# A SYSTEM OF ANALYSIS AND PREDICTION OF THE LOSS OF FORGING TOOL MATERIAL APPLYING ARTIFICIAL NEURAL NETWORKS

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*Abstract*

*The article presents the use of artificial neural networks (ANN) to build a system of analysis and forecasting of the durability of forging tools and the process of acquiring the source knowledge necessary for the network learning process. In particular, the study focuses on the prediction of the geometrical loss of the tool material after different surface treatment variants.The methodology of developing neural network models and their quality parameters is also presented. The standard single-layer MLP networks were used here; their quality parameters are at a high level and the results presented with their participation give satisfactory results in line with technological practice. The data used in the learning process come from extensive comprehensive performance tests of forging tools operating under extreme operating conditions (cyclic mechanical and thermal loads). The parameterization of the factors important for the selected forging process was made and a database was developed, including 900 knowledge vectors, each of which provided information on the size of the geometrical loss of the tool material (explained variables). The value of wear was determined for the set values of explanatory variables such as: number of forgings, pressure, temperature on selected tool surfaces, friction path and the variant of the applied surface treatment. The results presented in the study, confirmed by expert technologists, have a clear applicational character, because based on the presented solutions, the optimal treatment can be chosen and the appropriate preventive measures applied, which will extend the service life.*

*Keywords: Decision support system; Durability of forging tools; Artificial neural network; Loss of material; Wear*

## 1. Introduction

Punches, dies and other forging instrumentation applied in hot forging processes work under extreme conditions (high, periodic thermal loads from 80 to 1200 °C, and mechanical loads even up to 1000 MPa).Therefore, they are exposed to the action of multiple destructive factors and phenomena, causing their accelerated and excessive wear. For this reason, the analysis and prediction of durability remains a difficult, unsolved problem and a challenge for many researchers and scientific centers. The main process parameters affecting the forging process and durability include: temperature of stock material and tools, preform geometry, work settings and cycle of the forging units, friction conditions (lubrication and cooling) as well as tool shape and quality. Low durability of forging instrumentation, caused by the presence of destructive mechanisms, has a significant impact on the quality and cost of the fabrication of forgings. The most common destructive mechanisms are: plastic deformation and abrasive wear during

semi-hot forging [4] and hot forging [17], fatigue cracks [1,16,26], thermomechanical fatigue [3,8]. Among them, the most frequently occurring mechanism, as well as the most studied one, is abrasive wear, which is predominant, above all, in cold forging processes [30]. Many papers and studies concerning a comprehensive analysis of the primary tool destruction mechanisms in forging processes can be found in the literature [17,21]. There are also many articles and works of research concerning the development and application of various methods and techniques to improve the durability of forging equipment [12,19,20], which is both scientifically and economically justified. Many different informatics methods and tools are currently becoming increasingly popular, as they partially replace the costly and time-consuming physical experiments with virtual experiments [14,18,32]. Efforts are also being made to employ expert systems and decision support systems in the optimization and prediction of forging tools' durability. New formalizations of knowledge representation are also being developed in

computerized systems, such as: graph theory, fuzzy logic, artifical neural networks, and genetic algorithms, thus making it possible to build computer systems supporting various fields of human activity, including hot die forging processes [23,31]. In the work [15], Katayama et al. developed an expert system to design a cold forging process. Fuzzy logic was used to formulate the principles of the database of this system. Fuzzy logic was also used to develop an expert system for predicting the analysis results with the finite element method when solving the problem of rubber cylinder compression [27]. Gangopadhyay et al. elaborated an expert system for predicting the loads and axial stresses during forging [5]. Artificial neural networks have been applied to solve many problems [29]. The application of the finite element method and intelligent system techniques to predict the applied force during the radial forging process was studied in [2]. An artificial neural network was also applied to study the relationships between the mechanical properties and the deformation technological parameters of the TC11 titanium alloy, with the use of the data from the isothermal compression test and the conventional tensile test of the forged TC11 titanium alloy at room temperature [22,28].

The authors' own work may also provide information about the potential and large ANN capabilities, confirmed and verified by the results of the research. For example, the article [6] provides an expert system for a durability analysis, while the manuscript [13] shows the use of the ANFIS consumption analysis of forging tools. In the work [11], ANN were  demonstrated to work as a decision support system in the global analysis of the operation of forging tools under different operating conditions. For this reason, ANN are used for further applications, including attempts to develop a decision support system, analyze and predict the durability for forging tools coated with protective coatings (nitrided layer + PVD coating) and to perform nitriding and pad welding of their surface.

The goal of this work is to develop a system for the analysis and prediction of forging tools' durability based on artificial neural networks, with a particular emphasis on the loss of the tool material, as well as on the material test results and tests originating from the numerical analysis of forging tools used in the second cover forging operation, with different variants of thermochemical treatment, over the course of their work, thus creating the learning database.

## 2. RESEARCH METHODOLOGY

The research which made it possible to build a system for the analysis and prediction of the forging tools' durability, with the application of neural networks, was conducted in two stages:

The first stage covered operational tests, material tests and numerical modeling of the industrial hot die forging process of a cover-type forging. An extensive database containing the results of material analyses and simulations was created as a result of these comprehensive studies.

The second stage of research, related to the use of the developed database, aimed at building a model of representing the knowledge of the studied process. The obtained source data served as the training data for artificial neural networks, which were selected as the formal tool describing the tested phenomenon. Only a part of this extensive database was used in this paper. A set of neural networks determining the value of geometrical wear for tools working with specific surface layers was selected.

### 2.1 Description of the process

The industrial process of forging a cover-type forging (Fig. 1) is performed on a crank press with the pressing force of 18 MN (Fig. 2) in three operations. The first operation is upsetting, the second - preliminary die forging, and the third - finishing forging.
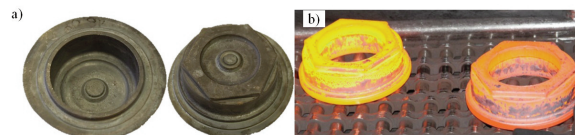


***Figure 1***. *Cover forgings: a) photo of a forging after finishing forging, b) "hot" forgings after the forging and trimming process, placed on a conveyor belt leading to controlled cooling [10]*
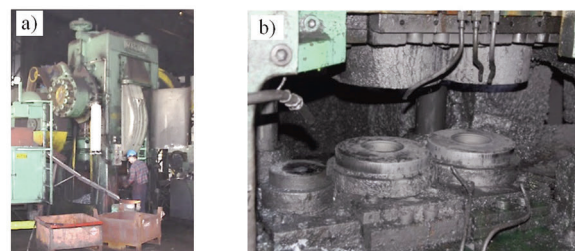


***Figure 2***. *Massey press with pressing force 18 MN; a) photo of entire machine, b) view of cover forging tool mounted on press [10]*

After the forging process, and after normalization and mechanical processing, the cover forging is a component of a gearbox for passenger vehicles (type of a seal at the exit of the drive shaft from the gearbox). The material of the forging is C45 steel, in the form of a cylinder with the following approximate preform dimensions: diameter 55 mm, length 95 mm, weight 1.77 kg. The stock material's initial

temperature is 1150℃.

The tools subject to analysis used in the process are made of WCL steel, pre-heated to the temperature of approx. 250 °C.

