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Prediction of Extrusion Pressure And Product Deflection Of Using Artificial Neural Network

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Abstract: - *In this paper artificial neural network was used as a modeling tool for simulation and prediction of extrusion pressure and product deflection of extrudes of lead alloys. An extensive experimental program was undertaken to extrude a lead (Pb) alloy on ELE Compact-1500 compression machine. The neural model of extrusion pressure and product deflection was developed based on groups of experiments carried out as samples, Eight (8) die bearing parameters (die bearing length, radius of curvature, slip angle, die angle, die ratio ram displacement, pocket depth and die diameter) were used as inputs into the network architecture of 8 $[4\text{-}3]_2$* ***2*** *in predicting the extrusion pressure and product deflection. After series of network architectures were trained using different training algorithms such as Levenberg-Marquardt, Bayesian Regulation, Resilient Backpropagation using MATLAB 7.9.0 (R20096, the LM8 $[4\text{-}3]_2$* ***2*** *was selected as the most appropriate model. Prediction of the neural model exhibited reasonable correlation with the experimental extrusion pressure and product deflection. The predicted extrusion pressure and product deflection gave reasonable errors and higher correlation coefficients indicating that the model is robust for predicting extrusion pressure and product deflection.*

Keywords: - *Artificial neural network, Extrusion pressure, die bearing, modeling, product deflection,*

I. INTRODUCTION

Extrusion is a plastic deformation process in which a block of metal called the billet is compressed through the die opening of a smaller cross-sectional area than that of the billet [1]. According to [2] extrusion is one of the forming techniques used in materials processing. The term is usually applied to both the process, and the product obtained when a cylindrical work piece or billet is pushed through a shaped die, thereby reducing its section. The resulting section can be used in long lengths or cut into shorter parts for use in structures, vehicles or as components. Also, extrusions are used as starting or feed stock for drawn rod, cold extruded and forged products. While the majority of presses used for extrusion worldwide are covered by the description above, some presses accommodate rectangular shaped billets for production of extrusions with wide sizes. Other presses are designed to push the die into the billet or indirect extrusion. The versatility of the process in terms of both alloys available and shapes possible makes extrusion most valued assets for solution to design requirements [3].

The design of extrusion dies depends on the experience of die designers. After production of the die, it is tested and modified severally until it works properly. Die design is therefore by trial and error and this is expensive. However, the die has been recognized as the heart of the extrusion process as product quality and productivity depends highly on its performance. A major challenge has been to maintain uniform flow throughout the cross-section to avoid twisted, bent or out-of-tolerance extrusion [4]; [5]. Traditionally, flow control has been achieved using different bearing configurations from shear to slip dies, dies with relieved bearings, dies with pocket bearings e.t.c. Each of these achieves improvements in product quality or reduction in extrusion pressure at the expense of the other.

One of the greatest challenges in the design of an actual extrusion operation is to obtain realistic manufacturing process parameters to plan t execution. Conventional finite element analysis and other numerical methods been applied to extrusion processes. However, these do not consider the manufacturing constraints in their modeling and hence, the process parameters obtained through such analysis were more theoretical and not realistic enough. Also, due to the inherent time consuming nature of such methods, quick and rapid problem solving as desired by industries have not been achievable. Also, these mathematical models when presented with new set of data, do not yield desired results [1].

Artificial neural network (ANN) as a modeling and simulation tool has been widely employed in engineering processes and systems. This is as a result of its capability to capture all input parameters that can be related to the output (s). Bajimaya et al [1] used neural network model to predict the manufacturing process parameters such as pressure, temperature and velocity, the results obtained were in agreement with the experimental values. Neural network modeling and optimization of semi-solid extrusion for aluminium matrix composite was also investigated by [6]. Satisfactory results were achieved with the deforming force of semi-solid extrusion being reduced significantly, indicating the feasibility of the proposed method according to derived data from experiment. Interest in artificial neural network (ANN) modeling in other field of engineering has also increased rapidly. For instance, predictions of friction and wear properties of composite and metallic alloys were carried out by [7] and [8]. Several other investigators like [9]; [10]; and [11] have found corrosion rates of different materials in different media effectively using artificial neural network.

