Management and Production Engineering Review
Volume 12 • Number 2 • June 2021 • pp. 27–32
DOI: 10.24425/mper.2021.137675

Maintenance Supervision of the Dies Condition and Technological Quality of Forged Products in Industrial Conditions

Joanna Krajewska-Śpiewak [1], Jan Turek [2], Józef Gawlik [1]

[1] *Cracow University of Technology, Faculty of Mechanical Engineering, Poland*
[2] *Jasło, Poland*

Received: 30 July 2020
Accepted: 26 April 2021

Abstract
Wear of the working surfaces of the forging dies in the process of manufacturing products with the die forging technique leads to deterioration of their operational properties as well as their technological quality. A characteristic feature of production in small and medium-sized enterprises is the high variability of the product range and short production series, which can be repeated in the case of re-orders by customers. In this type of production conditions, a technological criterion in form of – a change in the characteristic and selected dimension of forging is usually used to assess the quality of products. An important problem is, whether by taking up another order for a series of the same type of product, it will be possible to implement it with the existing die, or should a new die be made?

As a result of the research carried out in the company implementing this type of contract, a procedure was proposed for forecasting the abrasive wear of die working surfaces on the basis of a technological criterion, easy to determine in the conditions of small and medium-sized enterprises.

The paper presents the results of the wear assessment of a die made out of hot-work tool steel X37CrMoV5-1 (WCL) and dies made of 42CrMo4 alloy structural steel with hardfacing working surfaces by F-818 wire. To determine and forecast the process of die wear, a mathematical model in the form of neural networks was used. Their task was to forecast the ratio of the increment in introduced wear intensity indicator to the number of forgings made during the process. Taking into account the ability of neural networks to learn, their use in the diagnostic process is justified.

Keywords
intensity of die wear, forging technological quality, neural networks.

Introduction

Phenomena responsible for die wear are complex and depend on factors associated with a die itself, die operating conditions, material and shape of forgings (Gronostajski et al. 2014, 2016, 2011; Rauch et al. 2016). The research conducted in a medium-sized company that carries out orders for products made in series from several dozen to several hundred pieces, showed the purposefulness of developing a method that would allow for the initial determination of whether the reused die would be able to perform the planned series of products. It should be emphasized that the durability and reliability of forging tools has a significant impact on the production costs of forgings and the profitability of production included in the company's general costs (Hawryluk, 2016a; 2016b).

The deterioration of the product's technological quality can be observed by dimension changes and sometimes also by changes in the chemical composition of the surface layer of the product. Reduction of the die wear intensity of the working surfaces can be achieved by: wear resistance high alloy tool steel, thermo-chemical treatment (mainly ion or gas nitriding), chroming and carburizing, surface plastic forming (burnishing), creating forging die surfaces of wear-resistant layers by hardfacing electrodes or wires, welding with electrodes or wires, laser processing or powder hardfacing.

A practical method for evaluation of the wear process of the forging dies is to determine the relationship

Corresponding author: *Joanna Krajewska-Śpiewak – Cracow University of Technology, Faculty of Mechanical Engineering, Poland, phone: +4877 374 3255, e-mail: joanna.krajewska-spiewak@pk.edu.pl*

between changes in the dimension of the forgings and the number of made pieces. If the change of the forging dimension exceeds the assumed tolerance, the die is considered unfit for further service.

As a measure of the wear intensity of the working surfaces of dies in the forging process, the ratio of the increased wear index to the number of made forgings was assumed. The wear intensity strongly dependents on the rate of growth of the forged material's deformation, which affects the state of thermo-mechanical stresses of the die (Turek et al., 2012).

Supervision of the technological quality of the product includes the identification of selected parameters (state indicators) of the process and prediction of their changes in subsequent cycles of this process.

Destructive mechanism of die in the forging process

Phenomena responsible for die wear are complex and depend on factors associated with a die itself, die operating conditions, material and shape of forgings. Kinetics of die wear process is affected by friction and abrasive wear associated with this process. Dynamic loads during the forging process affect: mechanical and thermal fatigue, oxidation processes and local surface corrosion of the die material. As a result of the micro-cracks formation, build-up of forged material and adhesive wear of the working surfaces of the die pattern, micro-chipping may occur on the working surfaces of the dies. The relative movement of the die working surfaces and the forgings surface may be the reason for the die material loss and it can also lead result in grooves in the form of scratches on surfaces. These phenomena are the reason for the durability reduction of hot working die and as a result they lead to its decommissioning (Fig. 1).

