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APPLICATION OF ARTIFICIAL NEURAL NETWORKS IN THE ANALYSIS OF MECHANISMS DESTROYING FORGING TOOLS

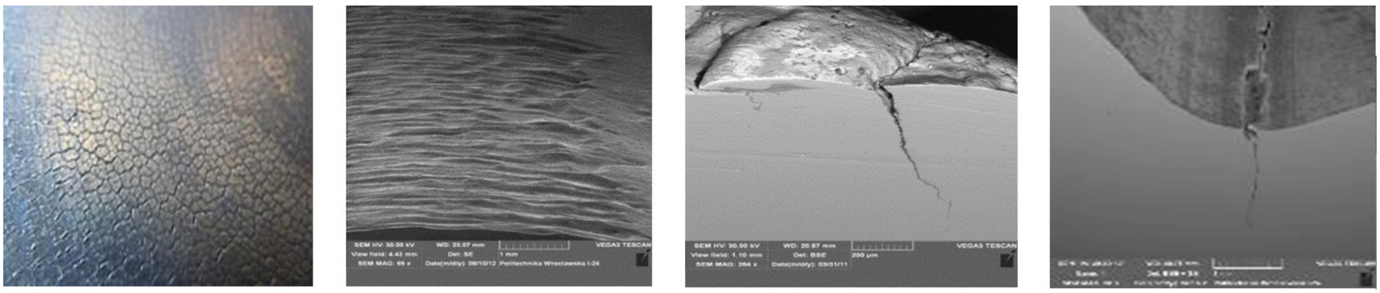
This article discusses the results of studies using the developed artificial neural networks in the analysis of the occurrence of the four main mechanisms destroying the selected forging tools subjected to five different surface treatment variants (nitrided layer, pad welded layer and three hybrid layers, i.e. AlCrTiSiN, Cr/CrN and Cr/AlCrTiN). Knowledge of the forging tool durability, needed in the process of artificial neural network training, was included in the set of training data (about 800 records) derived from long-term comprehensive research carried out under industrial conditions. Based on this set, neural networks with different architectures were developed and the results concerning the intensity of the occurrence of thermal-mechanical fatigue, abrasive wear, mechanical fatigue and plastic deformation were generated for each type of the applied treatment relative to the number of forgings, pressure, friction path and temperature.

Keywords: decision support system; durability of forging tools; artificial neural network; loss of material, wear

1. Introduction

The low durability of forging tools is caused by extreme operating conditions prevailing in industrial hot forging processes resulting from the simultaneous occurrence of many complex phenomena and destructive mechanisms. The most important mechanisms destroying the tool include: abrasive wear, thermal-mechanical fatigue, mechanical fatigue and plastic deformation (Fig. 1).

Forecasting the durability of forging tools used in the die forging process with indication of the dominant destructive mechanisms and their impact on the "life time" of the tool is a very important but still unresolved problem. Therefore any attempt to develop methods that would allow determining the wear (destruction) of tools and forecasting their durability is justified by many factors, including: continuous improvement of forging technology, reducing costs associated with the tool implementation or unit costs of making a single forging, and –



a) b) c) d)

Fig. 1. The most frequent causes of the failure of forging tools: a) traces of thermal-mechanical fatigue on the tool working surface, b) abrasive wear in the die used for forging a disc element, c) plastic deformation on the face of a punch used for the manufacture of CVJB housing, d) mechanical fatigue in the insert used for forging a forked element

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last but not least – ecological aspects [4,5]. At the moment there are many systems that allow partial replacement of expensive and time-consuming material experiments with one virtual experiment [1-3,6-11]. Numerous methods also exist for formal representation of knowledge in available computer systems (e.g. fuzzy logic, artificial neural networks, genetic algorithms).

Based on the long research conducted by the authors of this study on the use of various formal methods to create expert systems supporting production processes in the area of die forging, it turns out that very satisfactory results are obtained using artificial neural networks as a method of knowledge representation in a computer system. This article presents the results of the studies based on the recently developed expert system forecasting the wear of a forging tool and contribution of the four main destructive mechanisms considered as a function of the changing process conditions.

2. Research methodology

The study involved an expert system developed by the authors and described in [12,13], predicting the durability of forging tools. The developed system allows its users to calculate the value of the geometrical loss in the examined tool for given values of its operating parameters and to estimate the intensity of the typical mechanisms of the tool destruction.

The source data that has been used in the developed system comes from experiments carried out under industrial conditions and relates to selected die forging processes with particular emphasis put on the industrial process of forging a cover plate, carried out in three steps on the crank press at a pressure of 18 MN. The cover plate after the process of forging, normalizing and machining is a component of the gearbox in passenger cars; it operates as a type of seal at the exit of the drive shaft from the gearbox. As a result of the conducted comprehensive research, a large database was created and it served as model training instances to develop a model of knowledge representation for a computer system based on artificial neural networks. Figure 2 schematically presents the process of acquiring source knowledge necessary for the development of the system, while details related to the acquisition of knowledge are described in [12,13].