The mean tool durabilities in the particular operations (data from the technological department at Kuźnia Jawor) are as follows:

- preliminary forging: inserts: 5400 forgings; filler: 5400 forgings;

- finishing forging: inserts: 9000 forgings; filler: 4500 forgings.
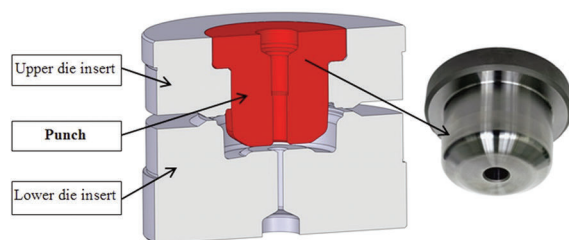


*Figure 3. Tool set in II operation of roughing (preliminary forging)*

The tools used in the second forging operation (preliminary forging) are subjected to the highest load because the preform is formed to the greatest extent during this operation. In this research, one of the tools applied in the second forging operation, i.e. upper insert filler (Fig. 3) was analyzed in detail. The operational studies included testing of the tools with the following coatings:

- nitrided layer;

- hardfacing;

- hybrid layer, type: nitrided layer/PVD coating. Two PVD hybrid layers were selected for the study:

- Cr/CrN,

- Cr/AlCrTiN.

The standard tools applied in operations II and III are nitrided (characterized by the surface hardness of 1100-1150 HV). Meanwhile, the application of hybrid layers increases the hardness to approx. 2100-3200 HV, and in the case of pad welding (hardfacing), the hardness equals 700 HV (thickcnes 5mm). The tools prepared in this manner underwent operational tests under the industrial conditions at Kuźnia Jawor S.A., where the forging processes were performed with the use of tools for different numbers of forgings.

Table 1 shows the chemical composition and the selected mechanical properties of forgings and tools, whereas Table 2 presents the main parameters of the different variants of the applied surface engineering treatment.

### 2.2 Operational and material tests as well as numerical modeling

Within the scope of this stage, the influence of specific forging process parameters (e.g. tool temperature, lubrication, pressing forces, deformation time, applied protective layer, etc.) on the tool wear after a specific number of forgings was measured and tested in every area. A database containing the results of these measurements was developed. Every record of the developed base contains information about the value of tool wear in a specific area for defined values of forging process parameters as well as information about the wear mechanisms occurring in this area (thermomechanical fatigue; abrasive wear; plastic deformation; mechanical fatigue). This was achieved through:

a) comprehensive operational investigations of tool surfaces covering:

- macroscopic analysis, enabling a visual assessment of the state of wear on the tools' working surfaces,

- dimensional analysis – 3D scanning of worn tools for the purpose of determining the geometrical loss (wear) of tool impressions, based on a comparison of the superimposed images obtained from laser scanning of new and worn tools after specific numbers of forgings, in every area.

b) microstructural investigations of tools, for the purpose of observing the structural changes in the surface layer in 5 selected working areas of the tool. Based on the analysis of the changes in the tools' surface layers, individual areas were assessed and assigned the appropriate shares of destructive mechanisms and material loss, regardless of the type of the mechanism.

c) microhardness measurements of the tested tools in the selected areas, at a distance of 0 to 0.5mm from the surface layer.

d) numerical modeling – the parameters difficult or impossible to determine experimentally or

**Table 1.** *The chemical composition and selected mechanical properties of forging and tools*

| Material | C | Mn | Si | P | S | Cr | Ni | Mo | Cu | Re (21 ℃) [MPa] | Rm (21 ℃) [MPa] | Hardness |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| C45 (1.0503) lid forging | 0.42-0.5 | 0.5-0.8 | 0.1-0.4 | max 0.04 | max 0.04 | max 0.3 | max 0.3 | max 0.1 | max 0.3 | 270-490 | 550-850 | 229 HB (after softeinng) |
| WCL (1.2343) forging tools | 0.32- 0.42 | 0.2-0.5 | 0.8-1.2 | max 0.03 | max 0.03 | 4.5-5.5 | max 0.03 | 1.2-1.5 | max 0.3 | 1570 | 1900 | 650 HV core material |

*Table 2. The main parameters of different variants of applied surface engineering treatment*

| | Nitriding layer | CrN coating | Cr/AlCrTiN coating | Pad welded layer |
|---|---|---|---|---|
| Thickness | $g_{800} \sim 70$ μm | g~8.5 μm | g ~ 6.7 μm | g ~ 5 mm |
| Hardness [HV] | 800 – effective hardness 1200 – max. hardness | 2100±140 | 3250±315 | 700HV |
| Young modulus [GPa] | E=220 – 240 | E = 215 ± 25 GPa | E = 360 ± 25 GPa | E=160 – 180GPa |
| Coeff.of friction–steel | μ=0.55 | μ= 0.32 | μ=0.48 | μ=0.45 |
| Roughness | Ra/Rz/Rt 0.49/2.16/3.32 | Ra/Rz/Rt 0.43/1.16/1.92 | Ra/Rz/Rt 0.29/2.28/3.40 | Ra/Rz/Rt 0.24/2.08/2.35 |
| Adhesion of coat. to substrate in linear scratch test[N] | - | $Lc_1 = 70 \pm 2$ $Lc_2 = 80 \pm 2$ $Lc_3 = 138 \pm 4$ | $Lc_1 = 41 \pm 2$ $Lc_2 = 65 \pm 2$ $Lc_3 = 166 \pm 4$ | $Lc_1 = 35 \pm 2$ $Lc_2 = 40 \pm 2$ $Lc_3 = 145 \pm 4$ |
| Abrasive wear resistance index at 500oC: Wz500 [mm3/N·km] | $5.41 \times 10^{-6}$ | $8.35 \times 10^{-2}$ | $8.41 \times 10^{-4}$ | $6.43 \times 10^{-2}$ |

analytically, such as: pressing forces, friction path, temperatures in contact, were determined by means of numerical modeling with the use of the Marc Mentat simulation package.

### 2.3 Development of a knowledge representation model for a computer system

The second stage of research involves the application of the database which was obtained for the development of a model representing the knowledge of the selected die forging process for a computer system. The system's primary task is to predict the durability of forging tools. A list of the parameters analyzed by the system, in the context of the input/output data, is presented in Fig. 4. The input variables are: number of forgings, temperature, pressure, path of friction, type of surface layer; the output variables are: material loss and percentage share of the four primary destructive mechanisms in tool wear. Many formal methods making it possible to model phenomena of a strongly non-linear nature, as was the case in the process under analysis, were applied.

Fuzzy logic was employed in the first approach [6], and models based on the hybrid ANFIS algorithm [13] were also developed. However, the best results

and the lowest prediction error, compared to the previous models, were achieved by the system developed with the use of artificial neural networks [24]. The data which was gathered was then used as a source of training data for the artificial neural networks.

### 3. Results and discussion

The summary of the research covers the presentation and analysis of the obtained results, both in the 1st stage of research - material and numerical tests, and in the 2nd stage - analysis of the results obtained from the developed artificial neural networks from the perspective of their correctness in comparison to the results obtained under industrial conditions.

### 3.1 Results of 1st stage of research

The performed comprehensive operational studies of the surfaces pertained to the phenomena occurring in the surface layer of the tools which had been used to fabricate a specific number of forgings and were withdrawn from further production for the purposes of the research. The tests serving as examples for the development of the database, which was then used in the decision support system, are presented below. The tests at this stage were divided into several substages.

#### 3.1.1 Macroscopic analysis of tools' working surfaces

Fig. 5 presents photographs of the working surfaces of the selected tools with four types of



*Figure 4. List of analyzed forging process parameters*

coatings. The macroscopic analysis of the studied tools' working surfaces revealed different types of damage. Strong abrasive wear, in the form of deep grooves propagating radially from the center of the die according to the flow direction of the material filling the impression, was observed on the face surface of the nitrided tool (Fig. 5a). The tools after hardfacing (Fig. 5b) and the tools coated with Cr/CrN (Fig. 5c) did not undergo either abrasive wear or plastic deformation, despite the similar operating



*Figure 5. Macro view of the face part of analyzed tools after manufacturing approx. 4000 forgings: a) after nitriding, b) after pad welding, c) with Cr/CrN layer, d) with AlCrTiN layer*

conditions; however, cracks propagating on the surface of the hybrid layer were visible.