The present study has been conducted to establish an appropriate artificial neural network model for predicting the extrusion pressure and product deflection of Lead Alloy extrudes. The neural model of the prediction of extrusion pressure and product deflection was used for the approximation between the technological parameter inputs such as die bearing length, radius of curvature, slip angle, die angle, ram displacement, pocket depth, extrusion diameter and die ratio against extrusion pressure and product deflection as outputs. Validity of the proposed model was also assessed using standard statistical parameters.

II. MATERIALS AND METHODS

2.1 Preparation of extrude billets

The lead alloy having appropriate composition 67% Pb, 26.5 %Sn and 6.5% Bi was obtained from automobile battery grids and terminals. The melts were cast in galvanized steel moulds of 26 mm diameter and later machined into test billets of dimension 24.4 mm by 25.4.

2.2 Extrusion procedure

The extrusion billets, machined to diameter of 25.4mm by 26mm were directly extruded on manual ELE Compact-1500 hydraulic press shown in Fig.1. Split dies were used to facilitate easy separation of extrudes after each extrusion. Load readings were taken at 1 mm of ram travel, and the maximum load noted for each extrusion. Average values of extrusion loads were obtained for each extrusion at the steady stage of the process, and by dividing the corresponding loads by the cross-sectional area of the billets, values of extrusion pressure were obtained. The extrusion dies were machined to extrude solid circular sections to reduction ratios of 0.21, 0.3, 0.4 0.48 and 0.62 (corresponding to extrude diameter of 11.5 mm, 16.0 mm, 17.01 mm, 20.0 mm and 22.4 mm. The dies for determining the effect of the die angles on extrusion parameters were produced.

Fig. 1: Extrusion setup on ELE Compact-1500 hydraulic machine

2.3 Experimental

2.3.1 Extrude curvature and deflection.

Extrudes were carefully separated from the dies and were held on a lathe machine using a three- jaw chuck. By rotating the chuck slowly the axial deflection of the extrudes were measured at a distance of 25 mm from the face of the chuck using a vertical height gauge with sensitivity of 0.001 mm [12]

2.4 Neural network modeling

The development of the neural network for prediction of extrusion pressure and product deflection was based on the experimental data. The experiment was carefully planned to provide the input/ouput quantities for neural networks training, validation, testing and simulation as explained in the methodology. The following steps were considered in modeling the extrusion pressure and product deflection of lead alloy extrudes [13]; (i) data generator (ii) definition of ranges (iii) data pre-processing, (iv) selection of neural network architecture (v) selection of training algorithms (iv) training the neural network, and (vii) testing or predicting.

2.4.1 Input data and output data

The input data or parameters captured in the artificial neural networks model are discussed and presented in **TABLE 1**, while the output data or parameters captured in the artificial neural networks model are also discussed and presented in **TABLE 2.**

Input data S_{T1}-ST_{10} was used for training the network while S_{P1}-S_{P5} for testing the prediction capabilities of the artificial neural network. The data for the neural network modeling was obtained from ten (10) groups of experimental data collected as samples and the working together of the influence of these eight (8) inputs parameters on extrusion pressure and product deflection are shown in Fig 2.

Table 1: Set of input parameters used for training and testing.

		Test Data set				
Parameters	**Training data set ST_1-ST_{10}**	**S_{P1}**	**S_{P2}**	**S_{P3}**	**S_{P4}**	**S_{P5}**
Die bearing length (mm)	1-18	1	2	5	8	10
Radius of curvature (mm)	200-460	269	301	355	434	355
Slip angle (deg)	20-80	40.8	43.75	46	53.75	60
Die angle (deg)	50-180	60	75	90	105	120
Die ratio	0.26-20	0.62	0.62	0.62	0.62	0.62
Ram displacement (mm)	5-20	8	10	12	14	16
Pocket depth (mm)	1-10	2	3	4	5	6
Die diameter (mm)	10.5-30.6	11.5	16	17.6	20	22.4