Each record in the database contains specific information about the degree of tool wear in a selected area at specific values of the forging process parameters and information about the contribution of individual destructive mechanisms.

The input variables analyzed in the system included: the number of forgings, the temperature of the tool at selected points, the type of protective layer used, the magnitude of pressure and the length of friction path, while the output variables included: geometrical material loss, wear and intensity of occurrence of the four basic destructive mechanisms. Representative sets of artificial neural networks have been developed to represent

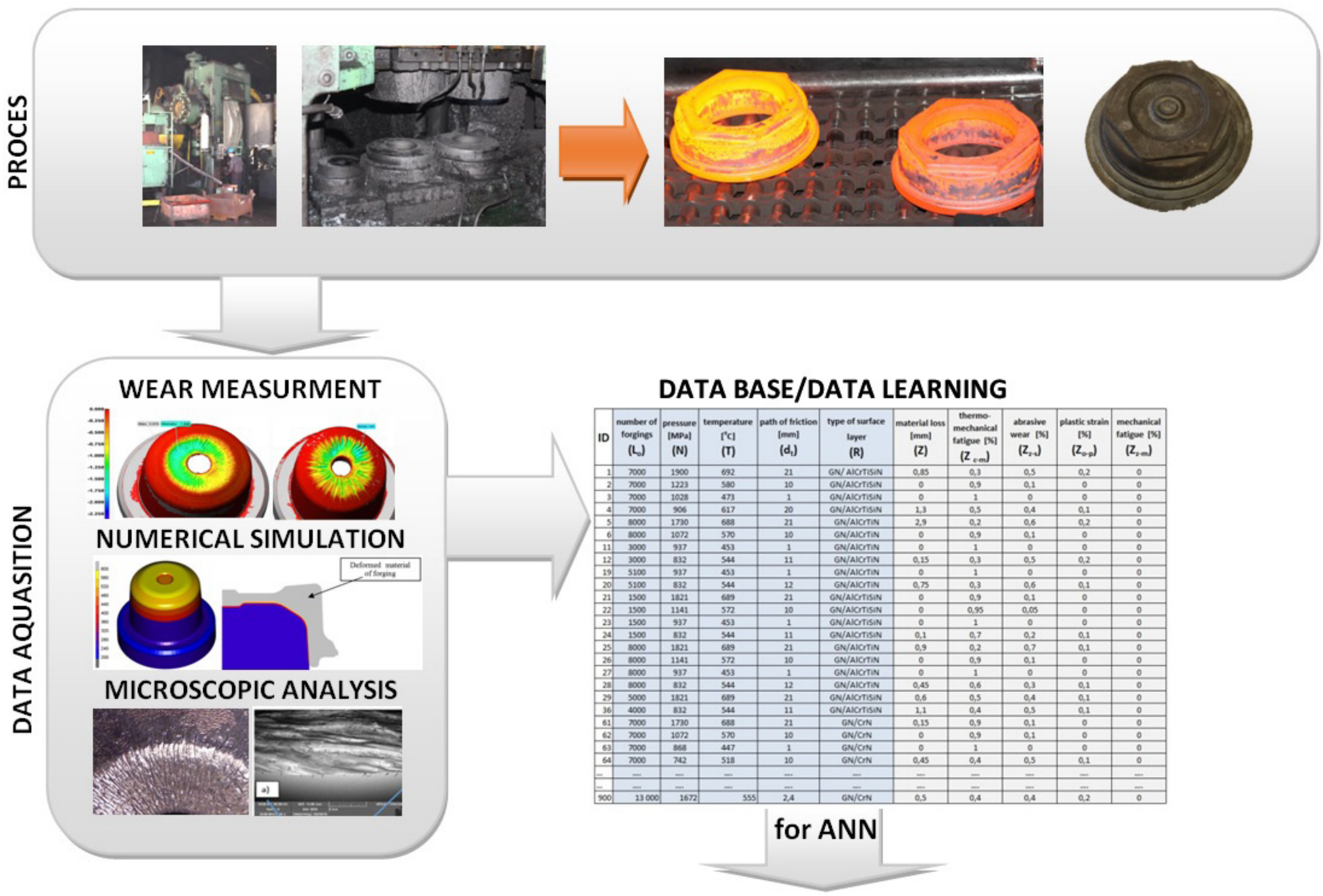


Fig. 2. Scheme of source knowledge acquisition with fragment of the developed database

knowledge in the system. Figure 3 shows a general scheme of the developed system.

In studies [12,13], the authors presented in detail the parameters and architecture of the developed networks and the results of computer simulation of the geometrical tool material loss (Z).

This work is a continuation of the research and presents the results of simulation based on the developed set of neural networks determining the intensity of the main destructive mechanisms, i.e. thermal-mechanical fatigue ($Z_{c\text{-}m}$), abrasive wear (Z_s), plastic deformation (Z_{op}) and mechanical fatigue (Z_p) considered as a function of the adopted operating conditions.

