APPLICATION OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) TO PREDICT THE WEAR OF FORGING TOOLS

HAWRYLUK Marek[1], MRZYGŁÓD Barbara[2]

[1] *Wroclaw University of Technology, Poland, EU, marek.hawryluk@pwr.edu.pl*
[2] *AGH University of Science and Technology in Cracow, Poland, EU*

Abstract

The work concerns an idea of the expert system for predicting the life of forging tools used in die forging processes, for which the knowledge representation and processing were based on Adaptive Neuro-Fuzzy Inference System (ANFIS). Using the results of extensive investigations and analysis, a knowledge base was developed for the three representative industrial hot forging processes (forging of front wheel, casing of constant velocity joint body, and fastener construction). The knowledge base contains elements of both theoretical knowledge about destructive phenomena and empirical knowledge gained from the experience of the authors and industry experts (forge employees) and also from the acquired values of selected forging parameters. The parameters, including the number of forgings, the billet and tool temperature, tool loading, contact time, path of friction and lubrication, were compiled in the form of knowledge vectors in respective tables. The task of the developed system is to quantify the amount of wear, which is a geometric loss suffered by the die cavity during successive operations of the industrial hot forging process, after entering some technological parameters as inputs for this process. It is an original approach, as, so far, the thematic literature has not provided any examples of the use of ANFIS to solve the problem faced by the system. Differences between the results obtained from the ANFIS- based system and empirical data derived from the study of worn tools are in the range of 0-10 %.

Keywords: Durability of forging tool, wear, expert system, ANFIS

1. INTRODUCTION

Forging tools used in the process of die forging, hot or semi-hot, are operating under extra hard, extreme even, conditions of cyclic mechanical loads (of up to 1000 MP) and thermal loads (from 60 °C up to 800 °C at the surface). Hence they are exposed to many, often mutually destructive, factors that cause their premature wear and, despite the significant technical progress, forging tools (dies and punches) are still characterized by relatively low durability. The life of tools is a complex issue, and the wear of forging equipment significantly reduces the quality of manufactured forgings, while increasing the production costs. The most common defects which occur in forgings, caused by the wear of tools, are related with improper and incomplete filling of the die cavity, resulting in unfilled sections, cold shuts, barbs, die shifts, scratches, delaminations, micro and macro cracks, etc. This, in turn, affects the functionality of final product made from the forging, which has a significant impact on production costs and lower quality of forgings. Currently, it is estimated that the cost of tooling can account for up to 8-15 % of the total production costs. In fact, taking into account the time needed to replace the used instrumentation and cases of unexpected destruction of tools, these costs may rise up to even 30 %.

From the point of view of the production process, durability in the technical literature usually means the number of produced forgings that meet quality requirements and have been manufactured using one tool. By contrast, from the scientific point of view, the tool life is linked to its resistance to the effect of damaging agents acting on this tool during its operation. In this case, very important is an objective assessment and analysis of the destructive mechanisms that cause wear or damage to the tool, and not as in the case of the definition used in production, the subjective assessment of the operator.

The life of tools depends mainly on the conditions under which the forging process is run, on the design and construction of tools, and further on the suitable heat treatment of these tools adequate to the selected tool material, the shape of the preform and the slug, and other similar factors. At present there are no clear criteria applicable in the evaluation or selection of methods to improve the life of tools [1-3]. What is known are only general guidelines, and therefore every industrial process of forging must be analyzed separately, because process parameters resulting from the technology, or tribological relationships between the shaped material and the tool, or many other factors, are closely related to a specific process. Therefore, various methods are being developed that are designed to analyze the wear and tear of forging tools and forecast their durability, which is justified by considerations of both financial and scientific character. Currently, numerous and different IT methods and tools are available to allow for partial replacement of costly and time-consuming physical experiments with virtual experiments. In addition to numerical modelling methods, increasingly important role in the industry start playing the expert systems, used primarily as advisory systems for the tasks of identification, classification, control, simulation and diagnostics [4-6]. Efforts are also made to use expert systems in optimization of the tools used in forging operations [7-9].

