International Journal of
Intelligent Systems and Applications in Engineering

ISSN:2147-6799 www.ijisae.org Original Research Paper

Weight losses estimation of industrial punch tools

Yusuf Arslan*[1]

Submitted: 10/07/2019 Accepted : 15/09/2019

Abstract: Many studies have been conducted on the estimation of weight losses of industrial tools; however, these investigations are scarce. And there is no prediction study on the weight loss of industrial punches. An artificial neural network model (ANN) was proposed in order to establish relationships with the field data including input parameters as punch diameter, punch stroke, stroke noise, and punch temperature and output parameter as weight loss of punch. Effect of each parameter on the weight loss of industrial punch was analyzed with the developed model. An empirical formula was also obtained with the generalization capabilities of the ANN system. Analysis results showed that the estimation results are in good agreement with the field data. And these numerical results with high efficiency can make it possible to use the neural designs for real-life industrial punch estimation applications.

Keywords: *Industrial punch, ANN, weight losses, punch diameter, punch stroke, stroke noise*

1. Introduction

Forming with die and punch has an essential place in the production of many sectors such as automotive. Developments in die design and manufacturing have both increased their lifetime and increased the quality of punching and cutting by enabling a more precise and cost-effective production process. The cutting process during material punching occurs plastic deformation, cutting and breaking stages. From the previous studies; the punching parameters, type, thickness, die clearance and piercing forces of the workpiece can see to affect the hole form (Fig. 2) [1-3]. To combat today's markets, long-lasting dies and punches, less waste, better quality production should be made. The quality of the parts affected by piercing parameters and punch wear is generally assessed by criteria such as hole edge geometry and burr height. The punch material and geometry can be held responsible for the rapid and excessive wear of the punches [4-10]. Due to the mechanical properties of the workpiece and the punch material, excessive stresses and major wear events occur during cutting. These tribological phenomena can be explained as adhesion, transfer between friction elements, fatigue and fatigue due to micro fractures. To maintain hole quality when these events occur, punches and dies must be replaced at optimum time. Corroded punches, which adversely affect the hole geometry, should be changed at the appropriate time to control production costs. Better hole quality can be obtained by selecting the punching and cutting parameters of the punch and workpiece materials accordingly [6-8]. In previous studies, much work has been done, such as tool life, wear, cutting clearance and material thickness, except for examining the hole quality of the products [9, 10]. However, there is no study investigating the relationship among diameter, wear, temperature and noise.

Due to the mechanical properties of the workpiece and the punch material, excessive stresses and major wear events occur during cutting. Therefore, traditional heat treatments are realized to increase the production speed and service life of die components made of such as cold work tool steels DIN 1.2080, 2379 running under large loads. So, the mechanical properties and abrasion resistance can be increased by heat treatment [3, 4].

Artificial neural networks (ANNs) are widely used to model the comportment of the brain functions and human nervous system [11,12]. In may engineering disciplines, the ANN systems are utilized with high accuracy to predict and evaluate the output factor [13-15].

2. Materials and Methods

2.1. Field Studies (Piercing Experiments)

In this work 1.2-mm-thick, the EN 14301 stainless steel sheets in dimensions of 250×250 mm were used. The chemical content and strength values of stainless steel are presented in Table 1 and 2. The piercing processes were carried out using a 25-ton capacity Trumpf TR 240 punch machine and 160 strokes per minute.

The piercing operations were performed under dry conditions in this industrial application. The cutting clearance used was as 12% of the workpieces thickness. The parts were measured at 5,000th, 10,000th, 15,000th, 20,000th, 25,000th and 30,000th strokes.

Table 1. Chemical content of EN 14301 stainless steel (wt.%)

C	Mn	Si	Cr	S	P	Ni	Balance
0.58	1.62	0.15	19.06	0.03	0.09	9.67	68.81

Table 2. The strength values of EN 14301 stainless steel

Tensile strength (Mpa)	Yield strength (Mpa)	Hardness (HRB)	Density (gr/cm^3)
505	215	70	8

The punches was designed to Ø5x100 mm, Ø6x100 mm and Ø7x100 mm in dimentional. They were made of DIN 1.2080 tool steel. Table 3 presents chemical composition and Table 4

[1] *Department of Mechanical and Metal Technology, Duzce University, Duzce– 81620, TURKEY, ORCID ID : 0000-0003-1731-5423*
** Corresponding Author Email: yusufarslan@duzce.edu.tr*

mechanical properties of punches (provided by the supplier).