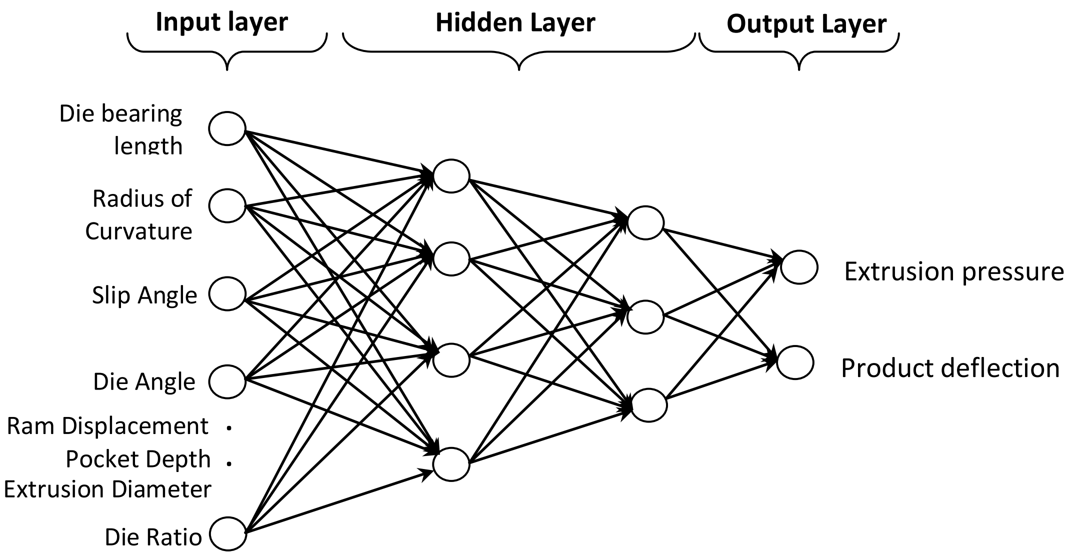

Fig.2: Neural network architecture used

Table 2: The experimental extrusion pressure and product deflection

Output parameter	S_{E1}	S_{E2}	S_{E3}	S_{E4}	S_{E5}
Extrusion pressure (MPa)	82.39	86.83	94.72	122.36	132.40
Product deflection (mm)	0.28	0.26	0.24	0.23	0.21

2.4.3 Data pre-processing

Pre-processing of the inputs and output parameters was carried out before the neural network training. The experimental data involving the inputs and outputs were measured in different units, the data of different types have great difference. Such difference will decrease the convergence speed and accuracy within the network. Therefore before network training, the input and output data set measured in different units need to be normalized into the dimensionless units to remove the arbitrary effect of similarity between the different data [14].

The eight (8) input parameters (excluding die ratio) were scaled within the range of 0-1 using the relation given in equation (2) [14]:

$$I_{Skal} = 1 + \frac{(I_{Curr} - I_{Max})}{(I_{Max} - I_{Min})} \quad (1)$$

Where; I_{Curr} –is current input value, I_{Max} - the maximum input value and I_{Min}-the minimum input value.

The output parameter extrusion pressure was normalized within the range from 0-1 using the relation in equation (3) [13]:

$$y_n = \frac{y - 0.95 y_{min}}{1.05 y_{max} - 0.95 y_{min}} \quad (2)$$

Where y_n the normalized value of y. y is the experimental data, y_{max} and y_{min} are the max and min value of y respectively.

2.4.4 Network training

The best neural network's architecture and learning algorithm are unknown in advance; a trial and error approach was used to find the best network's architecture for matching input/output relationship. The following networks architectures were investigated); one layered network 8 $[1]_1$ **2,** 8 $[5]_1$ **2,** two layered network 8 $[4\text{-}3]_2$ **2,** 10 $[4\text{-}3]_2$ **2,** three layered network 8 $[4\text{-}3\text{-}2]_3$ **2,** 10 $[4\text{-}3\text{-}]_3$ **2** in a MATLAB 7.9.0 (R20096)

These networks architecture were trained using the Levenberg- Marquard (LM), Bayesian Regulation (BR), and Resilient Backpropagation (RB). The sigmoid function given in equation (4) was used between the input and the hidden layers:

$$f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

and linear function f(x) =x was used between the hidden and output layer, where x is the value of weight used.

III. RESULTS AND DISCUSSION

The summary of the results of the tested ANN architecture is presented in **TABLE 3**. The neural model LM 8 $[4\text{-}3]_2$ **2,** was chosen because its exhibited higher correlation coefficient for both training and testing compared with the other architectures and algorithms. Training performance indicated values of correlation coefficient R=1.00 at epoch 12 for training, R=1.00 for testing with validation checks was 6 at epoch 18 while the overall correlation coefficient (R) for training, testing, and validation was 0.90458.