The development of computer science that allows the prediction of tool life depending on the parameters of the forging process is deliberate and economically viable. This will allow in the future further optimization of process parameters, owing to which, with the technology parameters kept at an appropriate level, the "life" of forging instruments will be prolonged to maximum.

The aim of this study was to develop a system, whose task is to predict the durability of forging tools depending on the process parameters and using three representative processes of die forging. The purpose of the system is to predict tool wear, understood as a geometric loss or gain of material, based on the selected process parameters, i.e. the number of forgings, pressure, path of friction, deformation time and process temperature. Knowledge representation and processing was based on adaptive neuro-fuzzy inference system (ANFIS).

2. DATA TO THE SYSTEM

The source data that are used in the developed system come from the experiments carried out under industrial conditions. They concern three representative processes that cover a vast majority of the conventional die forging variations (hot and semi-hot) carried out under industrial conditions. In these processes, different conditions occur that determine the durability of forging tools. The authors‘ experience suggests that strong differentiation of forging conditions (due to temperature, pressure, path of friction, thermo-chemical properties, tribological behaviour, etc.) can be obtained by selecting:

a) hot forging of front wheel in open dies - die inserts heated to 250 °C, and cooled and nitrided only in 2 or 3 operations, initial billet heated inductively to 1150 °C,

b) precision forging of CVJB casing in closed dies - tools not preheated, lubricated and cooled, initial billet heated inductively to 920 °C,

c) forging of fastener to move concrete slabs in closed die without lubrication and cooling of tools, billet heated inductively (locally) to 1000 °C.

The selected representative processes cover a vast majority of standard processes of die forging (hot and semi-hot), which are carried out under industrial conditions. Relevant information has been described in detail in the aforementioned article [10].

Some of the parameters, such as temperature of the billet, temperature of tools, shaping force, tribological conditions, the geometry of the preform and of the final product, are based on process sheets and outcome of numerous studies conducted by the authors. Other parameters, such as pressure, path of friction, contact temperature, were determined using numerical modelling verified by a measuring and monitoring system [11]. The geometric loss (wear) of die cavities was determined from a comparison of superimposed images obtained by laser scanning of new and worn out tools (after making a fixed number of forgings) [12]. As a result of conducted simulations and testing of materials, a database including 450 knowledge records was developed. Each record contains information about the rate of wear in a specific area of the tool and fixed values of the parameters of the forging process. A detailed description of the experiment, of the tests performed and of the process of data acquisition is included in an earlier publication of the authors [10].

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

Seeking suitable forms of knowledge representation for a computer system that is expected to operate based on the collected experimental data, it was decided to use fuzzy logic. A decisive impact on this choice had the nature of the data obtained, which are the results of measurements and observations and the results of computer simulations. This information represents only some specific cases, and hence it is the information incomplete and burdened by errors of measurement and simulation, which altogether means the data that, is uncertain. Fuzzy logic is applicable also to the processing of such materials. The first attempt made by the authors to develop an expert system using fuzzy logic was presented in [10]. An expert system applying Mamdani model [13, 14], where the linguistic rules and expressions of the strategy of inference are based on expert knowledge, was developed. The developed system, using fuzzy knowledge base, is operating with an error of 10%, but the data collected was insufficient to cover fully all the analyzed areas. In some cases, the system generated an answer about the lack of rules, based on which the decisions were to be made.

Seeking forms of knowledge representation which, based on the developed experimental data, would build a model characterized by a smaller error and covering all the areas analyzed, it was decided to use, known in the literature, adaptive neuro-fuzzy inference system (ANFIS) [15, 16]. Neuro-fuzzy systems (NFS) are systems combining the properties of neural networks that have the ability to learn and adapt to certain conditions and fuzzy systems that have the ability to describe and process quality knowledge incomplete and uncertain. Under this model, fuzzy inference systems (FIS) provide a scheme of inference and ease of interpretation of the model, while the determination of the optimal structure of the model, i.e. the interpretation of appropriate fuzzy sets, shapes of membership functions and fuzzy rules, is implemented by training methods used in artificial neural networks (ANN), based on the supplied training data. These methods have the ability to adapt to the structure of the data presented and will choose model parameters effective in minimization of the error of inference [17].