In turn, a fine mesh of cracks (probably caused by thermomechanical fatigue) is visible throughout the entire surface of the tool coated with an AlCrTiN layer (Fig. 5d), while slight abrasion and deformation were visible at the edge of the face surface and the side surface. Based on the observations, it can be surmised that the layers applied to the tools- regenerative hardfacing (Fig. 5b) and Cr/CrN layer (Fig. 5c), fulfilled their protective role and limited the influence of destructive mechanisms.

### 3.1.2 Geometrical analysis of material loss using laser scanning

An analysis of the tool wear (geometrical loss in the normal direction to the surface) was conducted based on scanning with the Romer Absolute Arm measuring arm in the PolyWorks software. The arm makes it possible to perform classical measurements by means of an additional measuring probe as well as contactless measurements by means of an RS3 linear
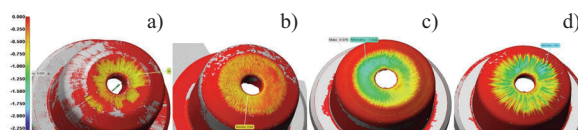


*Figure 6. Comparison of changes in tool geometry after manufacturing of 4000 forgings based on scanning results: a) nitrided, b) hardfaced, c) Cr/CrN, d) AlCrTiN*

laser scanner integrated with the arm, which provides the capability of collecting up to 460,000 points/s for 4600 points on a line at the linear frequency of 100 Hz with the declared 2-sigma accuracy of 30 μm. After the measurement, a shape and dimensional analysis was conducted based on the best-fit algorithms [7]. The results of the analyses employing images (scans) are presented in Figure 6.

On this basis, the degree of wear was determined, i.e. the material loss in the normal direction, which was the greatest in the face part for the majority of tools (except for the hardfaced tool), equalling from approx. 1mm (for the nitrided tool) to nearly 2mm (for the tools with the CrN layer and AlCrTiN layer). Among the tools presented and analyzed in Figure 6, only the tool with the AlCrTiN layer was not suitable for further production due to deep grooves propagating locally up to the radius – which disqualifies such a tool, since the flat face part on the forging is machined after the process. Of course, for the purposes of building the database, tools after different numbers of forgings (even up to 13000) were also analyzed. Also, the tools were additionally divided into a greater number of areas (Fig. 7a).

### 3.1.3 Microstructural investigations of tools' surface layer

For the purpose of a more complete analysis of the changes occurring in the surface layer of the tools, advanced microstructural investigations were conducted by means of an Olympus GX51 microscope and a TESCAN VEGA 3 scanning electron microscope, where attention was paid to the
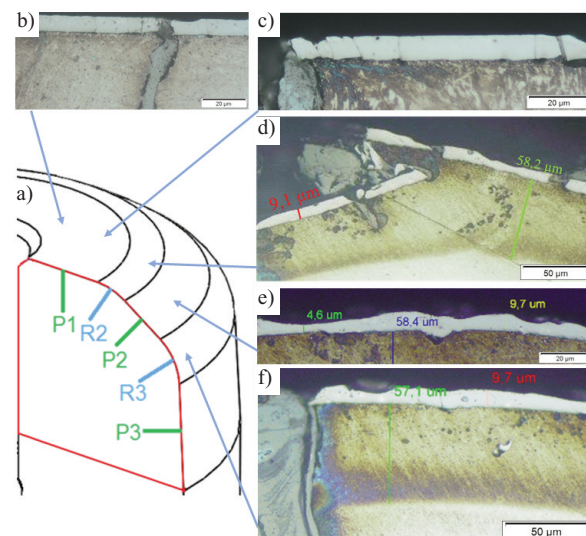


*Figure 7. SEM and light microscopy investigations of the surface layer of the tool with Cr/CrN coating in selected subareas: a) division of the tool into elementary areas, b), c), d), f) photographs of microstructure in selected areas of the tool [10]*

presence of the nitrided layer, the PVD layer, cracks and plastic deformations. Examples of the test results along with photographs of the microstructure of the tool coated with one of the Cr/CrN type layers are presented in Fig. 7. The tool was plasma-nitrided, and a homogeneous PVD coating built from chromium nitride (CrN) was applied, with the mean initial thickness of 7.2 μm and the hardness of 2100±140 HV. The observations show that the nitrided layer was preserved nearly on the entire tool, and its visible depth is 55÷65 μm. This is due to the presence of the PVD coating, which maintained cohesion with the substrate and was not chipped even on the face surface P1 (Fig. 7b and 7c). The coating's adhesion is perfectly illustrated by photo 7d, where the coating was not detached, despite the strong deformation of the surface layer. Thinnings of the coatings are visible on the surfaces (Fig. 7d and 7e), interpreted as abrasive wear, which is the most intensive, since the CrN coating has the lowest hardness among the applied coatings. However, the coating is not removed, since the losses are primarily within the range of 3÷5 μm.

Based on the microstructure observations, it can be stated that the hybrid layer remained nearly on the entire surface of the tested tool at the early stage of operation, up to 4000 forgings.

### 3.1.4 Microhardness measurements

For a more complete analysis, microhardness measurements were also performed, with the microhardness measured as a function of the distance from the surface. The microhardness was measured according to the Vickers method under 100g load by means of a LECO LM-100AT hardness tester, at several points distributed over a 2.5 mm segment into the material. The results are presented on charts (Fig. 8), which compare the tested tools in each of the 5 areas given in Fig. 7a. Examples of the HV microhardness distributions on the cross-section of the tools in area R2 and area P3 are presented in Fig. 8. The charts presented in Fig. 8 show that, essentially, all the analyzed tools partially maintained the effect of elevated hardness (except for the hardfaced tool) in

the surface layer during the operation, due to the presence of the nitrided layer. This is particularly visible in area R2, except for the hardfaced tool, where its hardness is even lower (Fig. 8a). Meanwhile, in area P3, only the tool with the nitrided layer and the AlCrTiN coating continues to exhibit elevated hardness.

Both the tools with the nitrided layer and the AlCrTiN coating are more resistant to abrasive wear. Meanwhile, a decreased hardness was observed in the tool with the Cr/CrN layer, which is decidedly more resistant to thermal fatigue. The case is similar for the tool after regenerative hardfacing, which exhibits constant hardness throughout the entire hardfaced zone.

