Estimation of the Clearance Effect in the Blanking Process of CuZn30 Sheet Metal Using Neural Network−A Comparative Study

Emre ÇELİK[1]*, Onur ÇAVUŞOĞLU[2], Hakan GÜRÜN[2], Nihat ÖZTÜRK[1]

[1]Teknology Faculty Electrical Electronics Engineering, Gazi University, Ankara, Turkey
[2]Teknology Faculty Manufacturing Engineering, Gazi University, Ankara, Turkey
emrecelik@gazi.edu.tr, onurcavusoglu@gazi.edu.tr, hgurun@gazi.edu.tr, ozturk@gazi.edu.tr
(Geliş/Received: 18.01.2018; Kabul/Accepted: 07.04.2018)
DOI: 10.17671/gazibtd.380961

Abstract— Clearance effects on the product quality and blanking force in sheet metal blanking process are first investigated experimentally, and then modelled through neural network (NN) approach. Using eleven clearance values ranging from 8% to 18% with sampling of 1%, blanking process is applied to sheet material CuZn30 with a thickness of 1mm. During the experiments, blanking force, smooth sheared/fractured rate and burr height for the resulting products are measured for each clearance value, and as such, 11 data samples have been prepared. Six of them are taken as training data to train the network while with the remaining for testing purposes. Several estimation results are illustrated which verify that the presented NN can estimate the nonlinear relationship of blanking force, smooth sheared/fractured rate and burr height with the clearance with a maximum error of about 1%. These results are also compared to those offered by a recent study benefitting from fuzzy logic whose design is a challenge requiring proper and sufficient expert knowledge for tuning of numbers and shapes of membership functions, linguistic control rules. We conclude that better estimation accuracy and design simplicity are important advantages of our proposal.

Keywords— sheet metal, blanking, smooth sheared, burr height, blanking force, neural network, fuzzy logic, estimation

1. INTRODUCTION

The blanking process is a basic method for shaping sheet metal parts. In this method, exceeding the limits of the material elastic and plastic deformations and forming the fracture process are required by applying a force to the sheet material with the help of punch [1]. Clearance, sheet thickness, tool geometry and friction conditions also affect the blanking process as well as the material mechanical properties [1, 2]. Clearance is called the distance between die and punch during the blanking process of sheet material. The amount of clearance must be given at the optimum amount due to the fact that it has a significant impact on the blanked product quality. When the clearance is higher than necessary, it will reduce the product quality by increasing the fracture amount and the length of burr. Giving it less than necessary will result in increasing stresses on the die and punch surfaces by increasing the amount of friction among the punch, die and sheet material [2]. The product obtained as a result of the blanking process consists of the four characteristic zones. There is a rolling zone on the upper part of product, forming due to the fact that the material shows a flow tendency towards interior with the start of the strain process. When side surface of the blanked product is examined, blanking zone shaped through the punch is located. This zone has a smooth surface. A rough surface quality rupture zone forming through rupture process is located following the blanking zone. In the last part of fracture zone, there is an excess amount of material that extends beyond the product. This excess is called as burr. These characteristic zones are the most important parameters in determining the quality of products [3].