3. Discussion of results

This chapter discusses the results of simulation generated by the developed system. Figure 4 presents the results of the simulation of the intensity of occurrence of each of the four destructive mechanisms referred to the number of forgings for the fixed process parameters such as: tool temperature = 500°C, pressure = 500 MPa, friction path = 10 mm. Individual graphs show simulation results for the five examined protective layers.

From the diagrams presented in Figure 4a-d it follows that for the adopted operating conditions, no traces of mechanical fatigue were observed in tools for any of the applied surface treatment variants. This is the correct result, considering the fact that in the industrial forging processes, mechanical fatigue is rarely observed, as in most cases it is caused by the wrong design of the tool shape. It should be noted that among all the knowledge records there were also such in which this mechanism was included in the input data.

Another issue that arises from the graph analysis is the occurrence of abrasive wear, which in almost all variants is the dominant mechanism; the only exception is the nitrided

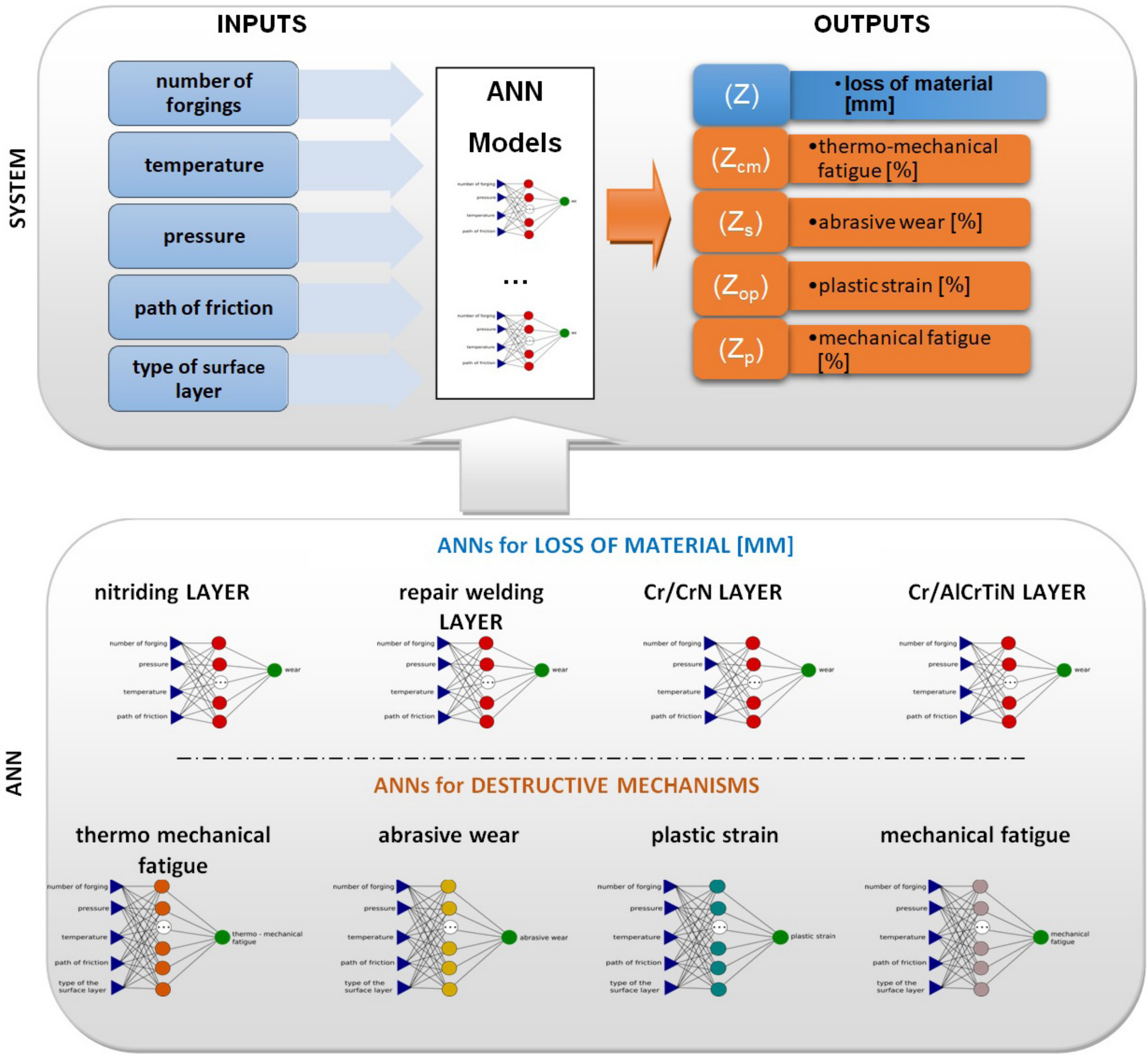
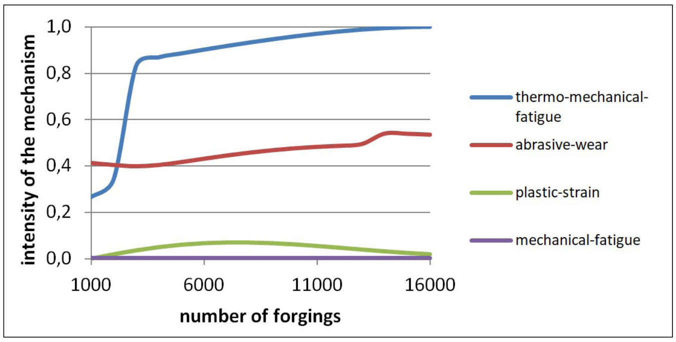
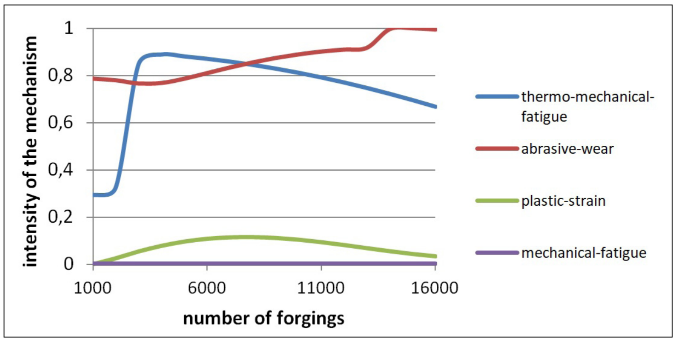


