-propagation algorithms is evaluated with average absolute error (%) values. It can be seen from Table 2 that the best back-propagation algorithm for the present application, with average absolute error (%) for minimum value, and maximum R^2, is the Levenberg–Marquardt (LM) algorithm while transfer function is TanhAxon.

2.3.4 Optimal neuron number

The ideal number of neurons in the hidden layer should be found through trial and error. It is started with a trial process by using four neurons in the hidden layer as an initial guess in the optimization of the network. Then, the neuron numbers were increased 4 by 4 till 28 neuron numbers to obtain the coefficient of multiple determinations (R^2). It can be seen from Fig. 4 that the R^2 values increased till 12 neuron numbers while they slowly decrease over that neuron number. Therefore, the optimal neuron number for the Levenberg–Marquardt algorithm is decided to be 12 neurons. In addition, the average absolute error (%) for minimum value also was evaluated with 12 neuron numbers. Furthermore, some addition ANN models with Momentum algorithm and TanhAxon function having 12, 20 and 28 neurons in hidden layers also were used. These neuron numbers for LM algorithm showed highest performance, they therefore were used also for Momentum algorithm. However, the results of both R^2 and average absolute error (%) obtained with them were not better than (LM) algorithm, TanhAxon function and 12 neuron combination. This case can be seen very well by comparing Fig. 4 and Table 2.

As a result, the optimal neural network structure for estimation of extrusion load in this study is determined with the Levenberg–Marquardt back-propagation algorithm, a TanhAxon transfer function at the hidden layer with 12 neurons.

3 Results and discussion

3.1 Experimental verification of FEM simulation

An extrusion experiment was performed to validate the FEM simulations with the die having four gears, extrusion ratio 2.39 and 15 mm die land length. The other conditions in the experiment are explained in the experimental study (subhead 2.1) above. Ayer [30] performed several extrusion experiments for different die set in his Ph.D. thesis. Average of

Table 3 Maximum loads (kN) calculated from FE simulations

	3 Teeth	3 Teeth	3 Teeth	4 Teeth	4 Teeth	4 Teeth	6 Teeth	6 Teeth	6 Teeth
R2.07	196	221	238	210	236	257	231	255	279
R2.39	310	358	373	330	381	405	353	406	431
R3.08	519	553	578	542	576	615	573	605	651
	L10	L15	L20	L10	L15	L20	L10	L15	L20

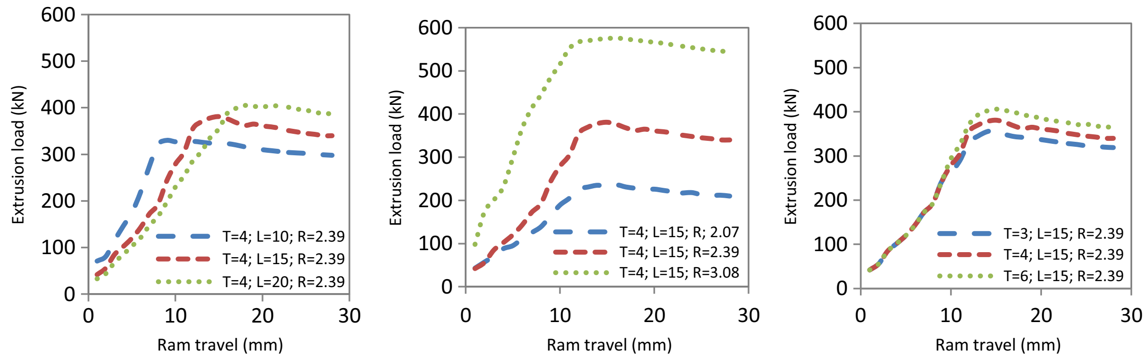

Fig. 7 Effect of different die parameters on the extrusion load (*T* teeth number of the gear profile, *L* die bearing length, *R* extrusion ratio)

extrusion load experimental results were used to compare with DEFORM-3D results, in this study. Comparison of extrusion loads versus the ram travel between experimentally measured and theoretically calculated load values which were obtained from DEFORM-3D simulations are shown in Fig. 5.

It can be seen from Fig. 5 that the experiment results agree well with the FE-simulated results at the same conditions. The average error between the FE-simulated load and experimentally measured extrusion load throughout the ram stroke is 4.9 %. In Fig. 5, the maximum extrusion load is of the most interest. The error between the FEM-simulated and experimentally measured maximum extrusion load is as small as 3 %. In addition, coefficient of multiple determinations (R^2) between the FEM-simulated load and experimental extrusion load was compared in Fig. 6, and it is clearly seen that there is a good agreement between the simulation and experiment.