When the studies performed on the blanking process in the literature are analyzed, the effects of the clearance on the blanking process are investigated in [1] by using the finite element method (FEM). In [2], by performing blanking process at different clearances, effect of clearance variation for the aluminum sheet materials is investigated on the product quality and blank forces [2]. The effect of clearance on the product shape is tried to be predicted in [3] by using FEM. Similarly, the blanking process is experimentally studied in [4] by using FEM. By performing sheet metal blanking analysis, a comparison between the FEM-based analysis results with the experimental ones is presented in [5]. In [6, 7], NN approach is benefitted in order to predict the amount of burr on the product formed during the blanking operation and also to determine the most appropriate clearance. In [8], the fuzzy logic (FL) method has been used for estimation of blanking quality of AA5754 alloy. Application of artificial neural networks (ANNs) on sheet metal works is reviewed in [9]. In this study, it is inferred that usage of ANNs on many different sheet metal areas can be seen broadly. The influence of tool clearance, sheet thickness and sheet material is studied in [10], then a method for optimum clearance prediction of sheet metal blanking processes is presented by using “Design of Experiment” [10]. As designing of blanking process depends on experimentations and trial-error iterations, it is costly and time consuming. Thus, in [11, 12], genetic algorithm and artificial neural fuzzy interface system are used for the optimization of process parameters. In the study reported in [13], taguchi method and grey relational analysis are benefitted to find out optimal parameters such as sheet thickness, clearance & wear radius in blanking to determine the variations in three performance characteristics such as burr height, accuracy and circularity value for blanking of medium carbon steel. The results obtained demonstrate that the taguchi grey relational analysis is an effective technique to optimize the parameters for blanking process.

ANNs or shortly neural networks (NNs) have evolved as the results of imitating and modelling the working structure of human brain on computers [14]. Formed by the interconnections of artificial neurons, NN models appear to give good performance in mapping the input to a given output data without knowing a prior relationship among those data. Thus, a NN can be considered as a black box that requires to be well-structured for the concerned problem [15]. The only thing before proceeding with NNs is to derive data samples (inputs and corresponding outputs) from analysis, simulation or experiment. During the last decade, they have been the focus of a great deal of attention, due to their capabilities in solving nonlinear problem by learning [16-20]. For instance, in [16], estimation of a 4,2V-100mA photovoltaic cell productivity is realized with the use of ANN by selecting wind speed, temperature, ambient humidity and angle of the cell with regard to horizontal axis as inputs to the network. Using the NN approach, output quantities such as power output and electric efficiency of a newly designed axial flux permanent magnet synchronous generator are predicted in [17] with promising testing errors less than 3% and 4% for the output power and efficiency estimations, respectively. The authors of the article [18] have proposed a NN to estimate the optimal tilt angle at a given location which is a nonlinear function of the location, time of year, ground reflectivity and the clearness index of the atmosphere. By allowing an estimation of the amount of energy available from the photovoltaic in a microgrid, the study tries to improve the stability, constancy and reliability of electrical power network as well as power system planning on yearly basis and operation control on daily basis. Since the operation of switched reluctance motors is on the basis of inductance variation, obtaining their turn on and turn off switch angles properly are a challenging task for the torque ripple and speed ripple. To address this concern, a controller based upon NN is presented in [19] to determine the optimum turn on and turn off angles for varying speeds. In [20], the nonlinear relationship of the harvested electrical power of a piezoelectric pendulum with its resistive load and magnetic excitation frequency is estimated by the successful application of NN without going through complex analytical model.

By applying blanking process to sheet material CnZn30 at different clearance values, some characteristic parameters affecting the product quality such as blanking force, smooth sheared/fractured rate and burr height are determined, and a NN is proposed in this article for the estimation of those variables depending upon the clearance value. In this regard, a total of 11 experimental data samples have been prepared. Six of the prepared experimental data are utilized to train the developed feedforward NN in order to obtain a neural model that approximates the nonlinear relationship of blanking force, smooth sheared/fractured rate and burr height with the clearance without dealing with complex mathematical method. After training the NN model with 6 samples, its generalization/estimation capability is tested for 5 sample cases which are not experienced during training. To confirm the NN-based estimation results, comparisons are made with those provided by an existing study where FL is considered for the similar estimation task [21]. According to the findings, it is inferred that our proposal is able to reflect the concerned relationship in a higher accuracy. In addition to good performance, design simplicity is another advantage of our contribution because design of a FL system is often tedious and time-consuming suffering from many parameters to be tuned depending upon expert knowledge if available.

2. MATERIAL AND METHOD

2.1. Material

In this study, 1mm sheet material CnZn30 is used. Chemical analysis results and mechanical properties of this material are given in Table 1.