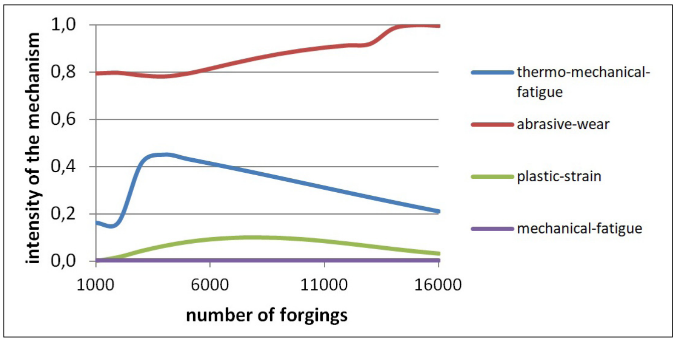
Fig. 3. Global scheme of developed decision support system regarding the durability of forging tools



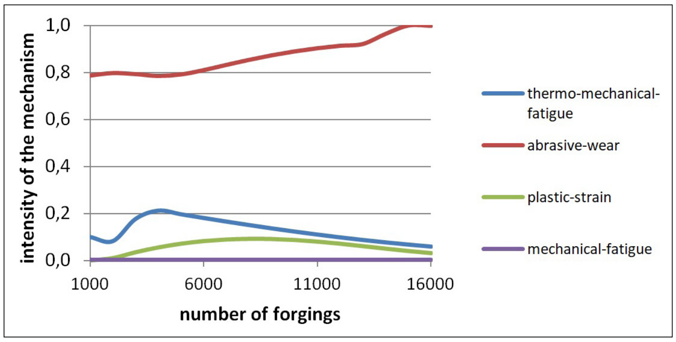
a) nitrided



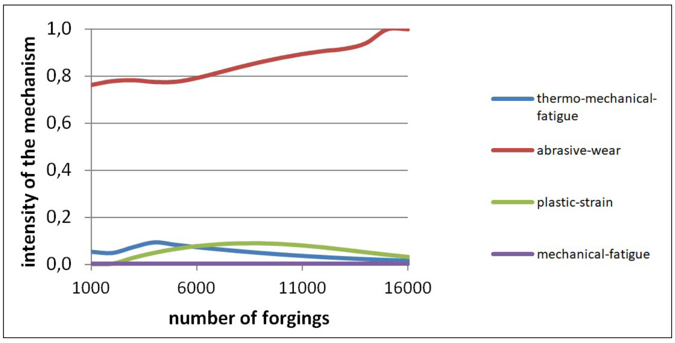
b) pad welded



c) hybrid: GN/CrN



d) hybrid: CN/ AlCrTiN



e) hybrid GN/AlCrTiSiN

Fig. 4. The intensity of occurrence of the four main destructive mechanisms affecting tools operating under the following conditions: temperature 500°C, pressure 500 MPa, 10 mm friction path, subjected to different variants of the surface treatment: a) nitrided, b) pad welded, c) hybrid GN |CrN layer, d) hybrid GN|AlCrTiN layer, d) hybrid GN AlCrTiSiN layer

layer (Fig. 4a), where thermal-mechanical fatigue dominates. This may be due to the fact that under the adopted operating conditions, larger particles of the worn out nitrided layer are removed. In the case of other variants, the nitrided layer can be protected by superimposed thin films. In the pad welded layer, no additional thin protective film is applied and the thickness of the layer amounts to a few millimetres. Only in the case of the nitrided layer, the mechanism of thermal-mechanical fatigue becomes more intensive with the increasing number of forgings. For other variants of the surface treatment applied (Fig. 4b-e), its intensity reaches a maximum at about 4000-5000 forgings and then drops at different rates, while the intensity of abrasive wear increases for these variants with the increasing number of forgings (Fig. 4b-e). The lowest intensity of thermo-mechanical fatigue is observed for the variants with nitrided layer (Fig. 4a) and AlCrTiSiN coating (Fig. 4e). All the discussed surface treatment variants include the destructive mechanism in the form of plastic deformation.