Table 3: Summary of the results of tested ANN architecture.

Architecture	Training	Testing
LM 8 $[1]_1$ **2**	0.701	0.641
BR 8 $[5]_1$ **2**	0.997	1.000
LM 8 $[4\text{-}3]_2$ **2**	**1.000**	**1.000**
BR 10 $[[3\text{-}2]_2$ **2**	0.840	0.572
LM 10 $[4\text{-}3\text{-}2]_3$ **2**	0.731	1.000
RB 10 $[5\text{-}4\text{-}3]_3$ **2**	0.812	0.761

The correlation coefficient (R) was used to examine the strength of linear relationship between predicted and experimental values using the relation in equation (4) [16]:

$$R = \frac{\sum_{i=1}^{N}(E_i - \bar{E})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N}(E_i - \bar{E})^2 \sum_{i=1}^{N}(P_i - \bar{P})^2}} \quad (4)$$

Where E is the sample of the experimental value, p is the sample of predicted value by an ANN model $\bar{E}$ and $\bar{P}$ are the mean value of E and P respectively, N is the number of sample. This established neural model was used to predict extrusion pressure and product deflections.

Table 4 shows the values of the predicted extrusion pressure and experimental (real) extrusion pressure with their respective mean square errors and correlation coefficients. It was observed that the neural network prediction of extrusion pressure was in consonance with the experimental (real) extrusion pressure with minimal network errors of -0.1380, 0.0105, 0.00113, 0.0000349, 0.0000092, and higher correlation coefficient of 1.0000, 1.0000, 0.9956, 1.0000 respectively.

The values of the correlation coefficients were better compared with the values of 0.99997, 0.99999, 0.99997 and 0.99998 by [14]. The slight disparity in some of the predicted and experimental could be attributed ro errors in tha data arising from poor experimental design, fault in equipment or miscalculation.

TABLE 5 shows the predicted and experimental values product deflection with their corresponding networks errors and correlation coefficients (R). It was also observed that the neural network prediction of the product deflection of the lead alloy extrudes showed good agreement with the experimental values. The minimal network errors of 0.05976, 0.32981, -0.00012899, -0.000005 -0.00000095 and higher correlation coefficient R=1 for all the predicted and experimental values were observed.

Table 4: Predicted and experimental (real) extrusion pressure

Predicted (MPa)	Experimental (MPa)	Mean square error (MSE)	Correlation coefficient (R)
84.17	82.89	-0.13072	1.0000
93.1	86.83	0.010595	1.0000
95.02	94.72	0.001127	0.9956
122.75	122.36	0.000349	1.0000
132.40	132.40	0.000009	1.0000

The quality of the prediction of the extrusion pressure and product deflection of the lead alloy extrudes was evaluated taking into cognizance the following points (i) the quality of prediction of extrusion pressure against die bearing length (ii) extrusion pressure against die diameter (iii) product deflection against die bearing length (iv) product deflection against die diameter (v) response 3-D stem graph of extrusion pressure against die bearing with die diameter for predicted and the experimental values of extrusion pressure (vi) response 3-D stem graph of product deflection against die bearing length with die diameter for the predicted and experimental values.

Table 5: Predicted and experimental (real) product deflection

Predicted (MPa)	Experimental (MPa)	Mean square error (MSE)	Correlation coefficient (R)
0.28	0.28	0.05976	-1.0000
0.23	0.26	0.32981	1.0000
0.24	0.24	0.001127	1.0000
0.23	0.23	-0.000005	1.0000
0.21	0.21	-0.00000095	1.0000

Fig. 3 shows comparison between the experimental and predicted extrusion pressure against the die bearing length. The graph showed that both the predicted and experimental values of the extrusion pressure increased exponentially with increased die bearing length. The results generally agree with the findings of a related study by [17], and also confirm earlier findings by [18]. Fig. 4 shows the extrusion pressure against die diameter. It was also observed that both the predicted and experimental extrusion pressure increased with die diameter.

The influence of die bearing length on the product deflection of predicted and experimental values is shown graphically in Fig. 5. Deflection for the predicted and experimental values decreased as the die bearing length increased which shows that die bearing length has significant influence on the product deflection and lower product deflection were obtained with dies of larger bearing length. As shown on the graph, product deflections tends towards zero for the predicted and experimental values as die bearing lengths become large. Fig. 6 shows the plot of product deflection against die diameter. It was observed that the predicted and product deflection decreased as the die diameter increased.