Table 3. Chemical composition of DIN 1.2080 tool steel (wt.%)

C	Mn	Si	Cr	S	P	Ni	Balance
2.09	0.17	0.01	12.35	0.001	0.015	0.21	85.14

Table 4. Mechanical properties of DIN 1.2080 tool steel

Tensile strength (MPa)	Yield strength (MPa)	Hardness (HRC)	Density (gr/cm^3)
970	850	28	7.86

The heat treatment of the 2080 tool steel has carried out with salt bath in the vacuum heat treatment furnace. This operation has involved hardening and tempering (Fig. 1) [16, 17].

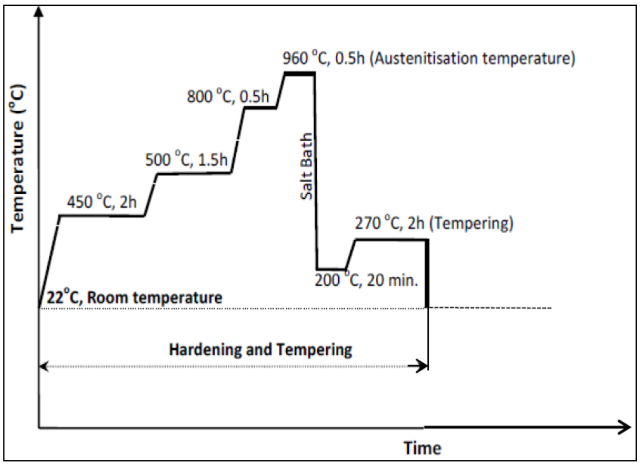

Fig. 1. A schematic presentation of the heat treatment schedule consisting of the hardening, tempering cycles of the punches (DIN 1.2080)

The PCE-778 Laser Thermometer is a device used to measure temperature using an infrared laser at a specified distance. This non-contact measuring Laser Thermometer is suitable for measuring up to 800 °C (Fig. 2b). The technical specifications of the temperature measuring instrument are given in Table 5. At the end of each stroke, temperature measurements were taken from a fixed location and at a distance of 3 m. The punch temperatures were measured three times and averaged.

The PCE-318 noise instrument was used measure the punching noise of the punch machine at a distance of 3 m. The PCE-318 noise device was used to measure punching noise of the punching machine using at 3 m distance. This measuring device is suitable for measuring up to 26-100 dB and 70-130 dB (Fig. 2a). The technical specifications of the noise measuring instrument are given in Table 6. At the end of each stroke, punching noise measurements were taken from a fixed location and at a distance of 3 m. The punching noises were measured three times and averaged.

Weight loss of the punches to assess the wear resistances were measured on the sensitive scale of 1×10^{-3} g (ELEL 200 S). The weight losses of the tools were measured at the end of each stroke. They were measured after cleaning. This process was repeated three times and averaged.

Table 5. Technical specifications of the PCE-778 Laser Thermometer measuring instrument

Technical Properties	
Optical Resolution	12: 1
Measurement Range	-40 °C ... 800 °C / -40 °F ... 1472 °F
Measurement Sensitivity	-40 °C ... 0 °C: ±4 °C 0 ... +400 °C: ±1.5 °C +400 °C ... +800 °C: ±2 °C
Resolution	0.1 °C at 0 ... +199.9 °C 1 °C at > 199.9 °C
Emission	0.1...1 (adjustable)
Spectral	8 ... 14 mikron
Transaction Terms	0 ... +50 °C, RH 10 % ... 90 %
Storage conditions	-20 °C ... +60 °C, RH < 80 %
Power source	9V battery
Laser	Class 2

The HOYTOM 1003 test machine was used for makro hardness evaluation of samples prepared in accordance with the required standard. The main load 1.5 kN for 20 seconds was applied after a preload of 0.1 kN. The average of five measurement values was used as hardness value.