3.2 Effect of the selected parameters on the extrusion load

It can be seen that extrusion ratio is the main parameter which affects the extrusion load most. The increasing extrusion ratio leads to the increasing extrusion load which is expected; however, in addition to this normal issue, an excessive increase was observed when the ram travel arrived to a specific point where maximum extrusion load occurs. Effect of linearly changing die land length is significant and dominant compared to change of tooth number. For the evaluation of these influences, tooth number, die land length, and extrusion ratio is used for three-level combinations and 27 different die combinations were obtained corresponding to these three-level combination and then simulations were realized. The maximum loads obtained from these die combinations by FEM simulations can be seen at Table 3.

On the other hand, the ram travel distance of which the maximum load occurs varies with die land length. The extrusion load was observed as maximum either in case of the shorter ram travel distance for the shorter die land length or the longer ram travel distance for the longer die land length. Maximum extrusion load also occurs at shorter ram travel distance for the higher extrusion ratios while die land length is constant. The two mentioned situations are related with the fulfilling of the die land length. It should be noticed in the performed FEM simulations in this study that the billet and container diameter were increased for obtaining the higher

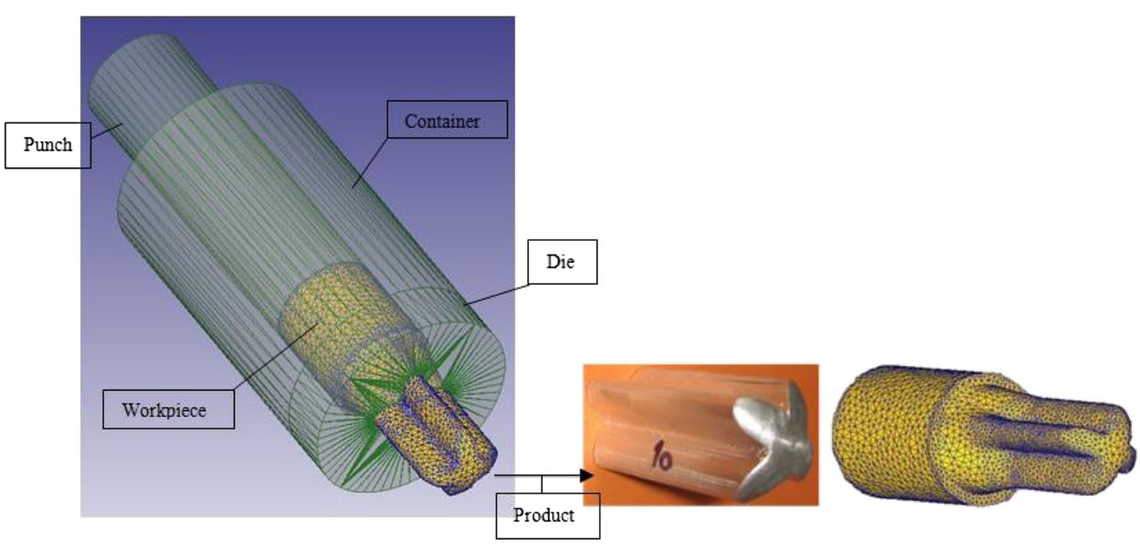

Fig. 8 FE schematical view of die set, simulated and experimental images of the product with gears having four teeth

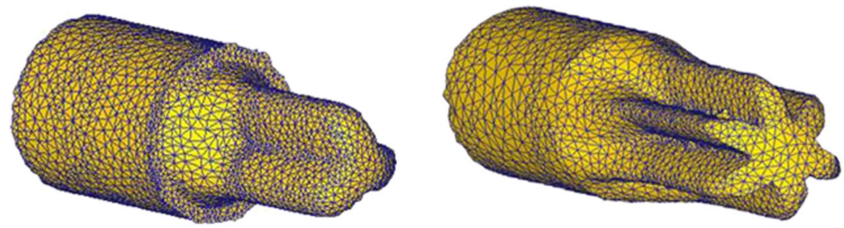

Fig. 9 FE simulated images for gears having three and six teeth

extrusion ratio while the die was constant. The change of extrusion load according to the die land length, the extrusion ratio, and tooth number is given in Fig. 7. In order to avoid the inclusion of too many figures to this paper, only some curves are shown in Fig. 7. It is clearly seen from the figure that the extrusion ratio is more effective on extrusion load than the die land length and the tooth number. When extrusion ratio is R= 2.07, container diameter is the same as die orifice but as the extrusion ratio increased by the increased container diameter, a 90 ° die entrance angle occurs and causes a dead metal zone at the die entrance which leads to a high increase in the extrusion load.