Table 1. Chemical analysis results and mechanical properties of sheet material CnZn30

Chemical Composition of CuZn30 (Element. %)					
Sn	P	Ni	Bi	Cu	Fe
0,030	0,021	0,022	0,010	69,81	0,058
Zn	Mn	Si	S	Al	Sb
30,02	0,005	0,002	0,005	0,006	0,008
Mechanical Properties of CuZn30					
Tensile Strength	Yield Strength	Elongation	Elastic Modulus	Poisson’s Ratio	Density
420MPa	350MPa	32%	110GPa	0,375	8,53gr/cm^3

In order to perform blanking experiments, a blanking mold set and female molds in eleven different clearances are used. For measuring blanking force, load cell, data acquisition card, amplifier and data visualization software are benefitted. Figure 1 displays a sample image showing the characteristic zones of the blanked product under consideration.

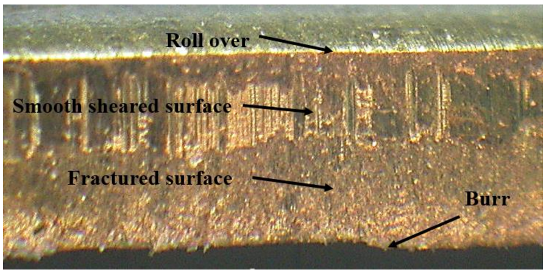

Figure 1. A sample image of the blanked product

2.2. Method

The experimental setup together with its schematic view is given in Figure 2. 30 blanking processes are performed for eleven different clearance values by using 1mm sheet material CnZn30, where each blanking process is repeated five times. ø20 mm punch is used in blanking processes. The measurements of smooth sheared surface, fractured surface and burr height are made by examining the obtained product in an optical microscope. Besides, forces occurring during the blanking process are transferred into the computer with the aid of a suitable load cell.

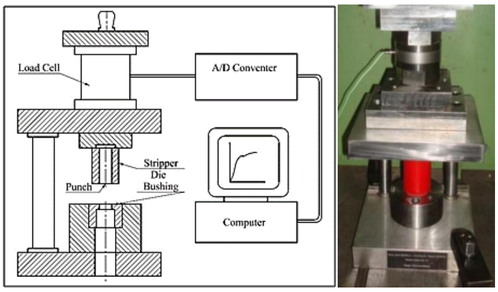

Figure 2. The experimental setup and its schematic view

2.2.1 Artificial neural networks

In general, neural networks can be defined as a system that models the brain working principle of human beings. NN is comprised of artificial neural cells connected to each other in various ways and is typically arranged in layers [22]. During the last decade, NNs have been the focus of a great deal of attention, due to their capabilities in solving nonlinear problem by learning. It has some other unique virtues, such as parallelism, superior generalizing capability and identification without explicit knowledge. The backpropagation (BP) supervised learning algorithm is developed for training feedforward networks, which iteratively adapts the network weights considering the derivatives of the activation function with respect to those weights and it is one of the most widely applied training algorithms for feedforward NN models [23]. In other words, the purpose of the training is to minimize the network error by adjusting the connection weights, where the error is the difference between the desired and predicted output. After training the network using the training data, the next step is to test the network by the test data that is not used during the training process. A three-layer feedforward network with hyperbolic tangent hidden neurons and linear output neurons arranged in this paper is illustrated in Figure 3, where the neurons are indicated by the circles and the weights by the dots in the connections. Input variable is clereance (cl) and the corresponding output variables are chosen as blanking force (bf), smooth sheared/fractured rate (ss/fr), burr height (bh). In order to estimate the nonlinear relationship of the selected output variables with regard to input variable clearance, two hidden layers and 15 neurons in the first hidden layer and 10 neurons in the second hidden layer are assumed in the NN structure. The input and output layers have neurons equal to the corresponding number of variables. Such a network configuration can be simply termed as 1-15-10-3 network.