The capability of neural network modeling of predicted and experimental extrusion pressure against die bearing length with die diameter was further illustrated by 3-D stem graphs as shown in Figs. 7 and 8. It was observed that both the predicted and experimental extrusion pressures increased with increased in die bearing length and die diameter. This indicates that the neural model has perform well as reported by other researchers, [16], and [11].

Figs. 9 and 10 also show the 3-D stem plot of ANN for the predicted and experimental product deflection against die bearing length with die diameter. It was equally observed that product deflection decreased as the extrusion diameter and bearing length increased thus, proving the capabilities of the model.

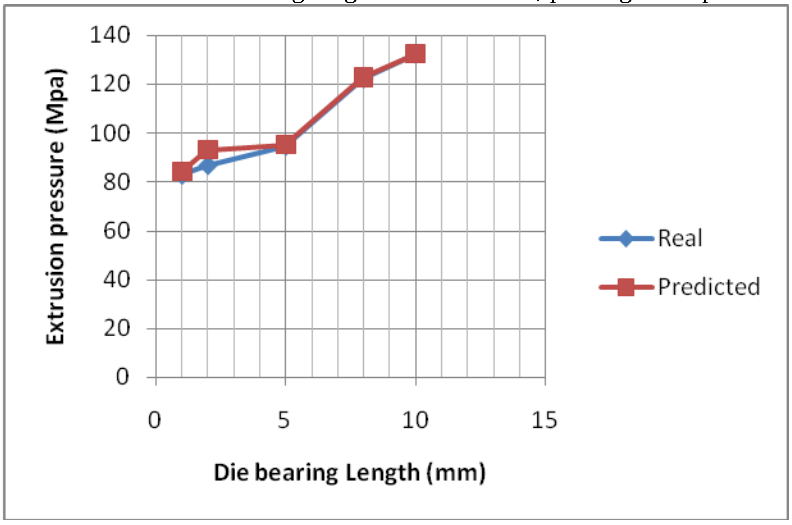

Fig. :3 Plot of predicted and experimental extrusion against die bearing length.

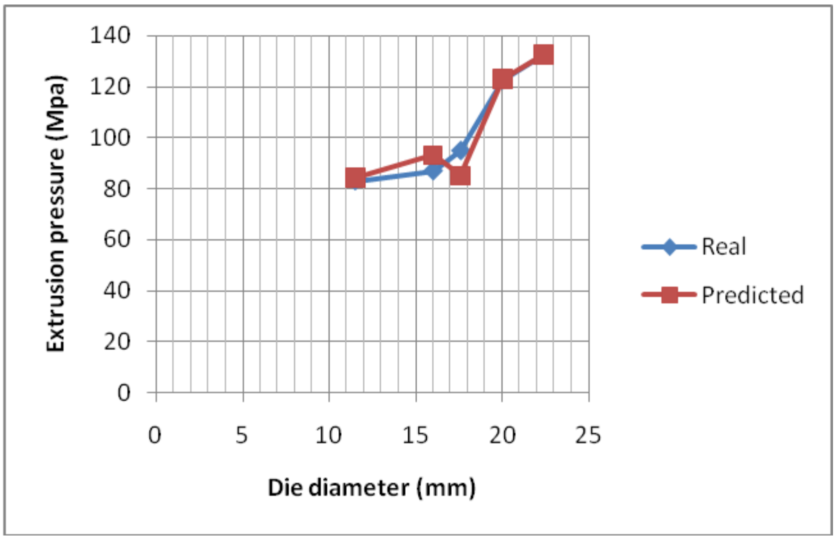

Fig. 4: Plot of predicted and experimental extrusion pressure against die diameter.