### 3.1.5 Numerical modeling

In order to determine the parameters which are difficult to find experimentally or impossible to determine by other methods, numerical modeling was applied. The numerical simulations were performed based on FEM in the Marc Mentat program, dedicated to the modeling of plastic working processes. The forging operation of the analyzed tool – a forging punch used in the second operation - was modeled in an axially symmetrical deformation state for the most complex thermo-mechanical model. The geometry of the tools and the initial material, as well as the remaining technological parameters of the process, were entered into the program on the basis of the original CAD models and the data provided by Kuźnia Jawor S.A. The data of the material of the forging and the tools was taken from the Matilda materials base. The SHEAR bilinear friction model was applied, and the friction coefficients between the dies and the deformed material were accepted to be 0.35. The initial uniform billet temperature was 1150 °C and the initial tool temperature was 250 °C. In the numerical modeling, the surface layers (hybrid and nitriding) were not included. The simulations were carried out for standard tools after heat treatment. A FEM punch analysis was conducted in order to determine: the normal contact stress (Fig. 9a) and the temperature distribution on the punch (Fig. 9b), since
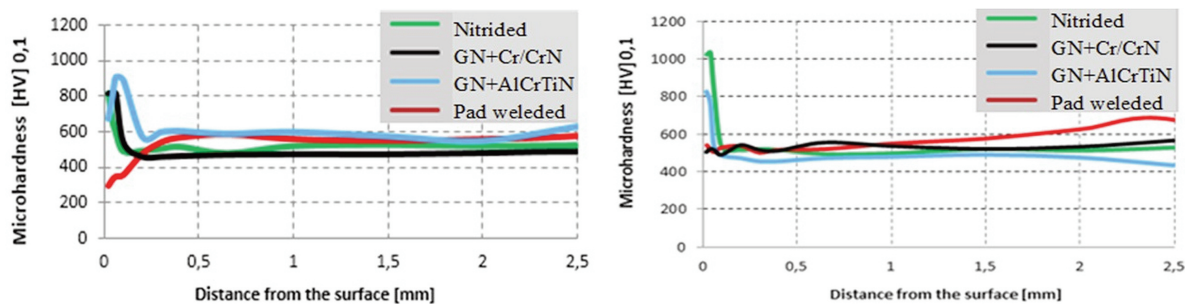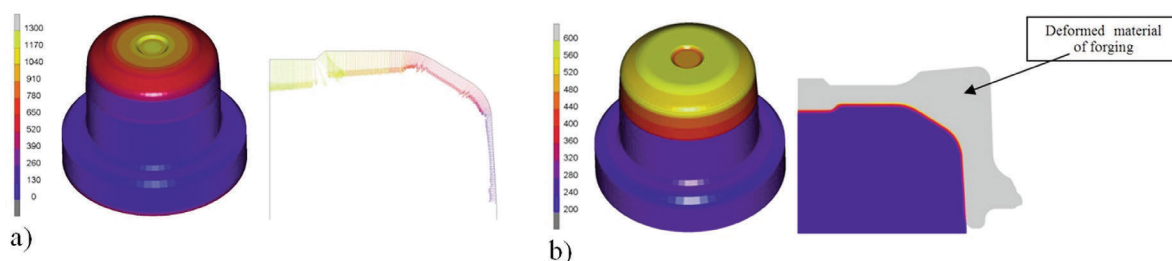


***Figure 8****. HV microhardness distribution on the cross-section of tools in area: a) R2, b) P2*

***Figure 9****. Contact normal stress [MPa] on the contact surface of the filler and the forging: a) general view (left) and longitudinal section (right), b) temperature of the filler in the lower dead centre of the press slide: 3D image (left) and longitudinal view (right)*

it is known that they have a decisive influence on the tool life. The simulation of the forces and the temperature points to a diversified intensity of the degradation mechanisms affecting the tool wear. The normal contact stress values were observed in the vicinity of the ejector hole, where they reached the values of up to 1200 MPa.

Their mean values were in the range of 600-800

***Table 3.*** *Part of the developed database*

| number of forgings | pressure/ MPa | temperature/ °C | path of friction/ mm | type of surface layer | layer label | material loss/ mm | thermo-mechanical fatigue/ % | abrasive wear/ % | plastic strain/ % | mechanical fatigue/ % |
|---|---|---|---|---|---|---|---|---|---|---|
| 7000 | 1900 | 692 | 21 | GN/ AlCrTiSiN | 5 | 0.85 | 0.3 | 0.5 | 0.2 | 0 |
| 7000 | 1223 | 580 | 10 | GN/AlCrTiSiN | 5 | 0 | 0.9 | 0.1 | 0 | 0 |
| 7000 | 1028 | 473 | 1 | GN/AlCrTiSiN | 5 | 0 | 1 | 0 | 0 | 0 |
| 7000 | 906 | 617 | 20 | GN/AlCrTiSiN | 5 | 1.3 | 0.5 | 0.4 | 0.1 | 0 |
| 8000 | 1730 | 688 | 21 | GN/AlCrTiN | 4 | 2.9 | 0.2 | 0.6 | 0.2 | 0 |
| 8000 | 1072 | 570 | 10 | GN/AlCrTiN | 4 | 0 | 0.9 | 0.1 | 0 | 0 |
| … | … | … | … | … | … | … | … | … | … | … |
| 3000 | 832 | 544 | 11 | GN/AlCrTiN | 4 | 0.15 | 0.3 | 0.5 | 0.2 | 0 |
| 5100 | 937 | 453 | 1 | GN/AlCrTiN | 4 | 0 | 1 | 0 | 0 | 0 |
| 5100 | 832 | 544 | 12 | GN/AlCrTiN | 4 | 0.75 | 0.3 | 0.6 | 0.1 | 0 |
| 1500 | 1821 | 689 | 21 | GN/AlCrTiSiN | 5 | 0 | 0.9 | 0.1 | 0 | 0 |
| 1500 | 1141 | 572 | 10 | GN/AlCrTiSiN | 5 | 0 | 0.95 | 0.05 | 0 | 0 |
| 1500 | 937 | 453 | 1 | GN/AlCrTiSiN | 5 | 0 | 1 | 0 | 0 | 0 |
| 1500 | 832 | 544 | 11 | GN/AlCrTiSiN | 5 | 0.1 | 0.7 | 0.2 | 0.1 | 0 |
| 8000 | 1821 | 689 | 21 | GN/AlCrTiN | 4 | 0.9 | 0.2 | 0.7 | 0.1 | 0 |
| 8000 | 1141 | 572 | 10 | GN/AlCrTiN | 4 | 0 | 0.9 | 0.1 | 0 | 0 |
| 8000 | 937 | 453 | 1 | GN/AlCrTiN | 4 | 0 | 1 | 0 | 0 | 0 |
| 8000 | 832 | 544 | 12 | GN/AlCrTiN | 4 | 0.45 | 0.6 | 0.3 | 0.1 | 0 |
| 5000 | 1821 | 689 | 21 | GN/AlCrTiSiN | 5 | 0.6 | 0.5 | 0.4 | 0.1 | 0 |
| 4000 | 832 | 544 | 11 | GN/AlCrTiSiN | 5 | 1.1 | 0.4 | 0.5 | 0.1 | 0 |
| 7000 | 1730 | 688 | 21 | GN/CrN | 3 | 0.15 | 0.9 | 0.1 | 0 | 0 |
| 7000 | 1072 | 570 | 10 | GN/CrN | 3 | 0 | 0.9 | 0.1 | 0 | 0 |
| 7000 | 868 | 447 | 1 | GN/CrN | 3 | 0 | 1 | 0 | 0 | 0 |
| 7000 | 742 | 518 | 10 | GN/CrN | 3 | 0.45 | 0.4 | 0.5 | 0.1 | 0 |
| …. | …. | …. | …. | …. | …. | …. | …. | …. | …. | …. |

MPa. The further away from the tool axis, the lower the forces and the temperature, which points to the fact that the most difficult conditions are present in the central part of the front surface, and this is where the wear should start to occur. The temperature value at the level of 550 ºC corresponds to the tempering temperature of WCL steel, from which the dies were made, which may cause local tempering in the case of prolonged contact with the forging, whereas periodical changes of temperature may cause thermal fatigue on the tool surface. In consequence, this can also lead to plastic deformation in these areas. The lowest temperature values occur on the radius of the rounding of the tool, where the contact with the formed forging is the shortest.

Detailed information on the subject of the conducted tests has been given in earlier publications by the authors [5-10], based on which an extensive database was developed, from which the results for the analyzed cover forging process were selected. Table 3 presents a part of the developed database.

### 3.2 Results of the 2nd stage of research - developing a model of neural networks

With the integrated knowledge of the selected die forging process contained in the developed database, attempts can be made to construct algorithms and inferencing systems enabling automatic processing of this knowledge. As a consequence of this, it is possible to build computer systems which provide the possibility of creating new knowledge without the need to perform additional material experiments.