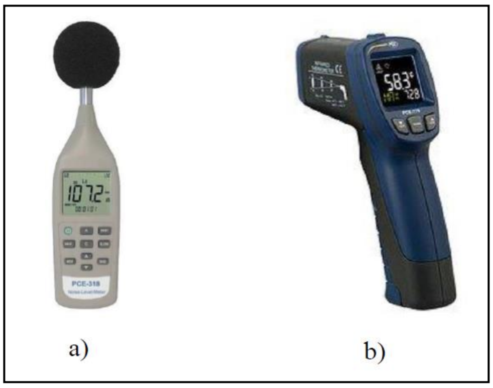

Fig. 2. a) Noise measurement device, **b)** Laser thermometer device

Table 6. Technical specifications of the PCE-318 noise measuring instrument

Technical Properties	
Standards	IEC651 Type 2, ANSI S1.4 Type 2 IEC61672-1: 2002 2. class
Frequency range	31,5 Hz… 8 Khz
Measurement Range	26… 130 dB / Resolution 1 dB
Microphone	½ inch electrode condenser microphone
1. Display	4 position LCD display
Data update	every 0.5 seconds
Screen 2	50-segment bar chart
Data update	every 50 ms
Measuring ranges	Lo: 26 ... 100 dB Hi: 70 ... 130 dB
Sensitivity	Reference conditions 94 dB and ± 1,5 dB at 1 Khz
Fixing	Standard mounting for a tripod
Power supply	9 V battery (generally for 50 hours of operation)
Working temperature	0 ... +50 °C

2.2. Artificial Neural Network Development

Quasi- Newton was utilized as the training algorithm in the ANN system for the weight losses estimation. Eighty-six datasets were utilized for the improvement of the proposed ANN system. Data classification of ANN models was carried out as proposed: 80% of the data for training and 20% for testing Quasi- Newton method using the gradient data in each iteration calculates an approximate value of the inverse Hessian. Teaching algorithm is presented in Table 7.

Table 7. Training algorithm information

Description	Value
Training rate method	Brent method
Training rate tolerance	0.006
Min. parameters increment form	1e-009
Mx. Selection loss increases	100
Min. loss increase	1e-012
Max. training time	4000
Max. iterations number	1000

The ANN system was proposed with four input parameters. These parameters are punch temperature, punch stroke, punch diameter and stroke voice. The other factors that may affect the weight losses of punch such as punch material, cutting clearance were kept constant and ignored in field studies. The ANN structure is given Fig. 3. The number of layers in the neural network is 2. The architecture of this neural network can be written as 4:3:1.

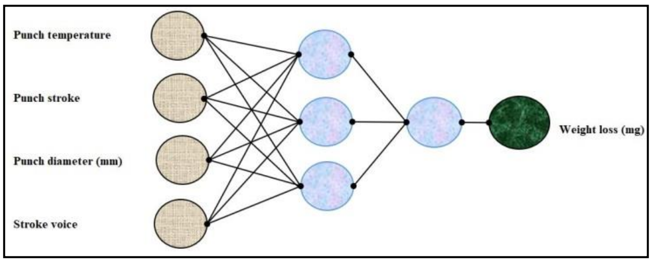

Fig. 3. ANN structure

Table 8. Order selection algorithm

Description	Value
Minimum order	1
Maximum order	15
Trials number	5
Tolerance	0.01
Selection loss goal	0
Maximum selection failures	7
Maximum iterations number	1000

A scaling layer, a neural network and an unscaling layer form the structure of the ANN. The complexity, represented by the numbers of hidden neurons, is 3. Incremental order was used as order selection algorithm. Details of this algorithm is presented in Table 8. ANN model performance was tested with Sum Squared Mistake (SSM), Mean Squared Mistake (MSM), Root Mean Squared Mistake (RMSM), Normalized Squared Mistake (NSM) and Minkowski Mistake (MM) methods. Proposed network errors are shown in Table 9.

Table 9. Proposed network errors

	Training	Selection	Testing
Sum squared error	2.47631e-010	0.0942242	0.141491
Mean squared error	2.25119e-011	0.0314081	0.047163
Root mean squared error	4.74467e-006	0.177223	0.217172
Normalized squared error	3.72273e-010	7.18793	2.27548
Minkowski error	9.09183e-008	0.209518	0.274712

The rule of the parameters provides a hint about the complexity of the estimation pattern. Parameters norm were 2.6. This value was not very high, and the model was also stable. The neural parameters norm was used as the regularization method. It was applied to control the complexity of the neural network by reducing the value of the parameters. Neural parameters norm weight was obtained as 0.001. Neural Designer software was utilized during the development of ANN system.