3.1. System model

To develop a model of the system, as training data was used an experimental summary of the results of measurements where the influence of certain parameters of the forging process on tool wear (geometric loss) was measured. Some data, such as the number of forgings, pressure, path of friction, deformation time and process temperature, have been treated in the system as explanatory (input) variables, while the dependent (output) variable was the wear of tools expressed as a geometric loss. To develop a model of the system, an implementation of the ANFIS structure from the Fuzzy Logic Toolbox package of Matlab was used [18]. The structure of the fuzzy model variables is shown in **Figure 1**. The adaptive neuro - fuzzy inference system (ANFIS) used in this study is an algorithm that, based on the training data, can automatically adjust the parameters of the fuzzy inference system (FIS) of Sugeno type. The parameters of membership functions are adjusted with backpropagation learning algorithm or combined with the method of least squares (hybrid learning method). When constructing

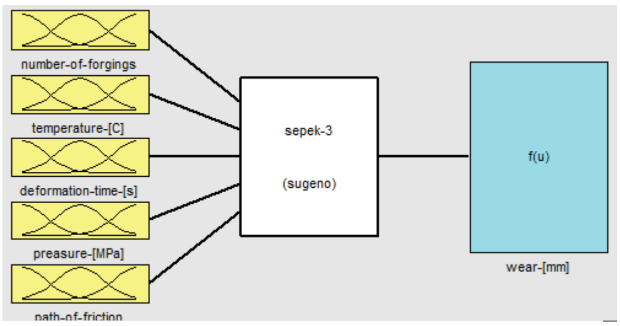


Figure 1 The structure of fuzzy model

a model, the data space was first divided into the corresponding subspaces. The input to the system was provided by 5 input variables, each of which was divided into three fuzzy sets with Gaussian membership function. This corresponds to the formation of 243 subspaces, each of which is represented by a single fuzzy rule describing operation of the system in this sub-area (1)

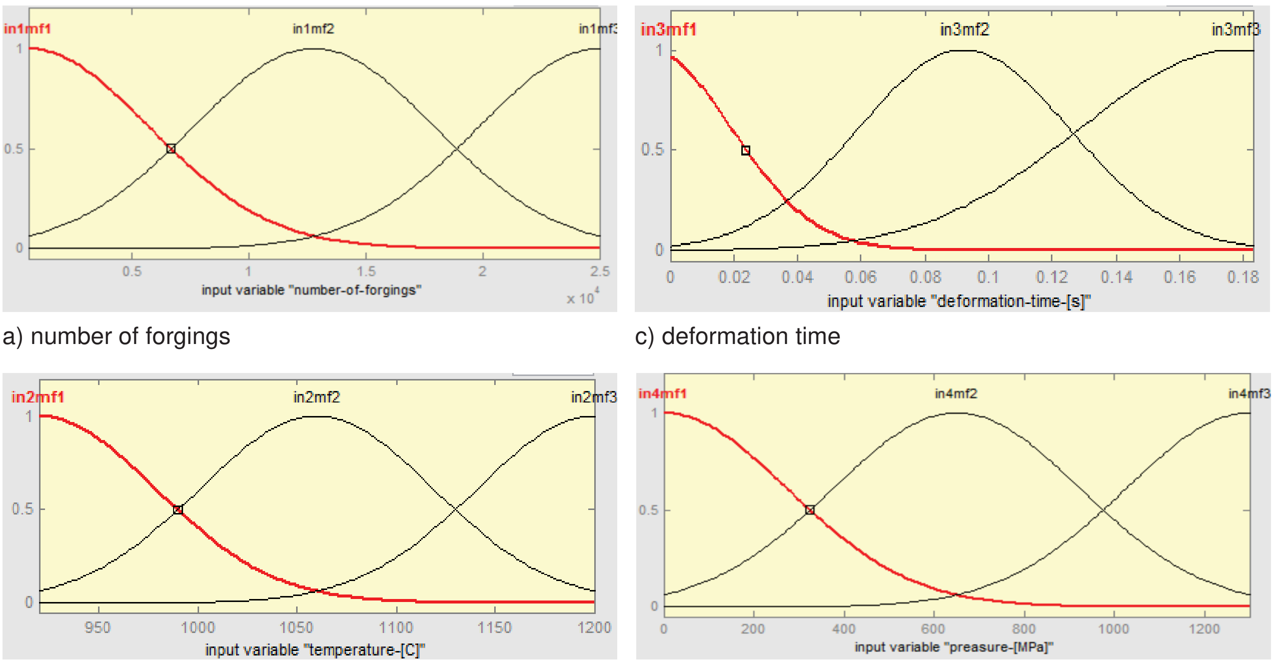
$$R^i: IF\ (x_1\ is\ A_1^i) and\ ...\ and\ (x_n\ is\ A_n^i\ ) THEN (y = b^i\ ) \tag{1}$$