The obtained source data served as training data for the artificial neural networks, which were selected as the formal tool describing the tested phenomenon [24].

#### 3.2.1 Development of the model of neural networks determining geometrical loss

The process of selecting the networks' architecture and parameters was realized in multiple stages. It was initially assumed that all the selected dependent variables (number of forgings, temperature, pressure, path of friction, type of surface layer - Fig. 4) will be treated as the input parameters of the network, which
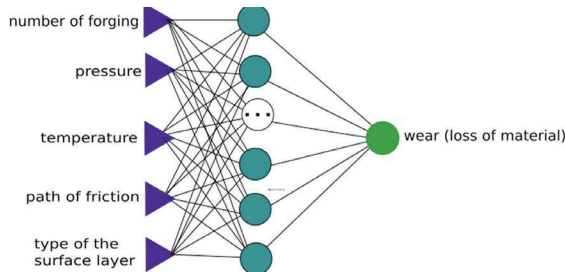
will determine the value of geometrical loss in mm on the output. The general scheme of the neural network accepted at the beginning of the studies is presented in Fig. 10.

Several hundred architectures were tested, with different numbers of neurons in the hidden layer and with different activation functions in the hidden and output layer. Among all the tested networks, the best learning and testing parameters were displayed by the MLP 5-13-1 single-layer network with 5 input

**Table 4.** *Quality parameters of MLP 5-13-1 network*

| neural network architecture | $R^2$ | | | MSE | | |
|---|---|---|---|---|---|---|
| | Learning set | Test set | Validation set | Learning set | Test set | Validation set |
| MLP 5-13-1 | 0.809 | 0.789 | 0.859 | 0.049 | 0.065 | 0.031 |

neurons, 13 neurons in the hidden layer, and one neuron in the output layer. The quality parameter values of the developed network for individual sets (learning, test, validation) are presented in Table 4.

The Pearson's linear correlation coefficient (R2) determined from formula (1) was equal to 0.78, and the mean square error determined from formula (2) for the test set was equal to 0.065.

$$R^2 = \frac{\sum_{i=1}^{n}(\widehat{y}_i - \overline{y})^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \qquad (1)$$

where:

$y_i$ - actual observed value,

$\widehat{y}_i$ - theoretical value of output variable determined on the basis of the model,

$\overline{y}$ - arithmetic mean of empirical values of the output variable.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2 \qquad (2)$$



**Figure 10**. *General scheme of the adopted neural network*
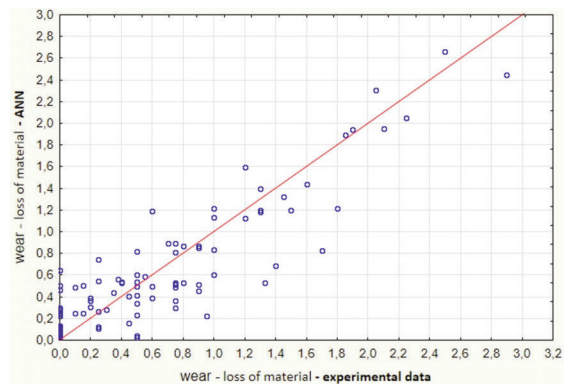


**Figure 11**. *Correlation chart prepared on the basis of the observation results and the test results generated based on the MLP 5-13-1 network model*

*Table 5. Quality parameters of neural networks determined for each analyzed surface layer*

| Type of surface layer | neural network architecture | Learning algorithm | Activation (Hidden) | Activation (Output) | R² | | | MSE | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Learning set | Test set | Validation set | Learning set | Test set | Validation set |
| nitriding | MLP 4-12-1 | BFGS 170 | Exponential | Exponential | 0.957 | 0.891 | 0.874 | 0.014 | 0.056 | 0.031 |
| pad welding | MLP 4-5-1 | BFGS 41 | Exponential | Exponential | 0.967 | 0.993 | 0.956 | 0.008 | 0.001 | 0.004 |
| GN/CrN | MLP 4-13-1 | BFGS 78 | Tanh | Linear | 0.9 | 0.816 | 0.923 | 0.017 | 0.021 | 0.032 |
| GN/AlCrTiN | MLP 4-5-1 | BFGS 126 | Exponential | Linear | 0.918 | 0.838 | 0.882 | 0.03 | 0.069 | 0.063 |

A correlation chart prepared on the basis of the observation results and the test results generated based on the MLP 5-13-1 network model is presented in Fig. 11.

The tests which followed demonstrated that the removal of the type of surface layer input variable and the development of 4 separate neural networks determining the geometrical loss for each type of layer decidedly improved the model's parameters. Four neural networks determining the material loss in the tools with hybrid layers {GN/CrN, GN/AlCrTiN} as well as the tools after nitriding and the hardfaced (pad welding) tools were developed.

Presented above are the results referring to the quality of the parameters of the developed network models, both for the whole network -MLP 5-13-1 (Tab. 4) and for separate networks elaborated to determine the wear of the tools enriched with the particular surface layers (Tab. 5). For each of the above networks, a detailed analysis of the training, testing and validating data was performed. The presented tables show the results of the quality parameter analysis ($R^2$, MSE) for all the sets, i.e. the training, validating and testing set of the developed networks. At the network's learning stage, the training set was used, which constituted 70% of all the obtained source data. The testing set constituted 15% and was used to control the course of the network's learning process by way of verifying the extent of the neurons' training. The remaining 15% of the indutrial source data were the validating data, to which the

network had no access during its learning process and which were applied to validate the developed networks. The obtained results, presented in Tables 4 and 5, point to relatively good results of both $R^2$ and MSE for the whole architecture, as well as for the particular netwoks. What is more, in all the cases, the best results were obtained for the validating data. This suggests that the presented network models and architectures were developed in the appropriate way. Additionally, from among the many elaborated network models, those were selected for which the preliminary analyses showed the best matching. Of course, for the quality parameters of the developed model networks, the crucial issue is the quality and number of the input data, obtained from the database elaborated based on the source data from the industrial process. In turn, as it can be noticed e.g. in the diagrams in Fig. 15a (the case of 500 MPa) and Fig. 16b (the case of 1000 MPa), in the results obtained from these networks, certain courses appear which are difficult to explain. This can be a result of an insufficient number of input data and the presence of "empty" areas in the database. Finally, the results for the desiged and elaborated network models presented in this chapter confirm the high quality of the network parameters.
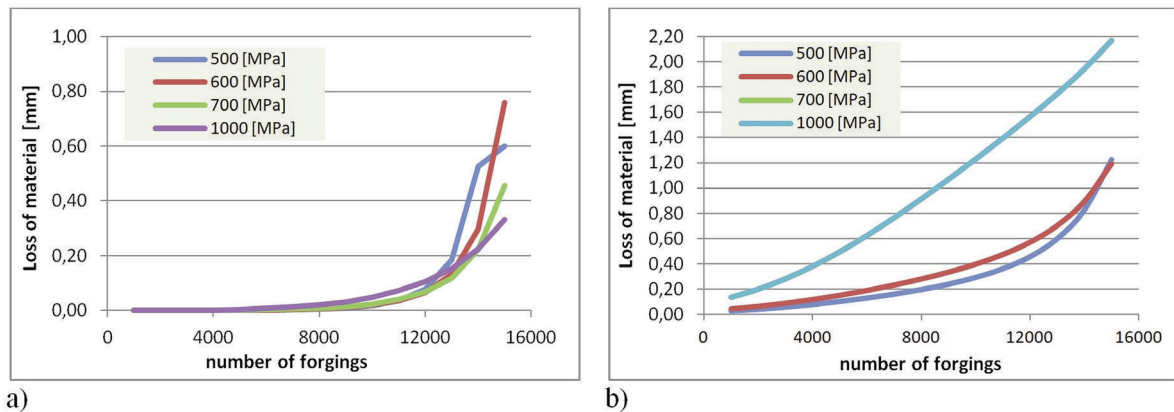
### 3.3.2 Results generated by network for input starting conditions