3. Discussions

3.1. Field Study Results

The heat treatment of the 2080 tool steel involved hardening and tempering. The hardness of the punch was measured 58 HRC after heat treatment. The heat treatment procedure was seen to increase the hardness of the DIN 2080 tool steel material. Also the increased hardness was increased wear resistance. The researchers have known that the hardening and tempering for the samples in the heat treatment processing procedure were influential on mechanical properties and microstructure changes [14, 15].

The piercing processes were carried out using a 25 ton capacity the punch machine and 160 strokes per minute. The piercing operations were performed under dry conditions in this industrial application. The cutting clearance used was 12% of the workpieces thickness. In this work 1.2-mm-thick the EN 14301 stainless steel sheets were used. The weight loss (mg) in the unit area (mm^2) was evaluated as punch wear. The punch stroke and weight loss relationship for the 5, 6 and 7 mm diameter punches used are shows in Fig. 4. Increasing punch stroke increases weight losses.

The less amount of weight loss was obtained when the diameter was 5 mm, and the stroke voice was less than 88 dB (Fig. 5).

Punch temperature and punch stroke combined effects on the weight losses are presented in Fig. 6. Both increases in punch stroke and punch temperature resulted in increase of weight losses.

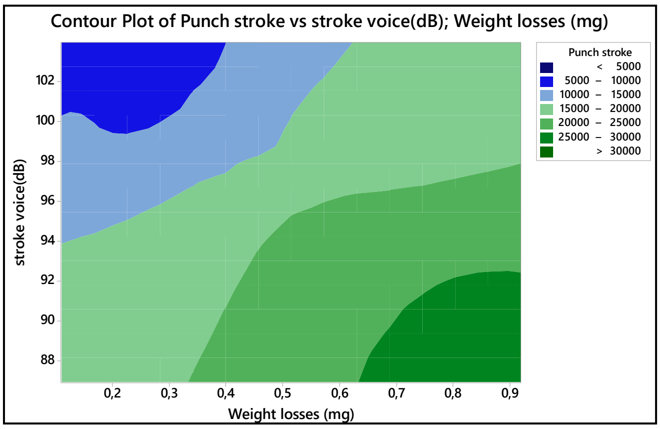

Fig. 4. Contour Plot of Punch stroke vs stroke voice (dB); Weight losses (mg)

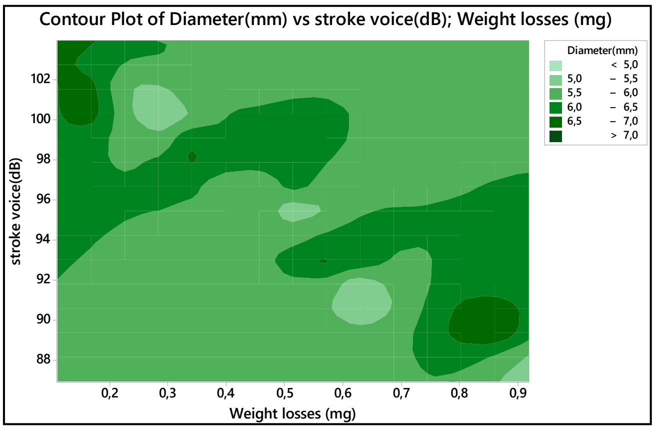

Fig. 5. Contour Plot of Punch stroke vs stroke voice(dB); Punch diameter (mm)

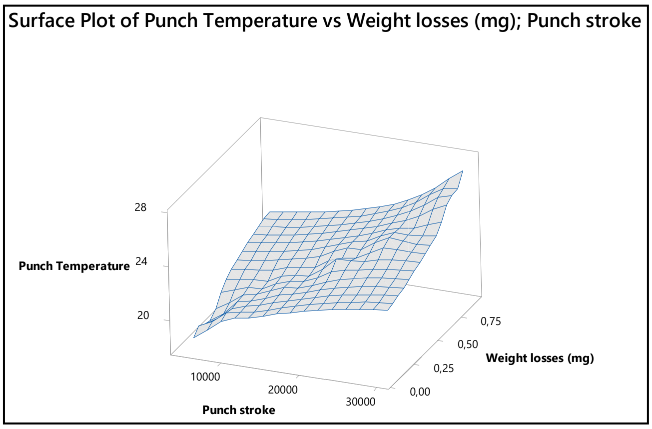

Fig. 6. Surface Plot of Punch Temperature vs Weight losses (mg); Punch stroke

3.2. Artificial Neural Network Results

Linear regression plot of the estimated weight losses is given in Fig. 7. The blue line indicates the best linear and the grey line would indicate the perfect fit. R-squared value accounts for 92.29 and it was found that utilized ANN model reflected a good fitting performance.