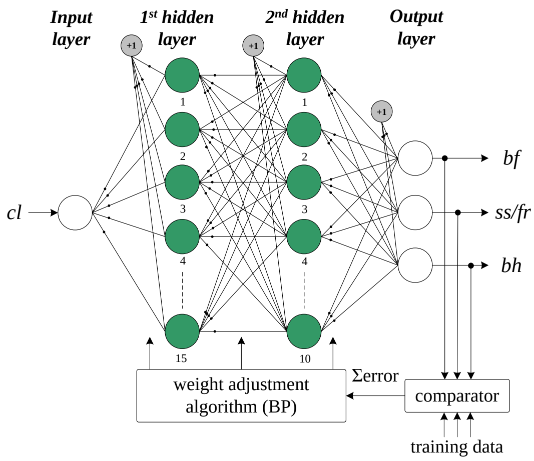

Figure 3. The designed NN architecture

For the experimental study, a total of 11 data samples are prepared. Six of them selected homogeneously from the dataset are assigned as training data which is used to train the network. The remaining 5 samples are preserved for test samples in order to test and confirm the generalization capability of the trained NN. For convenience, both training and test data are tabulated in Table 2.

Table 2. The prepared training and test samples

Data type	No.	cl	bf	ss/fr	bh
Training data	1	0,08	82910	0,481	0,092
	2	0,10	81400	0,468	0,100
	3	0,12	80730	0,430	0,103
	4	0,14	79590	0,414	0,108
	5	0,16	78360	0,415	0,114
	6	0,18	78960	0,412	0,116
Test data	1	0,09	82155	0,475	0,096
	2	0,11	81065	0,449	0,102
	3	0,13	80160	0,422	0,106
	4	0,15	78975	0,415	0,111
	5	0,17	78660	0,414	0,115

Before presenting the training patterns to the network, they are normalized using Eq. 1, as practice has dictated that with normalization, NN training often becomes more efficient, which gives rise to a better predictor. In this regard, input and output variables are transformed into the interval of 0 and 1, where x_r and x_n are the actual and normalized value of the variable, and x_{max} and x_{min} stand for the maximum and minimum value of the variable, respectively.

$$x_n = \frac{x_r - x_{min}}{x_{max} - x_{min}} \tag{1}$$

During the training and testing, the NN performance is evaluated by Eq. 2, which defines the root mean squared (RMS) error of the overall system. The learning algorithm aims to reduce the value of RMS error throughout the iterations.

$$RMS = \left(\frac{1}{P}\sum_{i=1}^{P}\sum_{j=1}^{O}\left(d_{i_j} - a_{i_j}\right)^2\right)^{1/2} \tag{2}$$

where P is the total number of patterns, O is the number of output neurons equal to 3 in this article, d_j and a_j are the desired and actual output of j-th output neuron.

3. EVALUATION OF EXPERIMENTAL STUDIES AND PREDICTIONS

The estimation program based on the BP learning algorithm is implemented in the Dev-C++ environment installed on a computer with an Intel Core (TM) i5-3.30Ghz processor and 8GB RAM. Thanks to the prepared BP-based NN algorithm, we have the ability to change any type of the NN parameters such as hidden layer number, number of neurons in hidden layers, activation function types, learning and momentum rates in between two layers etc., which can allow to design a more specific NN model than can be structured by the widely used available toolboxes, e.g. NN toolbox provided by Matlab. In such situations, the user does not have much degree of freedom to create their own design. The NN control parameters set by trial-and-error in the paper are shown in Table 3.

Table 3. NN control parameters

Property	Value/Technique
Network structure	Multilayer feedforward
Network configuration	1-15-10-3
Learning and momentum rates between output and 2nd hidden layer	0,15 and 0,015
Learning and momentum rates between the hidden layers	0,18 and 0,02
Learning and momentum rates between input and 1st hidden layer	0,18 and 0,02
Training algorithm	Backpropagation
Maximum training epochs	30000
Error measure during training	Equation 2

Using the parameters above, the NN is trained successively for 25 times in the case of randomly generated initial weights. The respective statistical NN training performance is delineated in Table 4. In this table, the average results of 25 independent training attempts are summarized. As the performance measures, the minimum, maximum and mean value of RMS error are reported as well as standard deviation of the distribution.