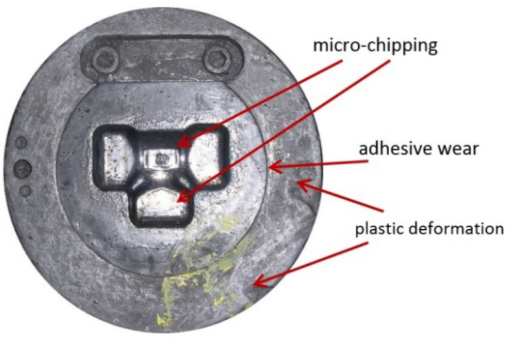

Fig. 1. A die out of service due to the wear (own research)

The highest intensity of abrasive wear occur in the zones of the largest unit pressure and displacements of the shaped material relative to the working surfaces of the tool. In the die forging process, abrasive wear depends on the shape of the product (surface geometry), pressures, oxide layers being formed, sliding speed and contact temperature of the die surface with the workpiece.

Thermal fatigue wear is a result of the formation of crack network on the surface layer and propagation of this mesh deep into the layer. Cyclic temperature changes result in variable thermal stresses related to the temperature gradient and heterogeneity of the physicochemical properties of the tool steel phases. With an increase number of heat load cycles, structural changes and a decrease in the strength properties of the surface layer occur. Consequently, a crack network is formed due to exceeding the yield point.

Inside of the multiphase alloys, such as the hot work tool steel, nucleation of fatigue cracks may occur which can take place inside grains or at interphase boundaries. Their occurrence depends on morphology and properties of individual phases. Carbide precipitation, grain boundaries and non-metallic inclusions impede dislocations movement, which accumulate in front of these obstacles under the influence of thermal stresses. During subsequent cycles of temperature changes, the number of network defects increases, because during cooling only some parts of created dislocations and vacancies are annihilated. Nonmetallic inclusions can be the germ of cracks, especially those whose dimensions exceed the critical values. As the temperature increases, the proportion of nucleating cracks at the grain boundaries increases which is caused by reduction of interatomic bond strength in these areas. Therefore, thermal fatigue is a process dependent on a variety of interrelated factors (Turek, 2019). The formation of a micro-crack mesh on the die surface can lead to strength wear of the die. An example is shown in Fig. 2.

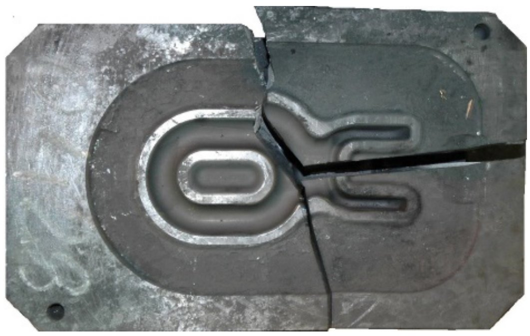

Fig. 2. Strength wear of the die (own research)

It should be noted that the cooling and lubricating fluids which are used during forging affect the wear and durability of the dies. For example, the use of an aqueous sodium chloride solution can cause tool corrosion. Too much oil with colloidal graphite may cause local carburization of the surface and intensification of crack development as a result of thermal fatigue.

Adhesive wear of the work surfaces of the forging pattern is caused by the formation of "sticks" (build-ups) of forged material. The material with a low yield point (especially in technically dry friction conditions) has a particular tendency to form adhesion joints with the material of the die. High temperature and significant unit pressure which occur in the contact zone of the die pattern favors the occurrence of adhesion and diffusion process.

Industrial research

Hot working dies made out of tool steel X37CrMoV5-1 (WCL a trade name of the steel which hardness is 50-53 HRC after heat treatment) and hardfacing dies made out of alloy structural steel 42CrMo4 (die hardness after heat treatment, before hardfacing – 33–36 HRC) were tested. The working surfaces of the die patterns were subjected to 4 layers hardfacing by F-818 type wire (hardness after hardfacing 53–55 HRC). The forging height deviation after making a determined number of products was a measure of the degree of wear of the tested dies. Three series of measurements were performed for each type of die, and the averaged results are presented in Table 1.