On the following graphs (Fig. 5-9) generated using the developed system, the results are presented for each of the applied tool surface treatments but under varying operating conditions.

Figure 5 presents the intensity of occurrence of the four main destructive mechanisms operating in tools with nitrided layer for a temperature of 500°C, pressure of 700 MPa and 10 mm friction path.

In the case of nitrided tools, for relatively high pressures and moderate friction path lengths, the mechanism dominant from the beginning of the forging process was abrasive wear, additionally observed to increase with the number of forgings. The high pressure value, compared to Figure 4a, caused changes in the dominant mechanism. Additionally, under these operating conditions, the effect of thermal-mechanical fatigue was not

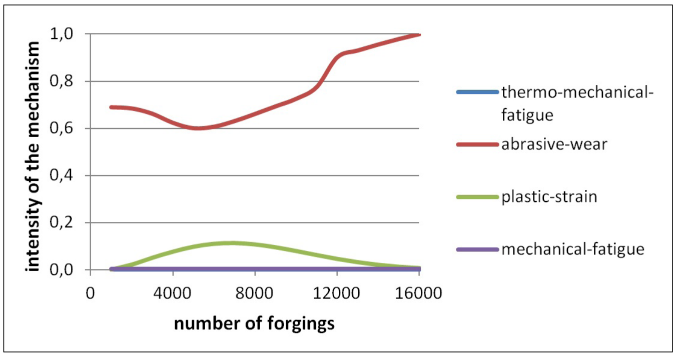


Fig. 5. The intensity of occurrence of the four main destructive mechanisms affecting tools with nitrided layer under the following operating conditions: temperature 500°C, pressure 700 MPa, 10 mm friction path

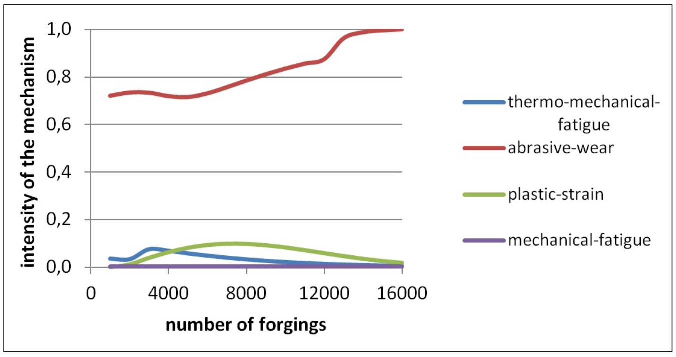


Fig. 7. The intensity of occurrence of the four main destructive mechanisms affecting tools with the deposited GN/CrN layer under the following operating conditions: temperature 500°C, pressure 700 MPa, 10 mm friction path

observed. Probably its contribution was completely taken over by abrasive wear.

Figure 6 shows the intensity of occurrence of the four main destructive mechanisms operating in tools with pad welded layer for a temperature of 500°C, pressure of 600 MPa and 1 mm friction path.

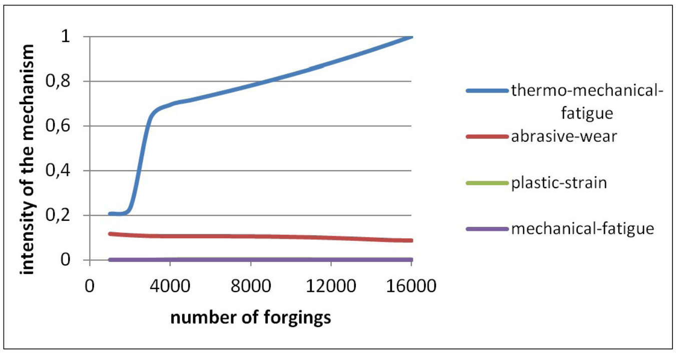


Fig. 6. The intensity of occurrence of the four main destructive mechanisms affecting tools with pad welded layer under the following operating conditions: temperature 500°C, pressure 600 MPa, 1 mm friction path

In the case of pad welded layer, for slightly higher pressures but shorter friction paths, the strong dominance of thermal-mechanical fatigue and a small contribution of abrasive wear were observed. This situation was quite different than the one shown in Figure 4b, where both mechanisms were active throughout the entire forging process. Under these conditions, total absence of the plastic deformation was also observed, which may indicate a relatively high resistance of the thick pad welded layer to the effect of this destructive mechanism.

Figure 7 presents the intensity of occurrence of the four main destructive mechanisms operating in tools with the deposited GN/CrN layer for a temperature of 500°C, pressure of 700 MPa and 10 mm friction path.