3.3 Comparison between FEM simulation and ANN

Finite-element method has been used for the last years and is also one of the most popular numerical methods especially for the complex geometries. In conventional ways of extrusion investigations, metal flow and forming load are determined by either using limit and slab analysis methods or trial–error methods. FEM gives much more faster and accurate results for complex geometries and gaining momentum in simulating process. Extrusion process is naturally complicated and is always related to complex product shapes so it is a wide range application area of the FEM eventually. DEFORM-3D software is a well-known FEM method, which is specialized on the metal forming processes, one of the most used effective tools for research and also in industrial applications, and gives very similar results to real problems. Die layout, product geometry and process parameters should be defined. Mesh density and element type is also important for DEFORM-3D. Simulations are carried out with respect to initial conditions and mesh density. Each parameter change requires new simulation sequence but for an ANN system, it is vice versa and is not necessary to set a new model with each parameter change. This is one of the most important advantages of the ANN. It is aimed to predict the output result after training data set by using the ANN model. The actual performance of an ANN model is understood with the stage of the testing data. Once an ANN model predicts the results at testing stage, then each input parameter's level can be changed with new ones for prediction of the output results. For this study, the number of gear tooth has been selected as 3, 4, and 6, so FEM simulations has been realized by these three level parameters (Figs. 8 and 9).

After performing FEM simulations, the obtained data were submitted for ANN training and testing. Coefficient of multiple determinations (R^2) between the FEM-simulated extrusion load and predicted extrusion load with ANN is shown in Fig. 10. As it is seen from the figure, a high R^2 value expressing a good agreement between FEM-simulated results and ANN-predicted results has occurred; the fact that the FEM-simulated and the ANN-predicted results are very close to each other and can also be seen in Fig. 11. The differences, called as error, between the desired and output results are given in detail in Fig. 12. It can be seen that the left Y-axis shows the error (kN) and the right Y-axis shows the error in percentages. X-axis is for the number of the performed tests. It is obvious that the differences between ANN and FEM results as error (kN) in the left Y-axis are values in the range of (−24.1)–(17.06), while error (%) results in the right Y-axis are in the range of (−9.66)–(7.89) and it is very meaningful to use the ANN model to estimate the extrusion load instead of performing much more FEM results for a new level of the parameters and to save the calculation times. In the graph, for most points, it is clear that there is no proportion between error (kN) and error (%) values. The reason of this observation is the change of the estimated extrusion loads' magnitude. Therefore, it is much more realistic to take into account of

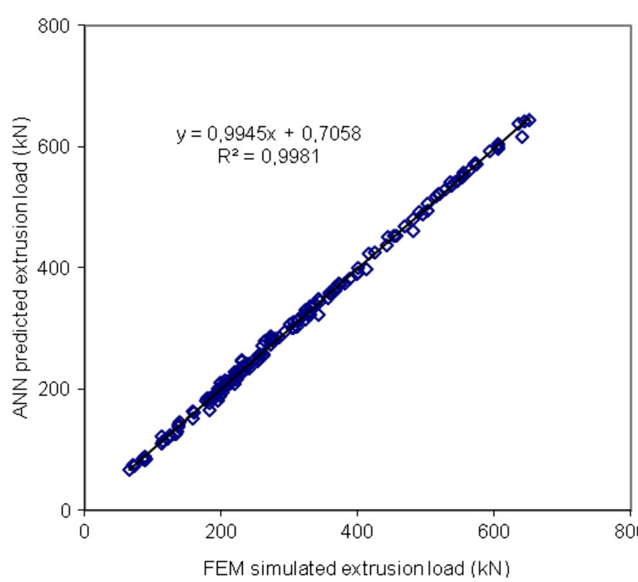

Fig. 10 Comparisons between the FE-simulated and the ANN-predicted extrusion load

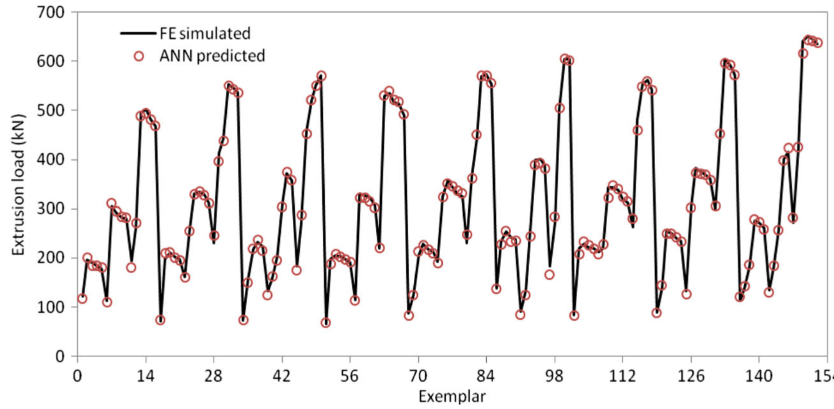

Fig. 11 FE-simulated and ANN-predicted extrusion load in the test period

the error (%) values instead of the error (kN) to see the forecast performance of the ANN model. In Fig. 13, it is shown in the histogram that most error (kN) values are between ±7.5, while error (%) values are just between ±3 %. It was calculated that the average of the errors (%) and the errors (kN) are just 1.96 % and 4.87 kN, respectively.