Table 1
The result of technological quality of the forging

Indicator	Measurement number					
	1	2	3	4	5	6
$\overline{\Delta w_i}$ [mm]	0.17	0.2	0.35	0.65	0.99	1.1
s	0.01	0.00	0.18	0.05	0.02	0
$\overline{n_i}$ [pcs]	875	1270	1650	2450	3380	3580
$\overline{\vartheta_i}$ $\left[\frac{\text{mm}}{\text{pcs}}\right]$	1.94	1.57	2.12	2.65	2.93	3.07
$\overline{\Delta w_i}^*$ [mm]	0.17	0.2	0.35	0.65	0.99	1.1
s^*	0.00	0.06	0.02	0.03	0.01	0
$\overline{n_i}^*$ [pcs]	1220	2200	5500	7850	9550	10200
$\overline{\vartheta_i}^*$ $\left[\frac{\text{mm}}{\text{pcs}}\right]$	0.76	0.77	0.76	0.85	1.02	1.07

Indicator name: $\overline{\Delta w_i}$ – average deviation of the forgings dimension in relation to the nominal size; s – standard deviation of Δw_i; $\overline{n_i}$ – average number of products made with a dies made out of 37CrMoV5-1 and $\overline{n_i}^*$ – made out of 42CrMo4; $\overline{\vartheta_i}$, $\overline{\vartheta_i}^*$ – average values of the change intensity in the forgings' size due to the wear of the working surfaces of the dies determined according to the formulas: $\vartheta_i = \frac{\Delta w_i}{n_i}\left[\frac{\text{mm}}{\text{pcs}}\right]$.

Figure 3 shows the relationship between the wear intensity index $\overline{\vartheta}$ and the number of made forgings (n).

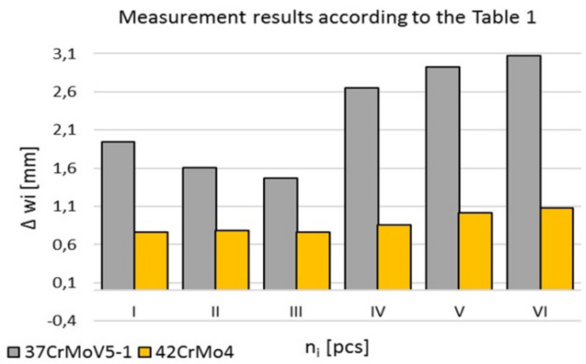

Fig. 3. Relationship between wear intensity index and the number of forgings made. grey columns – 37CrMoV5-1 die (n_{kr} = 3580 pcs); yellow columns – 42CrMo4 die (n_{kr} = 10200 pcs) Strength wear of the die (own research)

Where n_{kr} is the number of forgings made to take the die out of service that has reached the criterion value of the dimensional deviation Δw_{kr}.

Model of technological quality assessment of forgings

Irrespective of the shape of the product being made during die forging process, it can be assumed that for the same forging material, the dies form a set of tools with similar technological features. Therefore, it can be assumed that wear processes will be similar and can be assessed with the abrasive wear intensity index ϑ (apart from ad hoc strength wear).

The state of die wear which causes its withdrawal from current operation occurs when one of the measurable features of the forgings does not meet the quality requirements (e.g. dimension deviation). If the wear is repairable, then after regeneration the die is reusable.

Artificial neural networks have already found wide application in mechanical technology, among others for forecasting the process condition and properties of the surface layer of the workpiece (Azari et al., 2014; Young, 1989), designing forging tools

(Gubán et al., 2019), analysis of wear and durability of forging dies (Ciancio et al., 2015, Gronostajski et al., 2015; Hawryluk, Mrzygłód, 2018, 2017; Kocańda, Czyżewski, 2000) in expert systems supporting the decisions of technologists (Ciancio et al., 2015; Krajewska-Śpiewak, 2016; Mrzygłód et al., 2018).