In the case of the GN/CrN layer and given operating conditions, the abrasive wear was the mechanism dominating throughout the entire process, while the role of other mechanisms was only of a minor significance. Figure 4c shows that for higher pressures the contribution of thermal-mechanical fatigue has decreased considerably compared to abrasive wear.

Figure 8 shows the intensity of occurrence of the four main destructive mechanisms operating in tools with the deposited GN/AlCrTiN layer for a temperature of 500°C, pressure of 500 MPa and 5 mm friction path.

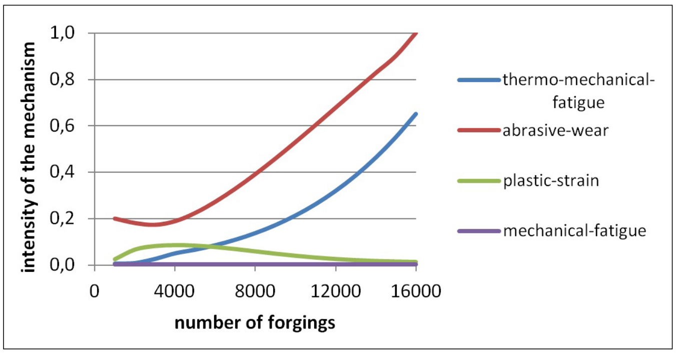


Fig. 8. The intensity of occurrence of the four main destructive mechanisms affecting tools with the deposited GN/AlCrTiN layer under the following operating conditions: temperature 500°C, pressure 500 MPa, 5 mm friction path

Using the generated results, for selected operating conditions of the GN/AlCrTiN layer, it can be observed that in principle for the whole range of forgings (0-16000) the dominant mechanisms are abrasive wear and (to a lesser extent) thermal-mechanical fatigue. There is a slight contribution of plastic deformation, especially in the initial period of the forging process (400 forgings). Comparing the results obtained for this layer to the results presented in Figure 4d, a much higher contribution of thermal-mechanical fatigue observed in this case can be explained by a longer contact between hot forged part and forging tool resulting from shorter friction path.

Figure 9 shows the intensity of occurrence of the four main destructive mechanisms operating in tools with the deposited GN/AlCrTiSiN layer for a temperature of 500°C, pressure of 700 MPa and 5 mm friction path.

The results plotted in Figure 9 indicate that in the case of unit pressures increasing up to 700 MPa and a friction path of

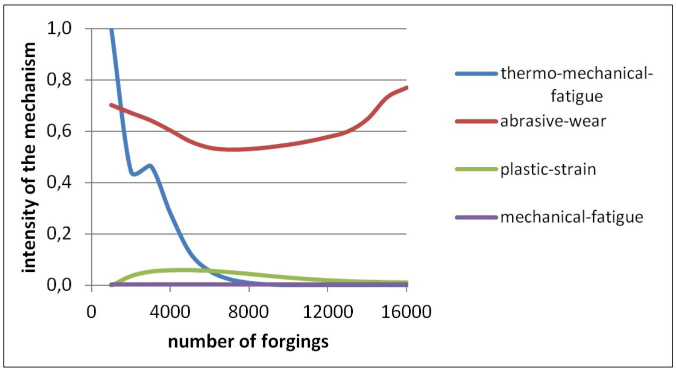


Fig. 9. The intensity of occurrence of the four main destructive mechanisms affecting tools with the deposited GN/AlCrTiSiN layer under the following operating conditions: temperature 500°C, pressure 700 MPa, 5 mm friction path

up to 5 mm, the initial high contribution of thermal-mechanical fatigue, starting with about 3 000 forgings, is later decreasing very rapidly. On the other hand, the contribution of abrasive wear remains high all the time. Studies conducted under industrial conditions have indicated that in selected areas of the tool (described by the above mentioned conditions), a loss of smaller particles of the hybrid layer took place along with the loss of the nitrided layer. Then, after this phenomenon had reached its peak, under the same conditions, in a large number of forgings, a uniform, slowly progressing abrasive wear of the tool surface was observed.

The results, generated thanks to the developed neural network architecture and presented in Figures 5-9, indicate that in the analyzed process, the dominant mechanisms include primarily the abrasive wear and, to a lesser extent, thermal-mechanical fatigue. The remaining mechanisms occur only sporadically.

Based on the preliminary analysis it can be concluded that the results are correct when compared with the results obtained under industrial conditions. Nevertheless, it seems that the data set is still insufficient and needs to be constantly expanded, because the contributions and characteristics of plastic deformation are almost the same, and mechanical fatigue is practically non-existent.

Based on the preliminary results generated by the developed network for given operational conditions, it can be stated that the results are correct and have a real impact on the situation observed in industrial processes. In spite of this it seems necessary to analyze the results for other operating conditions of the tools to confirm their correctness in a global aspect. Then the verified global analysis will give additional interesting information on the impact of the applied surface treatment variants examined in relation to the operating conditions, to allow for optimal design of protective layers increasing the durability of forging equipment.