4 Conclusion

Extrusion load is affected by a number of parameters and it is necessary to define them to control the whole process and for this aim, several empirical, numerical methods have been developed for this purpose. In this study, an integrated ANN

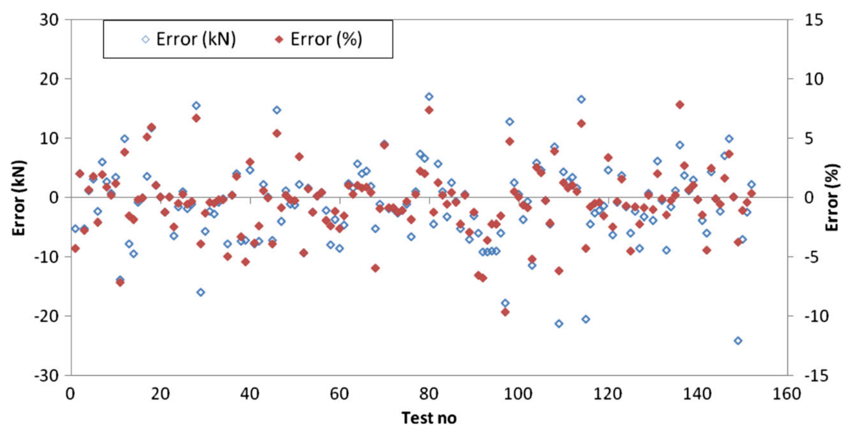

Fig. 12 Error (kN) and error (%) of the ANN prediction

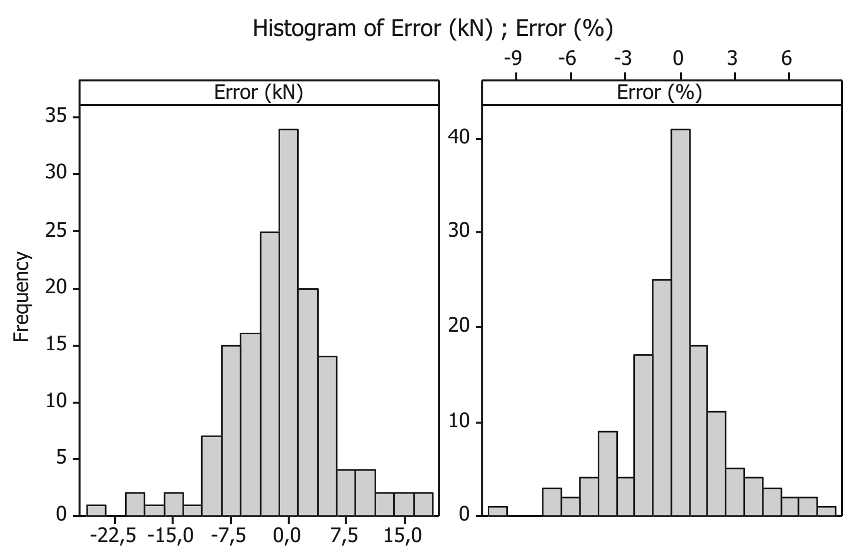

Fig. 13 Statistical analysis of the relative errors (kN) and errors (%)

and FEM methodology confirmed with the experiment was developed which focused to investigate the nonlinear effect of different die parameters on extrusion load. Complex interactions were observed from the results. Gear-like components have been manufactured by forward extrusion and simulated successfully using a DEFORM-3D software package and established a database in order to provide the data for ANN. Gear tooth number, extrusion ratio, die land length, and ram displacement were taken as the input data for ANN, while the extrusion load was selected as the output data. Comparisons demonstrated that a very good correlation between the FEM-simulated and predicted extrusion loads from the developed ANN model has been obtained. In the statistical model, R^2 value between the ANN and FEM results was found to be 0.9981; so, this case indicates that the excellent capability of the developed ANN model as a useful tool to predict the extrusion load for different die combinations to produce gear-like profiles is obvious. It is observed from the results that extrusion ratio (ER) is the main parameter that affects the extrusion load most comparing to the effect of teeth number and die land length. As a conclusion, an ANN model has been applied for gear profiles having different teeth number and it has not been studied in the literature and good agreement was obtained for extrusion load predictions of gear-like profiles.

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