Deviation values and corresponding quantities of forgings were determined based on the actual dimension of the forgings in relation to the nominal size (Table 1). The calculations were carried out with the use of several types of neural networks. The neural networks were the basis for the selection of regression networks (RBF) and multilayer perceptron networks (MLP) as an effective model for identifying and forecasting the state of the die forging process. Radial based function (RBF) and Multilayer Perceptron (MLP) are the most commonly used neural networks. Both networks consist of input layer, hidden layer and output layer, where data are transmitted only in one direction. There can be a different number of neurons in each layer. The number of neurons in the input layer usually corresponds to the number of input data. The number of neurons in the hidden layers is responsible for the capabilities of the model. Usually there are no connections between neurons inside layers – these connections are between adjacent layers. In RBF network the neurons in hidden layer have their centrum in a R^d space ($C_n \in R^d$, where C is centrum). The centers are initiated during the creation of the network structure, and in the learning process they are adapted to the training data. Neurons in the hidden layer work similarly to MLP networks. The appropriate weight and bias values, which are obtained in the training process, are assigned to each neuron. The values from the hidden layer of each neuron are summed up according to the weight assigned to it. Bias is added to the sum and passed to the output layer.

The effects of the network are presented in Table 2 and in Fig. 4.

From the generated networks, the MLP 2-7-1 network with the lowest error value of the predicted values was selected for further simulations. The structure of developed model consists of seven neurons in the hidden layer, two neurons in the input layer and one neuron at the output layer. An exemplary diagram and operation of the network is presented in Fig. 5. As a function of activation in the hidden layer, a hyperbolic tangent function was used, while in the output layer the exponential function was applied. Learning, testing and validation quality was obtained at the level equals to 100%. The BFGS (Broyden–Fletcher–Goldfarb–Shanno) learning algorithm was used, which belong to the group of quasi-Newtonian methods.

Table 2
The result of selected regression networks

Network ID	MLP 2-7-1	RBF 2-8-1	MLP 2-4-1	MLP 2-4-1
Learning error	0%	3%	0%	0%
Testing error	0%	6%	0%	0%
Validation error	0.00%	9.00%	0.00%	0.00%
Learning algorithm	BFGS 93	RBFT	BFGS 169	BFGS 210
Error function	SOS	SOS	SOS	SOS
Activation function (hidden layer)	Logistic	Gauss	Logistic	Exponential
Activation function (output layer)	Logistic	Linear	Exponential	Linear

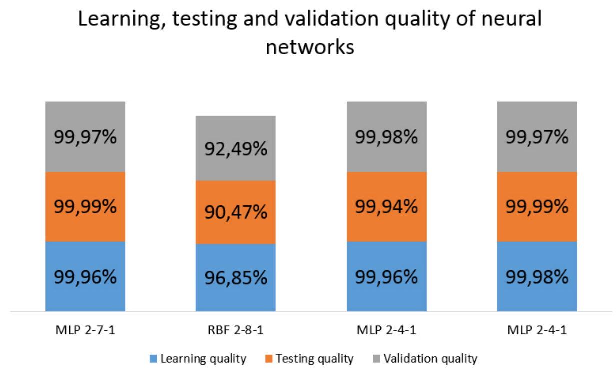

Fig. 4. Learning, testing and validation quality of examined neural networks

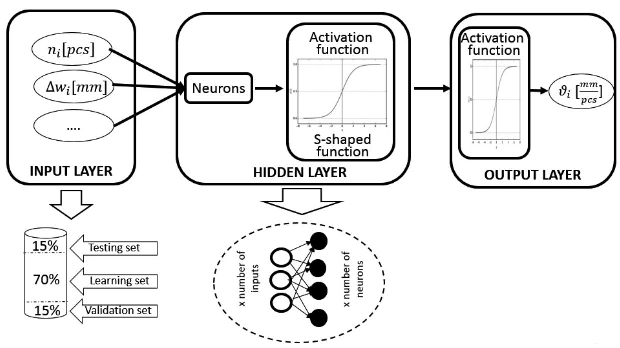

Fig. 5. Operation of the generated neural network

The designation BFGS 126 and BFGS 136 (the second generated network with the same architecture) indicates number of iteration at which optimal results were obtained. To indicate the current level/quality of network learning the error function was applied during learning process. In this case, the error function was used in the form of the sum of squares function (SOS).