In order to verify the obtained results, an exemplary worn-out tool was taken (after forging of 6,000 forgings with the GN / AlCrTiN layer) from the industrial process (not entering into the set of data used for artificial neural networks). In addition, for better analyze, Figure 10 shows the results of numerical modeling regarding distributions of normal stresses, temperature field and friction path at selected characteristic points of the tool.

Figure 11 shows the macro and microstructure images of the selected tool.

The tool was plasma nitrided to a depth of approx. 80 μm and coated with a two-layer AlCrTiN coating, which on the chromium substrate has a thin layer of chromium nitride less than 1 μm thick, and a thicker layer of AlCrTiN nitrides with a dominant aluminum content, whose thickness on the tested tool was 4.9 ÷ 6.2 μm, which together create a coating with a thickness of 6.5 ÷ 7 μm. On the face of the tool (Fig. 11a, on the right) show signs of wear and characteristic thermo-mechanical cracks network (Fig. 11a, on the left). The applied coating kept its properties relatively well during operation, remaining on the face (Fig. 11c) of the tool and preventing abrasive wear. At the same time over the entire surface it formed quite a fine mesh thermo-mechanical cracking. Small irregularities were also observed on the surface of the coating, as well as deep cracks and plastic deformation in the areas of the roundings (11b and 11e), where the cracking of the small shell chipping took place. However, one should emphasize the high resistance of the coating to abrasive wear and its proper adhesion to the substrate. Referring these results to the results obtained on the

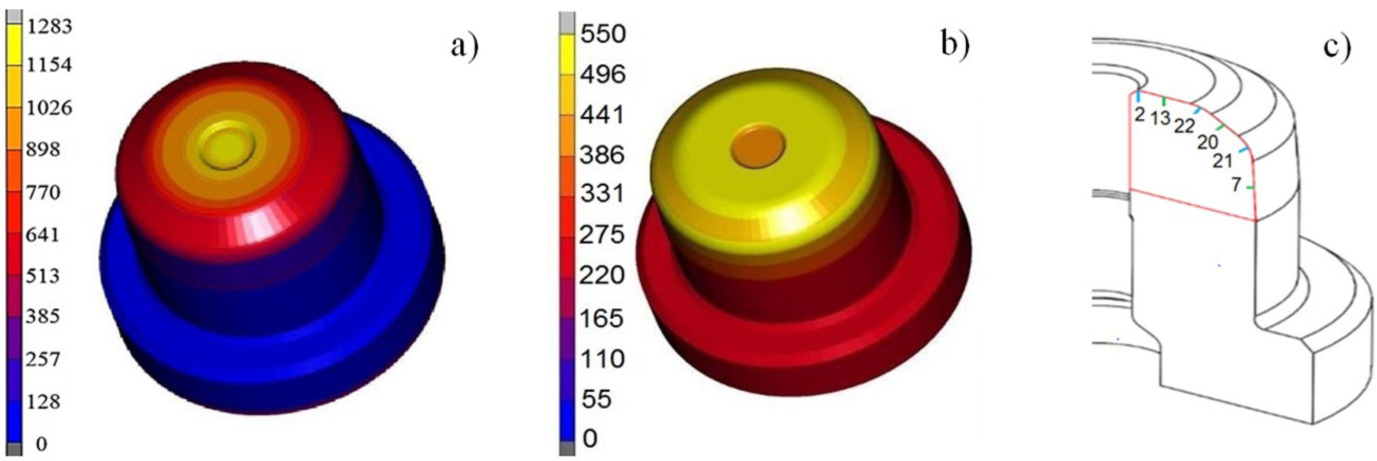


Fig. 10. Results of numerical modeling: a) distributions of normal stresses on the surface in MPa, b) distributions of the temperature field in °C, c) path friction at selected points in mm