Output parameter weight losses with effecting input parameters is presented in Fig. 8. The field study results and predicted data were compared. The relationship between field study results with the output data is not constant in proposed ANN environment. The main reason of this fact that each inputs significantly effect the neural network system.

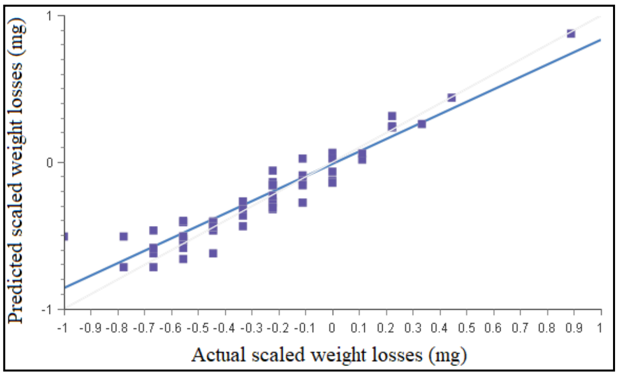

Fig. 7. Linear regression chart

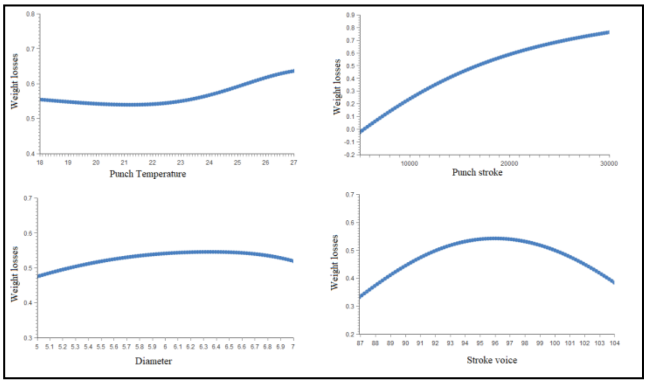

Fig. 8. Estimated weight losses as a function of inputs

Weight losses increased with the increase in punch stroke. The punch temperature exceeding 24°C significantly increased the weight loss amounts. The minimum estimated weight loss results were recorded when the punch with 5 mm was used.

The mathematical expression represented by the neural network is given below. The result is propagated in a feed-forward fashion through the scaling layer, the perceptron layers and the unscaling layer. The mathematical formulas as follows (Eq. 1-8):

Scaled punch temperature = (Punch temperature - 22.2353)/2.70484 (1)

Scaled punch stroke =2*(Punch stroke -5000)/ (30000-5000) -1 (2)

Scaled diameter =2*(Diameter -5)/ (7-5)-1 (3)

Scaled stroke voice= (stroke voice -96.0429) /5.11657 (4)

y_{11}=tanh (0.972607-0.549997* Scaled punch temperature + 0.797416* Scaled punch stroke+ 0.41634* Scaled diameter - 0.4915* Scaled stroke voice (5)

y_{12}=tanh (1.06284 - 0.679937* Scaled punch temperature- 0.215442* Scaled punch stroke -1.10267* Scaled diameter + 0.303153* Scaled stroke voice (6)

y_{13}=tanh (-1.03725+ 0.0845723* Scaled punch temperature - 0.610826* Scaled punch stroke+ 0.948722* Scaled diameter- 0.501023* Scaled stroke voice (7)

Scaled weight losses= (0.0313461+ 0.425691*y_{11}-0.456221*y_{12}- 0.681869*y_{13}) (8)

4. Conclusion

Eighty-six datasets of previously performed field studies on weight of punches were analyzed in the neural network system. The following results can be drawn from the results of the estimation study:

- The proposed ANN system approved the strong correlation between the input parameters and the output parameter weight loss amounts of punches.
- The weight factor of the analysis was well calibrated, it was found that results of the analysis showed good correlation with the previously conducted experimental study results.
- Increasing the punch temperature up to 27 ^{0}C, also increases the weight loss amounts in the ANN analysis.
- Minimum weight loss amount was recorded with stroke voice lower than 87 dB.
- The results of the study can be evaluated by other artificial and mathematical systems for better understanding of the effects on the weight loss of punches.