Table 4. Statistical results of training performance

Performance measure	Value
Best solution	2,41E−07
Worse solution	2,51E−02
Mean	1,70E−03
Standard deviation	5,61E−03

It is noticeable from Table 4 that good training performance is achieved with a best value of 2,41E−07. When the mean and standard deviation value are investigated, it can be inferred that NN training is consistent across each training process, which affirms that our parameter settings in Table 3 are appropriate. It is also worth mention that the number of solutions attained less than 1,0E−04 are 14 out of 25 successive independent runs. In order to give a better picture of a successful training process, Figure 4 is provided. As shown, the RMS error profile gives a quick fall from 1,839 in the initialization mode, then gradually decreases until about 600 epochs. Afterwards, only small amount of improvement is achieved and the training curve has finally converged to 5,61E−06 at the end of the training process. This outcome can mean that the network has been sufficiently trained and is ready for testing.

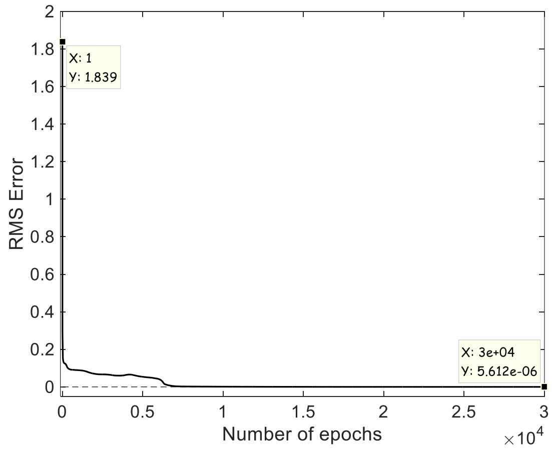

Figure 4. Convergence profile of RMS error for a successful training process

As a result of the blanking tests conducted at varying blanking clearance values, the effect of clearance on the blanking force, smooth sheared/fractured rate and burr height is determined. In any of the reported findings, the red and blue traces indicate the estimation results based on NN and FL, respectively, in a superimposed manner with the black trace showing the real/measured value of the corresponding variable. Also clearance value is composed of both training data and test data reported in Table 2. Figure 5 shows the relation between blanking force and clearance. It is obvious from this figure that the blank force reduces as the clearance increases until 0,16mm. Maximum blank force is measured to be about 83000N at the lowest clearance of 0,08mm, and accordingly the minimum blank force measured as around 78500N has emerged at a clearance value of 0,16mm. When evaluating the estimation results of the blanking force using the NN and FL, it is clear that the curve based on the proposed NN is closer to the one obtained by the experiment.

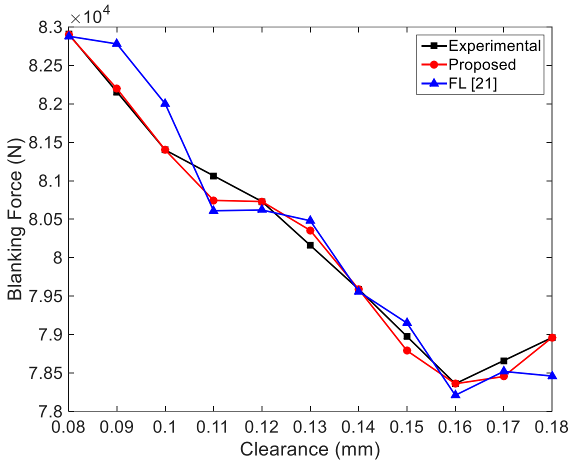

Figure 5. Estimation results of blanking force

During the blanking tests, smooth sheared/fractured rate is measured by means of an optical microscope. The relation of this rate with clearance is given in Figure 6. When Figure 6 is analyzed, one explicit trend is that smooth sheared/fractured rate decreases in conjunction with the increased clearance in the range 0,08 and 0,14. For the remaining range, it stays approximatively at 0,415 regardless of the clearance value. When estimating performances of NN and FL are concerned, it can be shown that the NN estimation is in better agreement with the experimental observations than the FL estimation.