The developed neural networks were used to



a)    b)    c)    d)
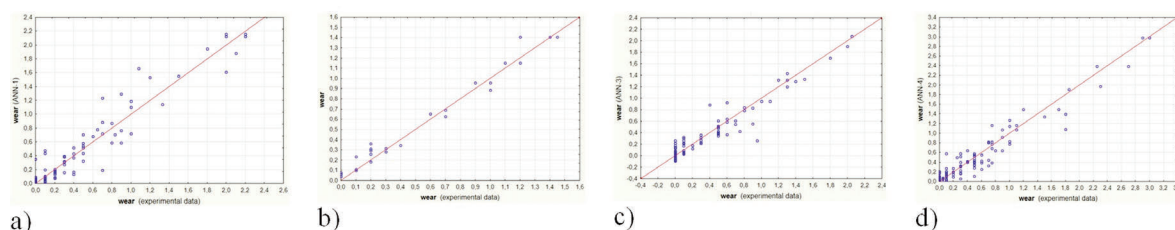
*Figure 12. Correlation charts prepared on the basis of observation results and results generated on the basis of developed network models: a) ANN-1 (nitriding layer), b) ANN-2 (repair welding layer), c) ANN-3 (GN/CrN), d) ANN-4 (GN/AlCrTiN layer)*

**Figure 13**. *Determination of wear (geometrical loss) for nitrided layer, a) T=500, path of friction=1, b) T=500, path of friction 10 mm*

conduct wear simulations of tools with different surface layers. Presented below are exemplary results obtained from the developed ANN simulations for specific process conditions:

The simulations were conducted at the constant process temperature of 500℃ and under different pressures (500, 600, 700, 1000 MPa). Figures 13-16 present the wear results for the tools with the given surface layer working under the aforementioned conditions, for the path of friction accepted to be equal to 1 mm (Figures 13a-16a) and 10 mm (Figures 13b-16b).

In the case of the application of the nitrided layer on the tools (Fig. 13), it can be observed that the effect of the pressure value cannot be seen for a short path of friction (Fig. 13a), which may point to the fact that a destructive mechanism other than that of abrasive wear is dominant in these areas during the forging process, which is most likely thermal or thermomechanical fatigue. Meanwhile, for a longer path of friction, equal to 10mm (Fig. 13b), it can be seen that the pressure value has a proportional effect

on the size of the material loss. This indicates that abrasive wear was dominant in these areas, which is consistent with the Archard's model. In both cases, i.e. for short and long paths of friction, the material loss curves grow logarithmically. The greatest loss values were observed for the path of friction of 10mm and the pressure of 1000 MPa, where the material loss reached over 2mm.

The effect of the pressure value is small in the case of the hardfaced tools (Fig. 14), for both the 1mm (Fig. 14a) and 10mm (Fig. 14b) path of friction. The maximum loss has the value of slightly over 1.4mm for all the pressure (from 500 to 1000 MPa) and path of friction values, and for the maximum number of forgings equal to 7000. Analogically, the maximum loss for the 10mm path of friction has the value of approx. 1.6mm. In the macro- and micro-structural investigations of the hardfaced tools, this variant of surface engineering was characterized by stable properties since the hardfaced layer is much larger (deeper) in comparison to the other applied surface treatments.
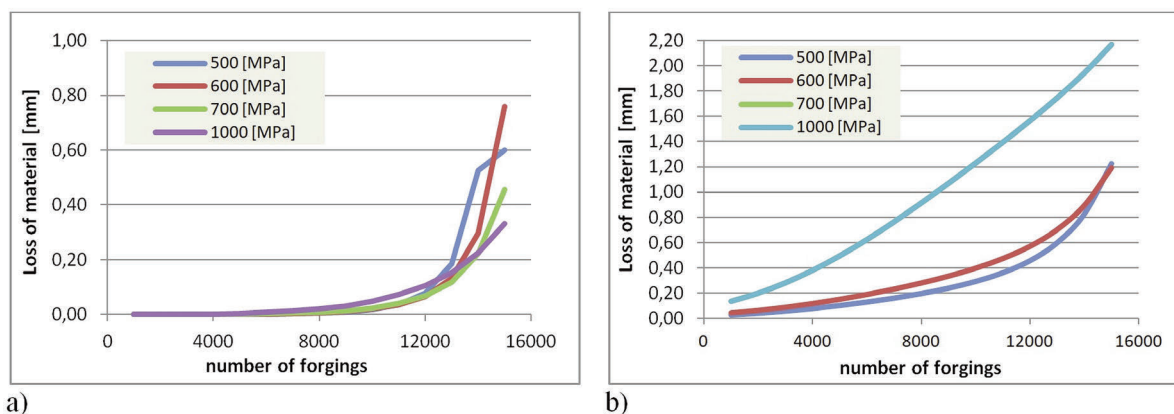


**Figure 14**. *Determination of wear (geometrical loss) for hardfaced layer, a) T=500, path of friction=1, b) T=500, path of friction 10 mm*
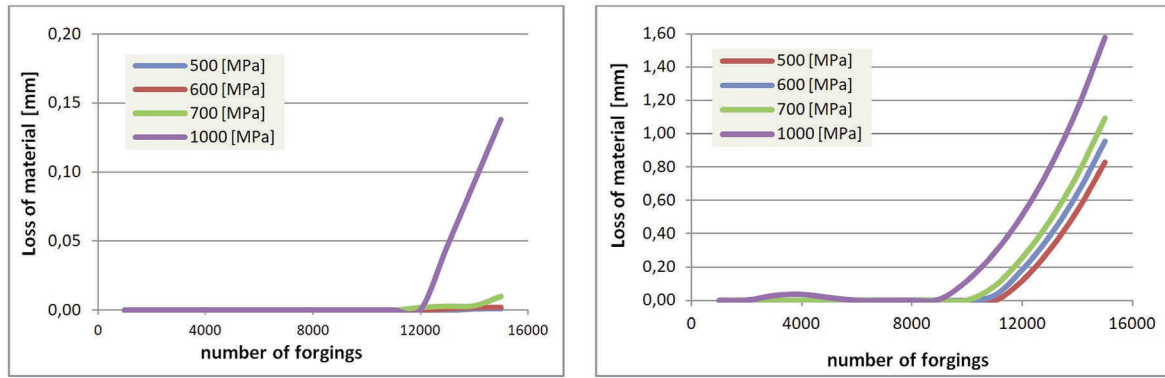
*Figure 15. Determination of wear (geometrical loss) for GN/CrN layer, a) T=500, path of friction=1, b) T=500, path of friction 10 mm*

No significant effect of the pressure was observed in the case of the tools with the GN+CrN layer for the short path of friction (Fig. 15a), except for the greatest pressure value equal to 1000MPa. This indicates that, in the case of the absence of movement of the deformed material, the CrN layer plays the role of a good insulator against thermal fatigue, which was confirmed in the case of the short path of friction. Meanwhile, a high pressure value for a greater number of forgings could have caused the data input into the system to include such information, and thus, the material loss is observed only for a single value. This result obtained from the network for such variant (1000 MPa) is difficult to explain in another manner. Therefore, it is necessary to expand the database so as to fill the missing areas with which the developed network model is not able to cope. In the case of the longer path of friction equal to 10mm, it can be seen that a relatively rapid growth of the material loss occurs, starting from about 9000 forgings (Fig. 15b). Additionally, this growth begins somewhat earlier under the pressure of 1000 MPa

than under pressures with other values. For the final layer among the applied hybrid layer variants, the obtained results indicate a relationship with the pressure value. This relationship is more visible for the short path of friction (Fig. 16a) than for the long path p=10mm (Fig. 16b). Meanwhile, the maximum loss values for the short path of friction are approx. 0.25mm, and the maximum loss for the 10mm path of friction reaches above 1.2mm. Moreover, the material loss appears earlier and for a lower number of forgings (approx. 3000) for the short friction path than for the long friction path (Fig. 16b), for which the material loss begins to grow starting from about 4000 forgings. It is probably also the result of the lack of data for these values, and the developed network attempts to approximate the curve on this basis. The obtained results point to high dependence of the network (system) on the input learning data; however, the obtained results are correct and consistent with the results obtained from the industrial process.