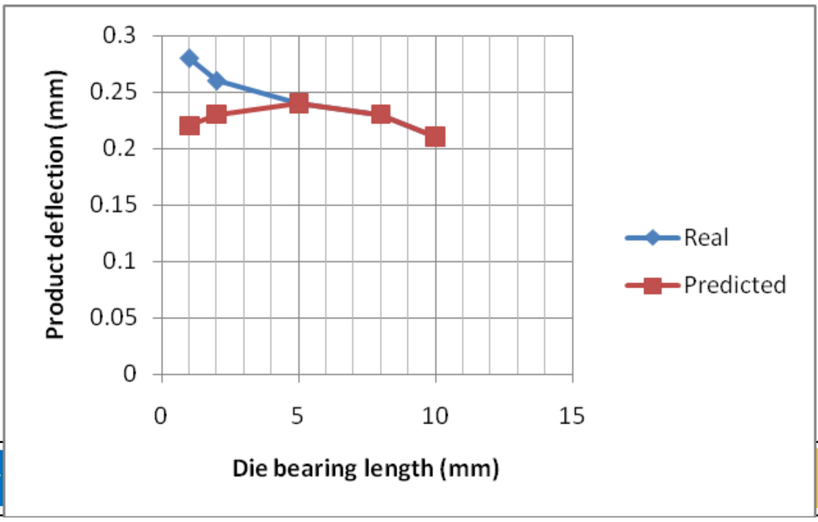

Fig. 5: Plot of predicted and experimental product deflection against die bearing length.

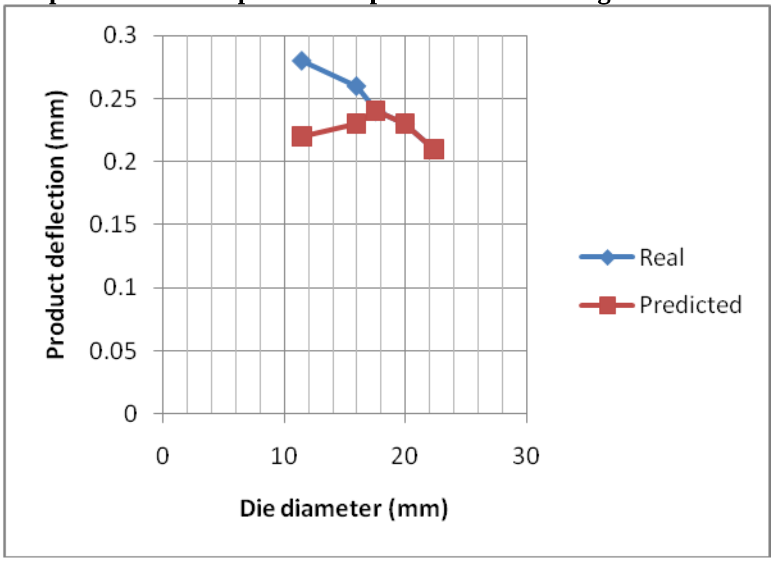

Fig. 6: Plot of predicted and experimental product deflection against die diameter.

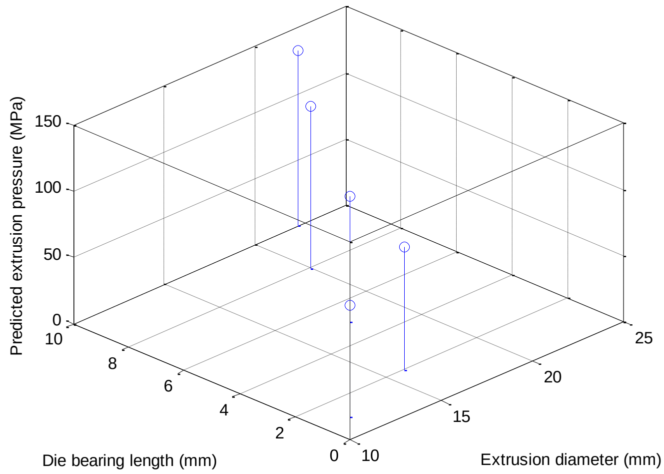

Fig. 7: 3-D stem plot of predicted extrusion pressure against die bearing length and diameter.