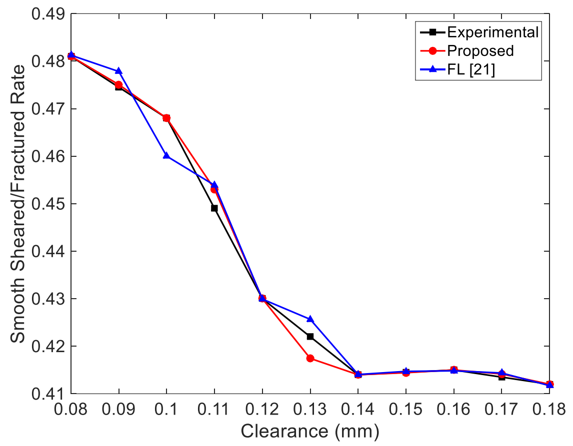

Figure 6. Estimation results of smooth sheared/fractured rate

As regards the relation of burr height with the clearance given in Figure 7, we see that burr height is clearly proportional to clearance. Starting from around 0,0925mm, burr height reaches a height of 0,117mm. When the burr height estimations are analyzed, promising results are obtained for both methods. However, the deviation from the experimental curve is apparently less in the NN-based approach than that based on FL.

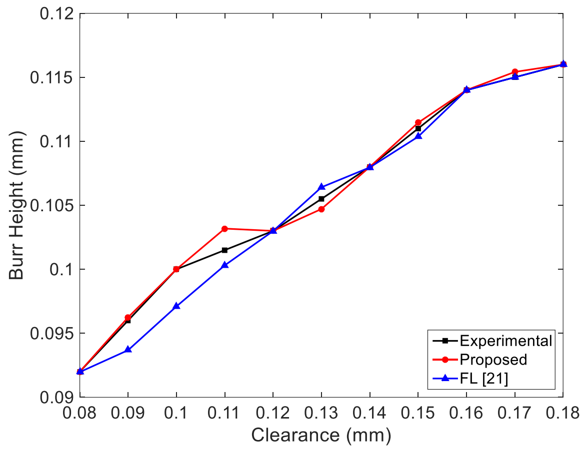

Figure 7. Estimation results of burr height

As the results of those estimation exercises of the output variables such as bf, ss/fr and bh in terms of the input variable cl, the performance of NN is found to have superior predicting power. Finally, a large set of obtained test results corresponding to the estimated variables such as blanking force, smooth sheared/fractured rate and burr height are included in Table 5 with results offered by the existing FL technique, where the best error value achieved is indicated by **bold** number. This table gives the measured respective variable O_M, the estimated variable by NN model O_N, the estimated variable by existing FL model O_F, the percentage difference between measured and NN estimated $D_{MN} = (O_M - O_N)/O_M\%$, and the percentage difference between measured and FL estimated $D_{MF} = (O_M - O_F)/O_M\%$. Notice that the clearance values are the test samples not presented to the network during training. It can be concluded from Table 5 that the introduced NN is able to reduce the percentage error, and it outperforms its fuzzy-based counterpart for 8 of the 15 cases. In 4 cases, FL exhibits better results, and in the remainder, both have similar accuracy of prediction. The percent error values in presence of NN are maximally around 1% for all the cases, which signifies the effectiveness of the NN in the estimation of considered three output variables. We also realize that the FL produces slightly better error values than does our proposal. Nonetheless, the improvements obtained by the NN are remarkable, particularly for burr height.