The simulations were conducted at the constant process temperature of 500°C and for different paths
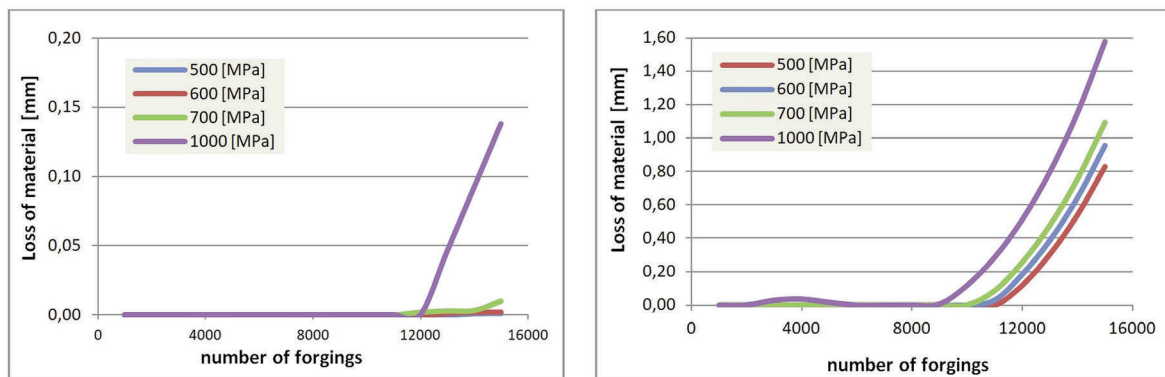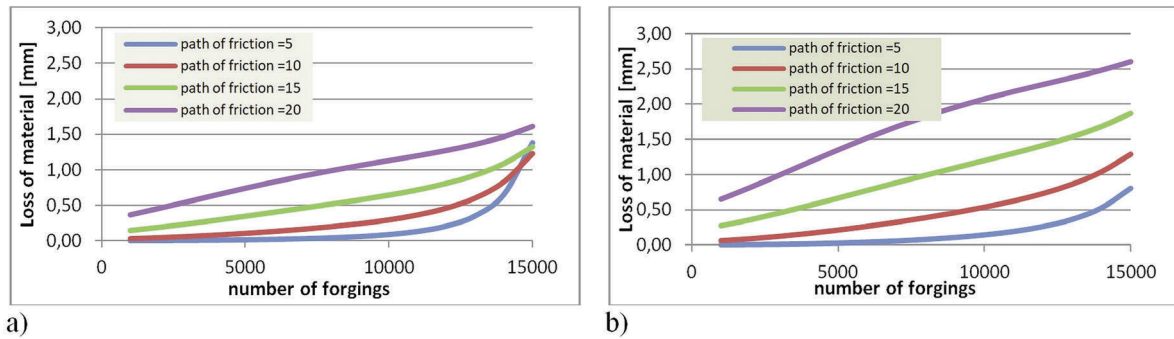


*Figure 16. Determination of wear (geometrical loss) for GN/AlCrTiN layer, a) T=500, path of friction=1, b) T=500, path of friction 10 mm*

**Figure 17**. *Determination of wear (geometrical loss) for nitrided layer,   a) T= 500,  pressure=500[MPa] , b) T=500, pressure 700[MPa]*

of friction in mm (5, 10, 15, 20). Figures 17- 20 present the wear results for the tools with the given surface layer working under the aforementioned conditions, under the pressure of 500 [MPa] (Figures 17a- 20a) and 700 [MPa] (Figures 17b-20b).

In the case of the application of the nitrided layer on the tools (Fig. 17), it can be observed that the material loss increases nearly proportionally up to approx. 12000 forgings as the path of friction increases (from 5 to 20mm), regardless of the pressure value. However, above this number of forgings, the shorter the path of friction, the earlier the loss begins to increase exponentially. A dynamic growth of the material loss under the pressure of 500 MPa and for the path of friction p=5mm (Fig. 17a) is the most noticeable change. Moreover, with lower pressure values (N=500 MPa), the maximum material loss for the longest path of friction p=20mm reaches the value of 1.6mm. Meanwhile, the loss value is over 2.5mm for the pressure (N=700 MPa - Fig. 17b) and the longest path of friction p=20mm.

In the case of the results for the second variant – the tool after hardfacing (Fig. 18) - no significant changes are visible in the evolutions of the loss curves as a function of the number of forgings, even for different pressure values. It can only be observed that, for the greater pressure value (N=700MPa), the

obtained loss evolutions are slightly higher for a larger number of forgings than in the case of a lower pressure value (N=500 MPa).

Also in the case of the application of the GN+CrN layer, a similar tendency can be observed to that of the layer after hardfacing, i.e. no clear difference can be seen in the loss values as a function of the pressure value. Only the decidedly greater influence of longer paths of friction (15 and 20mm) is deserving the attention for both pressures, where the material loss appears at a very low number of forgings in the case of the longest path of friction p=20mm, and at the maximum number of forgings, equal to 12000 pieces for this layer, the material loss for both pressure values is at the level of 4mm (Fig. 19 a and Fig. 19b).

Meanwhile, for the last of the analyzed layers (Fig. 20), a clear effect of the path of friction on the loss can be seen for both pressure values (N=500 MPa and N=700 MPa). In the analysis of the influence of the pressure value, it can be seen that the loss is at a level of nearly 1.5mm for 12 and 20mm paths of friction under the pressure N=500 MPa, and the loss increases up to 1.7mm for the pressure N=700 MPa. The clear effect of the path of friction on the material loss can be explained by the insufficient resistance of this layer to abrasive wear at elevated temepratures, which was also observed in the operational tests under industrial conditions.
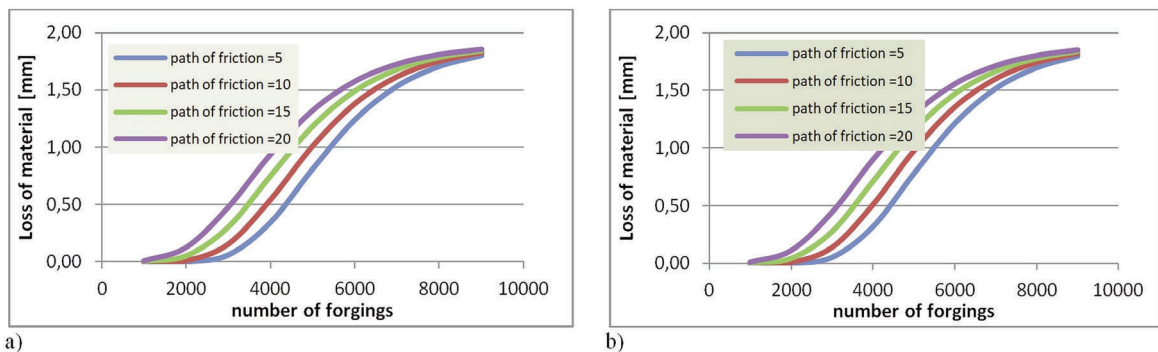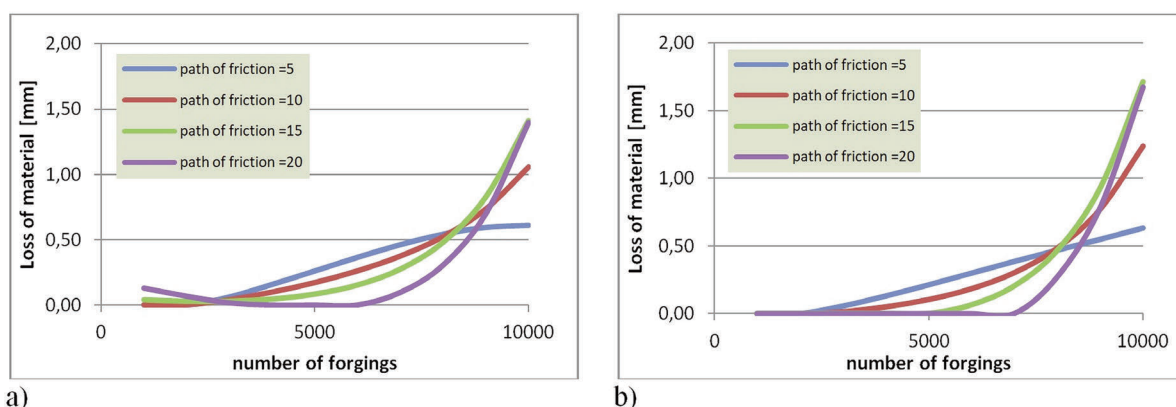