where: $x = (x_1 \dots x_n)$ is the input variable of the system, A_j^i are fuzzy sets, $y \in R$ is the output variable of the system. Example of rule (2) generated by the system is given below.

IF(number-of-forgings is in1mf1) and (temperature-[C] is in2mf1) and
(deformation-time-[s] is in3mf1) and (pressure-[MPa] is in4mf1) and (2)
(path-of-friction is in5mf1) THEN (wear-[mm] is out1mf1)

Initial parameters of the system, i.e. parameters of the membership function for fuzzy sets occurring in predecessor rules, are determined at random. Then they are "tuned" using two methods: the method of gradient steepest descent and a combination of the steepest descent method with the least squares method [14].

These methods have the ability to adapt to the structure of the presented training data and allow choosing model parameters minimizing the error of inference. **Figure 2** shows representations of selected linguistic variables in the form of fuzzy sets after fine tuning of the system.



a) number of forgings
c) deformation time
b) temperature
d) pressure

Figure 2 Membership function plot for inputs

The neuro - fuzzy ANFIS system can be presented in the form of network architecture (**Figure 3**), which resembles a multi-layer perceptron, where the role of weights perform functions of membership in fuzzy sets; instead of the activation function are used operators implemented on fuzzy sets.

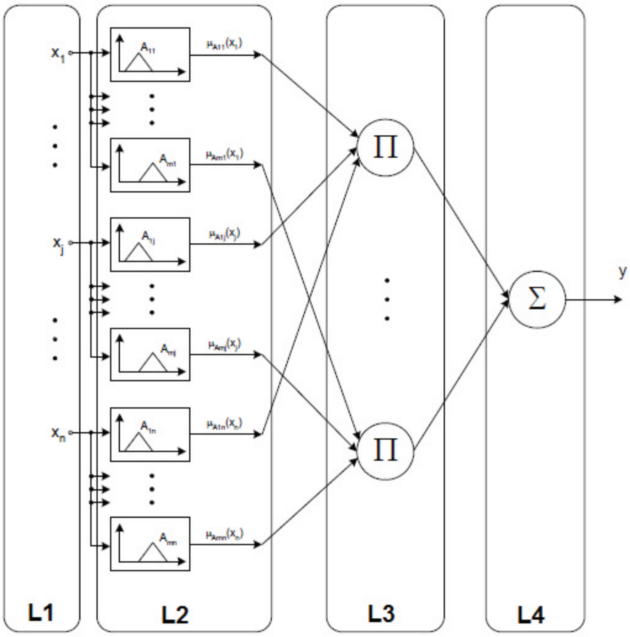


Figure 3 ANFIS model structure

In the first two layers (L1 and L2) are calculated the degrees of veracity of predecessors of logical rules. This operation is carried out in the same way as in the case of fuzzy inference systems (FIS). In the next layer (L3) are calculated the values of output functions, which then (L4) are weighted by the degrees of veracity of logical rules and summed up. At the output is obtained aggregate value of the dependent variable (output) for the modelled sample. Learning of NFS is iterative and involves matching parameters of membership functions (e.g. the width and position of the Gaussian function) to best predict the value of the dependent variable for the test sample. The established structure of inference of fuzzy-neural network model, consisting of 5 input variables divided into three fuzzy sets and 243 rules, is shown in **Figure 4**.