Table 5. Comparative estimation results of the NN with FL

Blanking force					
Clearance	O_M	O_N	O_F	D_{MN} %	D_{MF} %
0,09	82155	82198	82780	**−0,052**	−0,761
0,11	81065	80745	80610	**+0,395**	+0,561
0,13	80160	80355	80480	**−0,243**	−0,399
0,15	78975	78790	79150	+0,234	**−0,222**
0,17	78660	78454	78520	+0,262	**+0,178**
Smooth sheared/fractured rate					
Clearance	O_M	O_N	O_F	D_{MN} %	D_{MF} %
0,09	0,475	0,475	0,478	**0**	−0,632
0,11	0,449	0,453	0,454	**−0,891**	−1,114
0,13	0,422	0,417	0,426	1,184	**−0,948**
0,15	0,415	0,414	0,414	0,241	0,241
0,17	0,414	0,414	0,414	0	0
Burr height					
Clearance	O_M	O_N	O_F	D_{MN} %	D_{MF} %
0,09	0,096	0,096	0,094	**0**	2,083
0,11	0,102	0,103	0,100	**−0,980**	1,961
0,13	0,106	0,105	0,106	0,944	**0**
0,15	0,111	0,111	0,110	**0**	0,901
0,17	0,115	0,115	0,115	0	0

Bold implies comparably best error value.

4. RESULTS

In this study, the nonlinear relationship of blanking force, smooth sheared/fractured rate and burr height with the applied clearance during the blanking process of a 1mm-thick CuZn30 sheet material is initially investigated experimentally. Afterwards, this relationship is modelled with the help of a trained neural network by considering clearance as the input to NN and the others as outputs from the NN. In all cases of estimation, both training and test data are generated by experiment. Results in comparison with those offered by a state-of-the-art technique affirm the effectiveness and superior power of the proposed approach in estimating the evolutions of the concerned output characteristic variables against the clearance state. The computed maximum percentage error between the estimated and measured value of any output variable is found to be around 1%, which shows that a suitably designed NN can be a significant estimating tool in the field of interest. It can be realized that the presented approach is useful in situations where building a test bench is impractical or impossible owing to the experimental difficulties and costs, or even in the absence of mathematical model corresponding to the related system. Consequently, the results obtained can be further enhanced by considering more training samples. Moreover, different number of hidden layers and hidden-layer neurons can be tried out.

REFERENCES

[1] G. Fang, P. Zeng, L. Lou, "Finite element simulation of the effect of clearance on the forming quality in the blanking process", *Journal of Materials Processing Technology*, 122(2-3), 249-254, 2002.

[2] Z. Tekiner, M. Nalbant, H. Gürün, "An experimental study for the effect of different clearances on burr, smooth-sheared and blanking force on aluminum sheet metal", *Materials and Design*, 27(10), 1134-1138, 2006.

[3] D. Brokken, W. A. M. Brekelmans, F. P. T. Baaijens, "Predicting the shape of blanked products: a finite element approach", *Journal of Materials Processing Technology*, 103(1), 51-56, 2000.

[4] X. Shuqin, M. Hoogen, T. Pyttel, H. Hoffmann, "FEM simulation and experimental research on the AlMg4.5Mn0.4 sheet blanking", *Journal of Material Processing Technology*, 122(2-3), 338-343, 2002.

[5] M. Samuel, "FEM simulations and experimental analysis of parameters of influence in the blanking process", *Journal of Materials Processing Technology*, 84(1-3), 97-106, 1998.

[6] R. Hambli, F. Guerin, "Application of a neural network for optimum clearance prediction in sheet metal blanking processes", *Finite Elements in Analysis and Design*, 39(11), 1039-1052, 2003.

[7] R. Hambli, "Prediction of burr height formation in blanking processes using neural network", *International Journal of Mechanical Sciences*, 44(10), 2089-2102, 2002.