**Figure 18**. *Determination of wear (geometrical loss) for hardfaced layer,   a) T= 500, pressure=500[MPa] , b) T=500, pressure 700[MPa]*
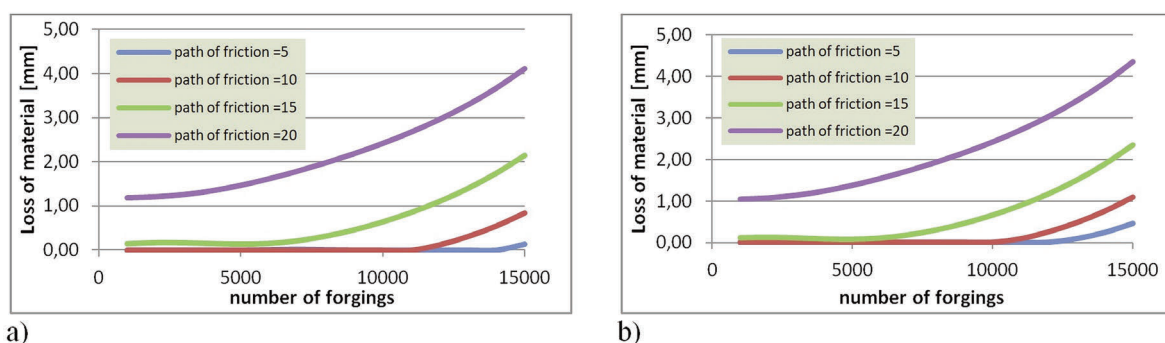
***Figure 19***. *Determination of wear (geometrical loss) for GN/CrN layer,   a) T=500, pressure=500[MPa], b) T=500, pressure 700[MPa]*



***Figure 20***. *Determination of wear (geometrical loss) for GN/AlCrTiN layer, a) T=500, pressure=500[MPa], b) T=500, pressure 700[MPa]*

## 4. Summary and conclusions

This paper presents the possibilities of building a decision support system predicting the durability of forging tools, with particular emphasis on the loss of the tool material in the direction normal to the surface, colloquially called wear. It should be emphasized that, in the majority of cases, the material loss is dependent on multiple destructive mechanisms (occurring at different times and with different intensities). Meanwhile, the results obtained from the developed system concerning the tool material loss, are only equivalent to the value of abrasive wear within a given area in a few cases. An analysis of the causes of the resultant loss and identification of the destructive mechanism responsible for it as well as its extent, will be the subject of future publications by the authors.

Artificial neural networks (ANN) were used to determine the model of the phenomenon, for which the source of learning data was the developed extensive, cumulative database of test results (operational, material and simulation), focused on the selected forging tools, i.e. upper fillers used in the 2nd hot forging operation of a cover-type forging. The dataset used for learning of the network contained 900

cases originating from the conducted experimental studies and computer simulations.

The obtained results show that by parameterizing factors significant to the forging process, it is possible to create a system predicting the value of geometrical loss on the tools.  The prediction of the extent to which a given tool will be worn, under the assumed parameters of its operation, is a very complex process, which is difficult to design; however, it provides valuable information about whether a forging falls within the shape and dimensional tolerances after the material loss.

The collected source data and the neural networks developed on its basis make it possible to achieve this with the error of estimation at the level of approx. 10%, which is a satisfactory result considering the complexity of the problem. Further work intended to improve this model will be related to the process of optimizing the network and introducing a larger set of learning data acquired from new experimental data. It is also planned to undertake a much greater challenge involving the prediction and analysis of the results for the main destructive mechanisms.

Considering the differences observed in the material loss on individual tools under different

operating conditions, it can be accepted that the developed system provides correct results, logically justified in the industrial forging process. The fact that the results obtained by the system were verified and positively assessed by experts should also be emphasized.

The results presented in this paper are clearly applicational in their nature, because the appropriate methods of preventive measures enabling an extension of the operating lifetime of forging tools can be used on the basis of the presented analyses.

### Acknowledgement

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# SISTEM ANALIZE I PREDVIĐANJA GUBITKA MATERIJALA ALATA ZA KOVANJE PRIMENOM VEŠTAČKIH NEURONSKIH MREŽA

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*Apstrakt*

*U ovom članku je predstavljena upotreba veštačkih neuronskih mreža (ANN) da bi se napravio sistem za analizu i predviđanje izdržljivosti alata za kovanje, kao i sticanje izvora znanja neophodnih za proces proučavanja mreža. Ova studija je fokusirana na predviđanje geometrijskog gubitka materijala alata posle različitih varijanti tretiranja površina. Takođe je predstavljena metodologija razvoja modela neuronskih mreža i njihovih parametara kvaliteta. Korišćene su standardne jednoslojne MLP mreže čiji su parametri kvaliteta bili na visokom nivou, i rezultati koji su dobijeni su zadovoljavajući i u skladu sa tehnološkom praksom. Podaci korišćeni u procesu učenja dolaze iz opsežnih ispitivanja performansi alata za kovanje u ekstremnim uslovima za rad (ciklična mehanička i termička opterećenja). Izvršena je parametrizacija faktora važnih za odabrane procese kovanja i razvijena je baza podataka, uključujući i 900 vektora znanja od kojih je svaki davao informaciju o veličini geometrijskog gubitka materijala alata (objašnjene varijable). Vrednost habanja određena je za utvrđene vrednosti eksplanatornih varijabli kao što su: broj kovanja, pritisak, temperatura na odabranim površinama alata, linija trenja, kao i varijanta primenjenog tretiranja površine. Rezultati dati u ovoj studiji, potvrđeni od strane stručnjaka iz oblasti tehnologije, imaju jasno primenljiv karakter jer se na osnovu predstavljenih rešenja može odabrati optimalan postupak i mogu se primeniti odgovarajuće preventivne mere, što će produžiti radni vek alata.*

***Ključne reči:*** *Sistem za podršku odlučivanju; Izdržljivost alata za kovanje; Veštačke neuronske mreže; Gubitak materijala; Habanje*