The, developed with the use of ANFIS algorithm, FIS system operates with a testing error set at a level of hermos. 12 %; training was carried out in 7 epochs. The model developed in this article operates within the whole range of input variables. The results in the form of 3D submodels that take into account the impact of selected input variables on material wear are presented under Section 3.2.

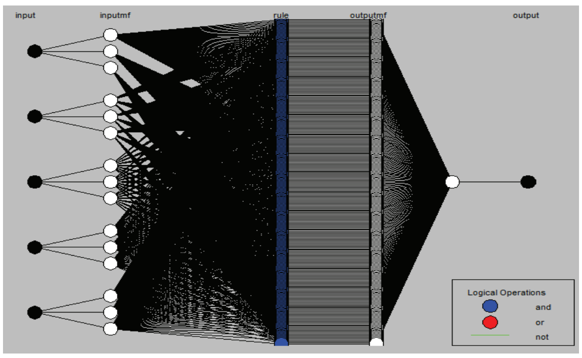


Figure 4 ANFIS model structure to predict the wear of forging tools

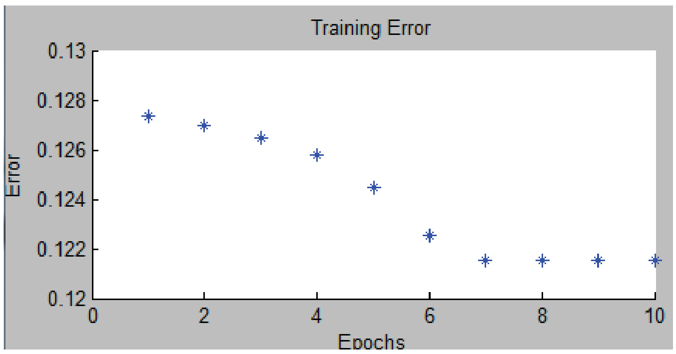


Figure 5 Change in training error for subsequent epochs

3.2. Discussion of results

Based on the obtained results it can be concluded (**Figure 6a**) that with the increase in the number of forgings and simultaneous increase in temperature of the billet, the loss of tool material increases, and the temperature rise considerably intensifies this process. This is due to thermal fatigue and local tempering of the tool material, which facilitates breaking off of larger particles caused by the flow of forged material suffering deformation. In the case shown in **Figure 6b**, it can be said that with the increasing number of forgings, the loss of the tool material also increases. Greater loss of material observed for the large number of forgings and the increasing hardness value can be explained by the fact that with the increasing number of forged components, the hard particles of hermos layers start breaking off, which accelerates the tool wear. The large number of forgings and the low value of plastic deformation of the tool material (**Figure 6c**) produce a high rate of wear, but with the increase of plastic deformation, the material loss is hampered. Plastic deformation is mainly responsible for changes in the tool geometry, but does not result in material loss. This state may be due to the fact that other degradation mechanisms take over the leading role. A similar situation is observed in **Figure 6f**, where the temperature rise with low contribution of plastic deformation (change in the shape of the tool but without any loss of material) increases the loss of material, which is partly the effect of 383 hermos-mechanical fatigue intensifying the abrasive wear.