For these two selected neural networks, 15 simulations were carried out, and the obtained results are presented in Table 3.

Table 3
The result of MLP 2-7-1 network

No.	[ϑ]	Error [%]	[ϑ^*]	Error* [%]
1	1.736	3.3%	3.296	1.3%
12	1.671	0.5%	3.235	0.6%
13	1.735	3.3%	3.287	1.0%
14	1.683	0.2%	3.279	0.8%
15	1.670	0.6%	3.240	0.4%
16	1.693	0.8%	3.245	0.3%
17	1.707	1.6%	3.302	1.4%
18	1.744	3.8%	3.239	0.5%
19	1.716	2.1%	3.178	2.3%
10	1.698	1.0%	3.238	0.5%
11	1.715	2.1%	3.177	2.4%
12	1.672	0.5%	3.197	1.8%
13	1.686	0.4%	3.236	0.6%
14	1.714	2.0%	3.274	0.6%
15	1.677	0.2%	3.248	0.2%

The response surface shown in Fig. 6 was used to illustrate the operation of the neural network model.

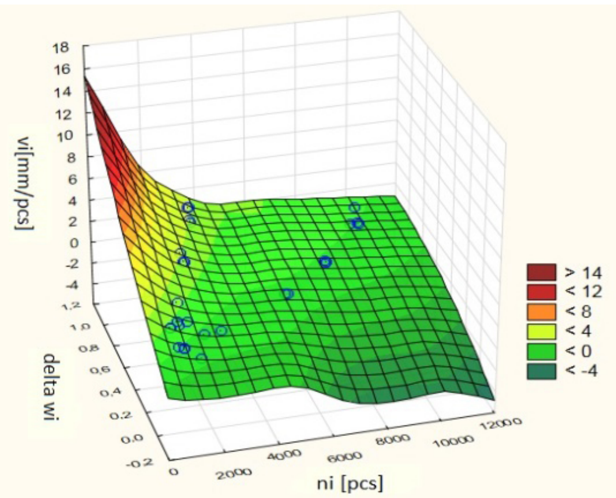

Fig. 6. An example of network response – the relationship $\vartheta = f(\Delta w, n)$

The results of the calculations are the basis for the conclusion that neural networks are a good mathematical model for forecasting the intensity of die wear and the dimensional accuracy of forgings in real production conditions.

Conclusions

The dies made of thermally improved 42CrMo4 structural steel with a pattern surfaces obtained by hardfacing with F-818 wire proved to be fully useful in industrial practice. Application of these dies in place of traditional hot working tool steel dies increased the durability of the dies by a factor of three.

Due to the absence of ad hoc strength wear and (cracking of the entire die) due to the lack of delamination at the boundary between the hardfacing layer and the substrate, the decrease in the intensity of abrasive die wear resulted in a significant improvement in the reliability of the technological process of die forging.

The introduction of hardfacing dies brought positive economic effects, because the possibility of regenerating die patterns increased by 3-4 times compared to dies made out of X37CrMoV5-1 steel. It should also be noted that the price of 42CrMo4 steel is about 4 times lower than the price of X37CrMoV5-1 steel. In addition, the labor cost is lower by approx. 35%, because the die after the process of technological regeneration of die pattern by hardfacing does not require repetition of heat treatment.

The introduction of the die wear intensity index makes it possible to forecast the die wear intensity of the forging process of technologically similar products, i.e. products of different shapes but made of the same material.

The main advantage of applied method is the possibility of learning, which is very important in relation to diagnostic processes. In order to determine the wear intensity index of forgings due to the wear of working surfaces of the dies, regression model of neural networks were applied. The 100% values of learning, testing, and validation quality were obtained for the MLP 2-7-1 network. Relatively low error values of the received results (network responses) were obtained (<=4%), considering not a very large teaching set of only 46 values. Therefore, it can be concluded that the use of neural networks is a useful method for modeling and supervising the condition of dies and technological quality of products in the die forging process in small and medium-series production conditions. The advantage of the proposed method is the possibility of its use in industrial conditions, with short series of products of various sizes and geometries.