References

[1] "2013 International Conference on Future Energy and Materials Research, FEMR 2013," Advanced Materials Research. 2013.

[2] N. Hatanaka, K. Yamaguchi, N. Takakura, and T. Iizuka, "Simulation of sheared edge formation process in blanking of sheet metals," in Journal of Materials Processing Technology, 2003.

[3] Y. Arslan and A. Özdemir, "Punch structure, punch wear and cut profiles of AISI 304 stainless steel sheet blanks manufactured using cryogenically treated AISI D3 tool steel punches," Int. J. Adv. Manuf. Technol., 2016.

[4] X. Wu, H. Bahmanpour, and K. Schmid, "Characterization of mechanically sheared edges of dual phase steels," J. Mater. Process. Technol., 2012.

[5] T. Z. Quazi, R. Shaikh, A. Totre, R. Nishad, S. Bodke, and A. Chauhan, "Blanking process optimization using Taguchi method," Int. J. Eng. Res. Dev., 2013.

[6] M. H. Myint, J. Y. H. Fuh, Y. S. Wong, L. Lu, Z. D. Chen, and C. M. Choy, "Evaluation of wear mechanisms of Y-TZP and tungsten carbide punches," in Journal of Materials Processing Technology, 2003.

[7] Z. Tekiner, M. Nalbant, and H. Gürün, "An experimental study for the effect of different clearances on burr, smooth-sheared and blanking force on aluminium sheet metal," Mater. Des., 2006.

[8] G. Fang, P. Zeng, and L. Lou, "Finite element simulation of the effect of clearance on the forming quality in the blanking process," J. Mater. Process. Technol., 2002.

[9] S. Y. Luo, "Effect of the geometry and the surface treatment of punching tools on the tool life and wear conditions in the piercing of thick steel plate," J. Mater. Process. Technol., 1999.

[10] T. S. Kwak, Y. J. Kim, and W. B. Bae, "Finite element analysis on the effect of die clearance on shear planes in fine blanking," J. Mater. Process. Technol., 2002.

[11] S. A. Yildizel and A. U. Öztürk, "A study on the estimation of prefabricated glass fiber reinforced concrete panel strength values with an artificial neural network model," Comput. Mater. Contin., 2016.

[12] I. Uygur, A. Cicek, E. Toklu, R. Kara, and S. Saridemir, "Fatigue life predictions of metal matrix composites using artificial neural networks," Arch. Metall. Mater., 2014.

[13] M. Uzun and K. Armagan, "Optimization of Compressive Strength of Concrete Added Glass Powder Using Taguchi Methods", International Journal of Scientific Research Engineering & Technology, vol. 7, no.12, pp. 864-868, Dec. 2018.

[14] [1] A. J. Tenza-Abril, Y. Villacampa, A. M. Solak, and F. Baeza-Brotons, "Prediction and sensitivity analysis of compressive strength in segregated lightweight concrete based on artificial neural network using ultrasonic pulse velocity," Constr. Build. Mater., 2018.

[15] S. Yildizel, M. Uzun, and M. Cogurcu, "Prediction of Bending Strength of Self-Leveling Glass Fiber Reinforced Concrete", IJISAE, vol. 7, no. 1, pp. 7-12, Mar. 2019.

[16] I. Uygur, H. Gerengi, Y. Arslan, and M. Kurtay, "The effects of cryogenic treatment on the corrosion of AISI D3 steel," Mater. Res., 2015.

[17] L. B. Ramos, L. Simoni, R. G. Mielczarski, M. R. O. Vega, R. M. Schroeder, and C. De Fraga Malfatti, "Tribocorrosion and electrochemical behavior of DIN 1.4110 martensitic stainless steels after cryogenic heat treatment," Mater. Res., 2017.