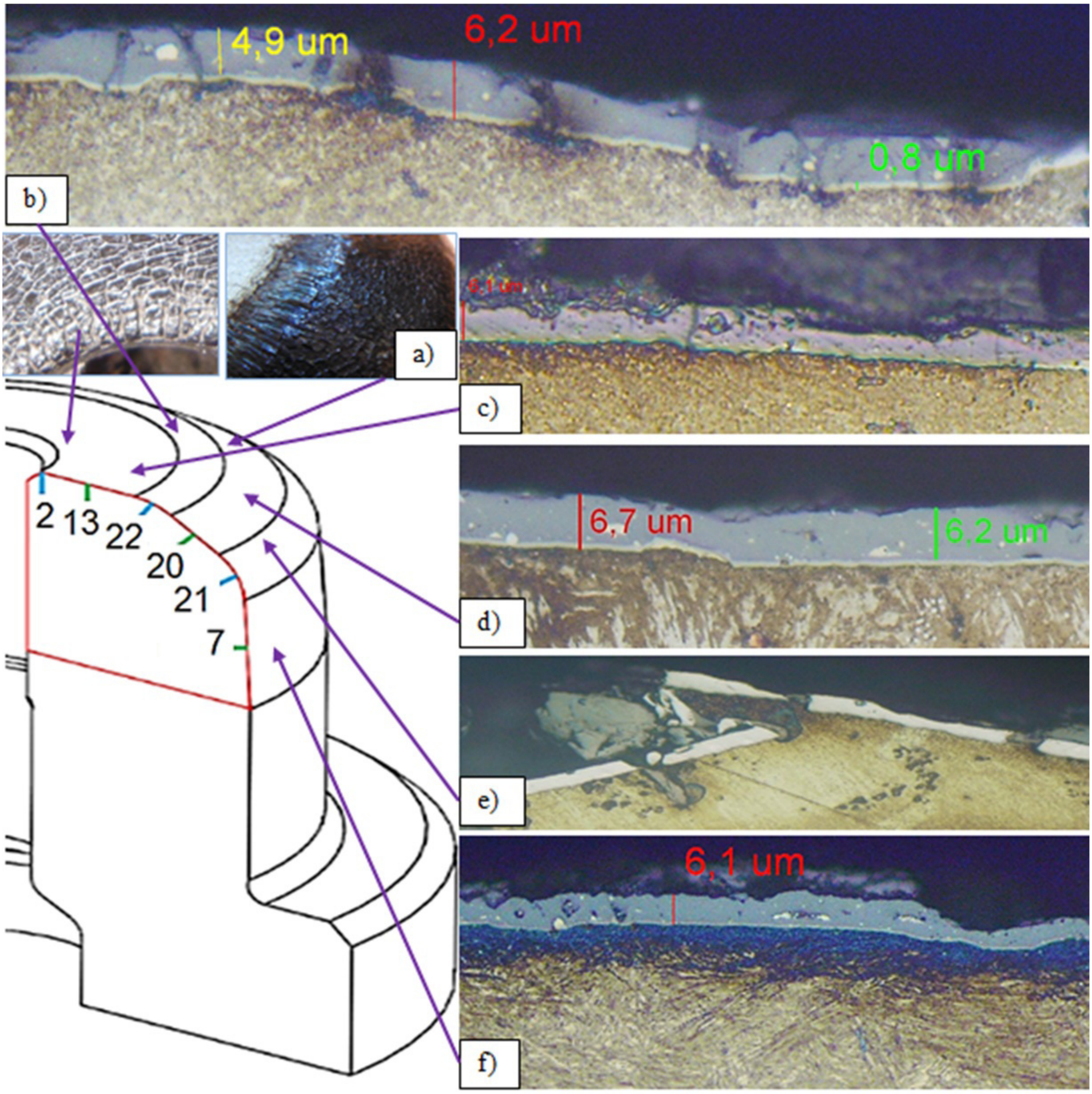


Fig. 11. Photos of macro and microstructures of the surface layer of tool after 6000 forgings (with AlCrTiN coating) in selected sub-areas at approx. 100× magnification

basis of the developed neural networks, it can be stated that the developed architecture predicts the wear of tools in industrial hot forging processes quite well.

It is worth noting that the data set has been created using the subjective assessment of experts in the forging process technology and it is often very difficult to precisely determine the contribution of individual mechanisms. The reason is, among others, the fact that the easiest to identify, due to its measurability, is abrasive wear, although, according to the research carried out by the authors, often the effects of other less measurable mechanisms, such as thermal fatigue, are included into this mechanism. It should also be remembered that in this study it has been decided to determine the four main destructive mechanisms, which often include also other less visible phenomena, such as oxidation, adhesion, fritting, etc. Therefore, it would be advisable to develop in the future even more advanced neural network architectures, including a larger number of the main destructive mechanisms. Nevertheless, even the networks developed right now allow for the selection of an optimal protective layer for tools, although, based on the presented results, one can claim that, in principle, there is no such thing as one optimal layer for one tool, and therefore another solution should be considered, namely the use of several different layers deposited on one tool in different areas, though until now it has not been fully clarified whether the presence of multiple layers on one tool would not cause some interaction and reduce durability in other places of the tool.

4. Summary

The article discusses the possibilities of using artificial neural networks (ANNs) in the decision support system to predict the durability of tools used in industrial hot forging processes, in particular in the aspect of the intensity of occurrence of the main destructive mechanisms. The system developed in this study has been based on the experimental data obtained for selected forging tools – fillers used in the second operation of forging a cover plate component. The architectures of the neural networks, developed using the training data set and selected correlation-based coefficients, generated the results for the intensity of occurrence of thermal-mechanical fatigue, abrasive wear, plastic deformation and mechanical fatigue under the adopted operating conditions. Initial analysis of the results showed their correctness when compared to the durability of forging tools operating under similar conditions, but further research is needed in this area for global analysis of other operating conditions. Thanks to this, it will be possible to better predict the durability of forging tools in terms of the intensity of occurrence of the main destructive mechanisms, and to optimize and select appropriate protective layers applied to forging tools and forging equipment.

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