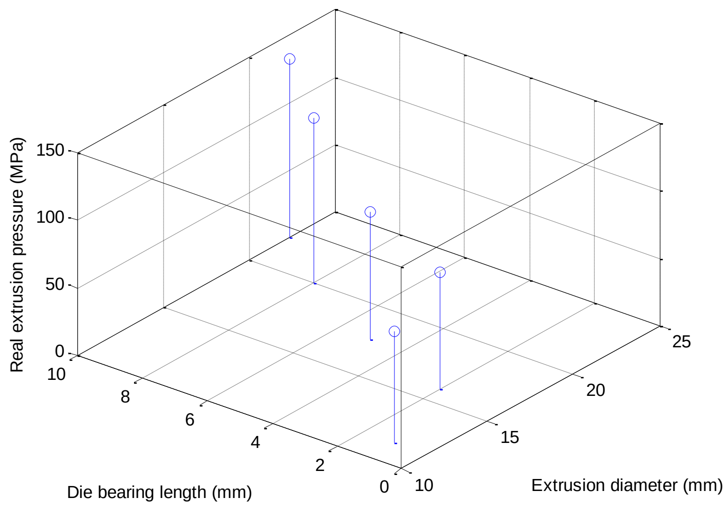

Fig. 8: 3-D stem plot of experimental extrusion pressure against die bearing length and diameter

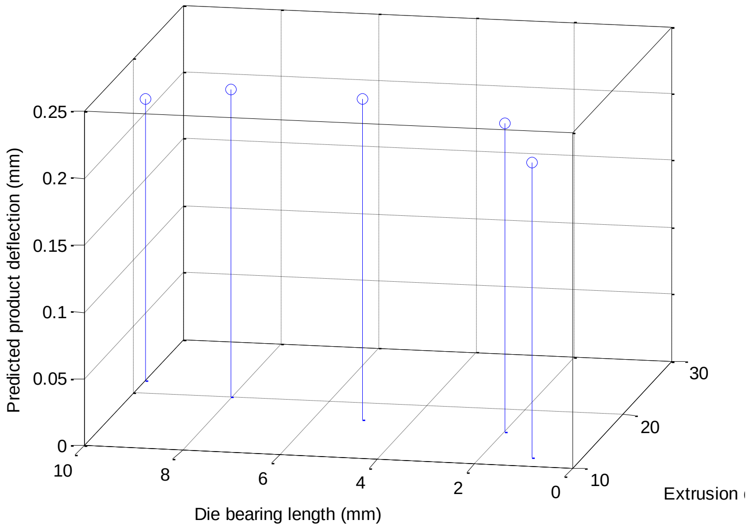

Fig. 9: 3-D stem plot of predicted product deflection against die bearing length and diameter

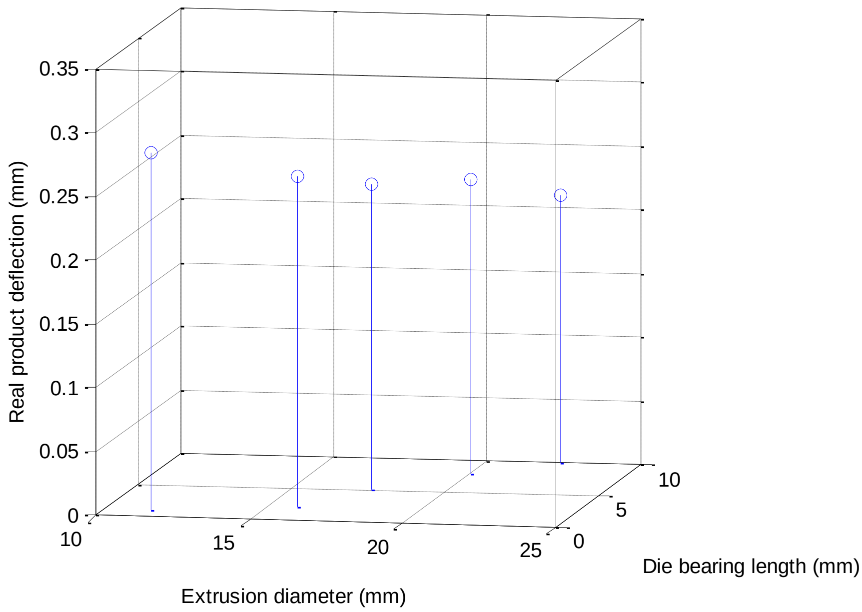

Fig. 10: 3-D stem plot of experimental product deflection against die bearing length and diameter

IV. CONCLUSION

The prediction of extrusion pressure and product deflection using artificial neural network provided an excellent matching with the experimental values. The ANN based model can be used with a high degree of accuracy and reliability, this was possible because reasonable number of variables were used during training of the neural model architecture LM 8 $[4\text{-}3]_2$ **2**.

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