References

Azari, A., Poursina, M. and Poursina, D. (2014). *Radial forging force prediction through MR, ANN and ANFIS models.* Neural Computing & Applications, 25, 3–4, 849–858.

Ciancio C., Citrea T., Ambrogio G., Filice L., Musmanno R. (2015). *Design of a high performance predictive tool for forging operation.* Procedia CIPR 33, 173–178.

Gronostajski, Z., Hawryluk, M., Zwierzchowski, M., Kaszuba, M. and Niechajowicz, A. (2011). *Description of the wear phenomena of hot forging dies for a gearbox disc.* [In Polish]. Metallurgist – Metallurgical News, 78, 8, 607–611.

Gronostajski, Z., Hawryluk, M., Kaszuba, M., Marciniak, M., Niechajowicz, A. and Polak S. (2015). *The expert system supporting the assessment of the durability of forging tools.* The International Journal of Advanced Manufacturing Technology, 82, 9, 1973–1991.

Gronostajski, Z., Kaszuba, M., Hawryluk, M. and Zwierzchowski, M. (2014). *A review of the degradation mechanisms of the hot forging tools.* Archives of Civil and Mechanical Engineering, 14, 528–539.

Gronostajski, Z., Kaszuba, M., Polak, S., Zwierzchowski, M., Niechajowicz, A. and Hawryluk, M. (2016). *The failure mechanisms of hot forging dies.* Materials Science and Engineering. A, Structural Materials: Properties, Microstructure and Processing, 657, 147–160.

Gubán, M., Kása, R., Takács, D. and Mihai, Avornicului M. (2019). *Trends of Using Artificial Intelligence in Measuring Innovation Potential.* Management and Production Engineering Review, 10, 2, 3–15. doi: 10.24425/mper.2019.129564.

Hawryluk, M. (2016a). *Methods of analyzing and increasing the durability of forging tools used in hot die forging processes* [in Polish], Monographic series of problems of exploitation and construction of machines, ISBN 97883-7789-410-1. Ed. Scientific ITE – PIB, Radom.

Hawryluk, M. (2016b). *Review of selected methods of increasing the life of forging tools in hot die forging processes.* Archives of Civil and Mechanical Engineering, 16, 845–866, doi: 10.1016/j.acme.2016.06.001.

Hawryluk, M. and Mrzygłód, B. (2018). *A system of analysis and prediction of the loss of forging tool material applying artificial neural networks.* Journal of Mining and Metallurgy. Section B: Metallurgy, 54, 3, 323–337. doi: 10.2298/JMMB180417023H.

Hawryluk, M. and Mrzygłód, B. (2017). *A durability analysis of forging tools for different operating conditions with application of a decision support system based on artificial neural networks (ANN).* Maintenance and Reliability, 19, 3, 338–348.

Kocańda, A. and Czyżewski, P. (2000). *Computer analysis of abrasive wear of forging dies* [In Polish], 14th Scientific and Technical Conference of Plastic Working "Design and Technology of Moldings", Poznan.

Krajewska-Śpiewak, J. (2016). *Application of neural networks in condition's modeling of the surface layer.* Business management, 1.

Mrzygłód, B., Hawryluk, M. and Gronostajski, Z. (2018). *Durability analysis of forging tools after different variants of surface treatment using a decision-support system based on artificial neural networks.* Archives of Civil and Mechanical Engineering, 18, 4, 1079–1091.

Rauch, L., Chmura, A., Gronostajski, Z., Pietrzyk, M. and Zwierzchowski M. (2016). *Cellular automata model for prediction of crack initiation and propagation in hot forging tools.* Archives of Civil and Mechanical Engineering, 16, 3, 437–447.

Turek, J., Okoński, S. and Piekoszewski W. (2012). *Testing the abrasion resistance of overlay layers and tool steels for forging dies.* [In Polish]. Metal Forming, Poznan.

Turek, J. (2019). *Structure and properties of surfacing layers on blanks of forging dies* [in Polish], Krakow University of Technology Publishing House, Kraków, pp. 224, ISBN 978-83-65991-82-9

Young, M. (1989). *The Technical Writer's Handbook*, Mill Valley, CA. University Science.