[8] G. Küçüktürk, "Experimental investigation of the effects of clearance on product quality in AA5754 sheet materıal blanking process and estimation by fuzzy logic", *Journal of the Faculty of Engineering and Architecture of Gazi University*, 31(2), 285-294, 2016.

[9] S. Kashid, S. Kumar, "Applications of artificial neural network to sheet metal work-a review", *American Journal of Intelligent Systems*, 2(7), 168-176, 2012.

[10] D. Kulkarni, R. AdhikraoShinde, J. P. Badgujar, "Clearance optimization of blanking process", *International Journal of Scientific & Engineering Research*, 6(12), 178-191, 2015.

[11] R. B. Lahoti, N. G. Phafat, "Optimization of blanking parameters for AISI 1018, A 653, AISI 304 using genetic algorithm", *International Journal of Innovative Research & Development*, 3(8), 114-119, 2014.

[12] R. B. Lahoti, N. G. Phafat, "Optimisation of blanking parameters for AISI 1018 and AISI 202 steel sheets using ANFIS", *International Journal of Innovative Research in Advanced Engineering*, 1(7), 187-192, 2014.

[13] P. G. Dhoble, R. R. Deshmukh, Y. M. Wankhade, S. D. Yeole, "Optimization of sheet metal blanking process parameters using taguchi method and grey relational analysis", *Indian Research Transaction*, 5(2), 100-104, 2015.

[14] K. K. Çevik, E. Dandil, "Yapay sinir ağları için net platformunda görsel bir eğitim yazılımının geliştirilmesi", *Bilişim Teknolojileri Dergisi*, 5(1), 19-28, 2012.

[15] S. Senan, "A neural net-based approach for CPU utilization", *Bilişim Teknolojileri Dergisi*, 10(3), 263-272, 2017.

[16] H. Özkişi, M. Topaloğlu, "Fotovoltaik hücrenin verimliliğinin yapay sinir ağı ile tahmini", *Bilişim Teknolojileri Dergisi*, 10(3), 247-253, 2017.

[17] E. Çelik, H. Gör, N. Öztürk, E. Kurt, "Application of artificial neural network to estimate power generation and efficiency of a new axial flux permanent magnet synchronous generator", *International Journal of Hydrogen Energy*, 42(28), 17692-17699, 2017.

[18] A. Chatterjee, A. Keyhani, "Neural network estimation of microgrid maximum solar power", *IEEE Transactions on Smart Grid*, 3(4), 1860-1866, 2012.

[19] E. F. I. Raj, V. Kamaraj, "Neural network based control for switched reluctance motor drive", **International Conference on Emerging Trends in Computing, Communication and Nanotechnology**, Tirunelveli, India, 678-682, 2013.

[20] E. Çelik, Y. Uzun, E. Kurt, N. Öztürk, N. Topalloğlu, "A neural network design for the estimation of nonlinear behavior of a magnetically-excited piezoelectric harvester", *Journal of Electronic Materials* 2018, doi: 10.1007/s11664-018-6078-z.

[21] O. Çavuşoglu, H. Gürün, "Investigation and fuzzy logic prediction of the effects of clearance on the blanking process of CuZn30 sheet metal", *Kovové materiály-Metallic Materials*, 54(2), 125-131, 2016.

[22] V. Özdemir, "Determination of Turkey's carbonizatıon index based on basic energy indicators by artificial neural networks, *Journal of The Faculty of Engineering and Architecture of Gazi University*, 26(1), 9-15, 2011.

[23] J. Li, J. Cheng, J. Shi, F. Huang, "Brief introduction of back propagation (BP) neural network algorithm and its improvement", **Advances in Computer Science and Information Engineering,. Advances in Intelligent and Soft Computing Advances in Intelligent and Soft Computing**, Vol 169, Eds: D. Jin, S. Lin, Springer, Berlin, Heidelberg, 553-558, 2012.