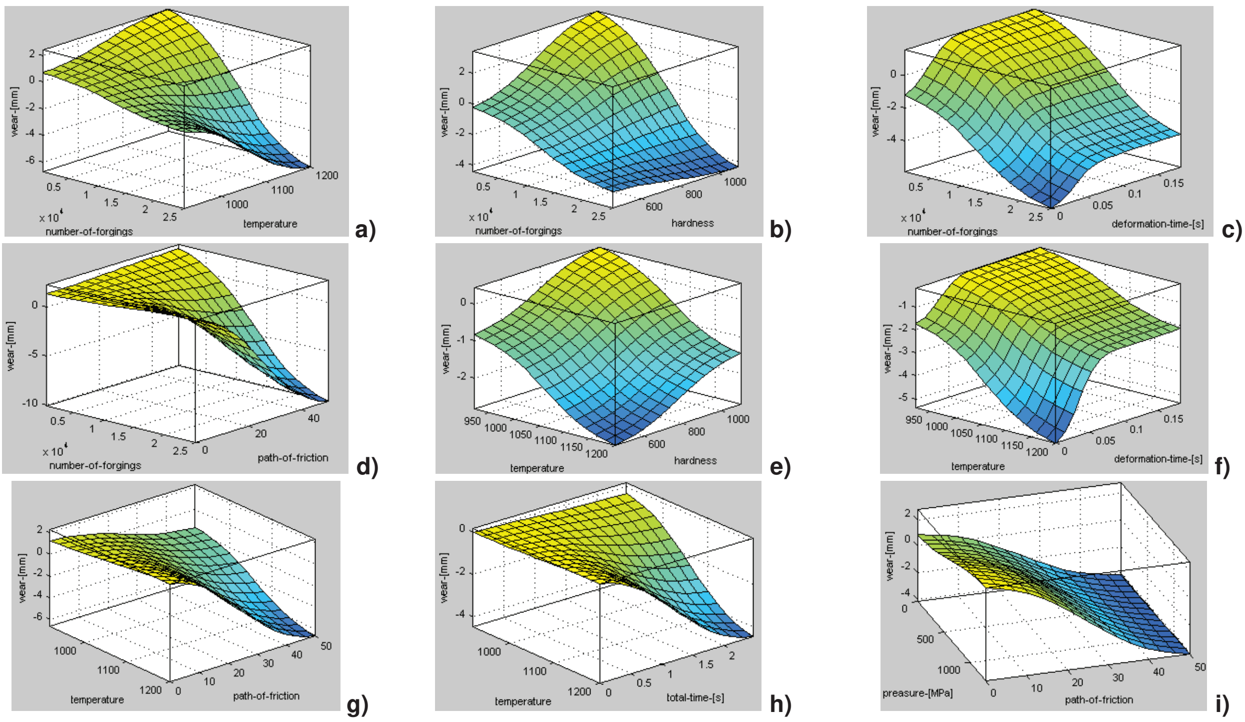


Figure 6 Presentation of the results in the form of 3D submodels that take into account the impact of selected input variables on material wear

The obtained model results (**Figure 6d**) indicate that with the increasing number of forgings and longer path of friction due to an intense flow of the forged material, a large material loss is suffered. Especially, when the number of forgings is at a level of 25,000 pieces and the path of friction is long, the material loss can reach even 8 mm. A similar trend is observed in **Figure 6g**, where the increase in the path of friction with increasing temperature results in accelerated wear. This situation is sometimes observed in industrial processes of forging, e.g. when the tool is in the final stage of operation, and additionally some of its areas shaping the forging, in places where piercing is expected, are already maximally worn out.

The results shown in **Figure 6e** confirm the relationship observed in the industrial environment, where the increase in temperature of the billet reduces the durability of the die, due to tempering of the tool surfaces most exposed to heating, which promotes and increases the wear. The longer contact time and the hot deformation of material also increase the tool wear (**Figure 6h**).

Detailed examination of the results shown in **Figure 6i** demonstrates that with an increase in pressure exerted on the tool and the short path of friction, the gain of material occurs, not observed in the industrial forging processes. On the other hand, longer path of friction and high values of pressure result in great material loss, which is confirmed by the results of studies carried out under industrial conditions. However, it should be remembered that the developed database (consisting of 450 knowledge records) could not provide for the case described in **Figure 6i** the sufficient number of records (especially for low pressure values), which means that the proposed ANFIS algorithm model gave results inconsistent with reality.

The results of the global analysis of adaptive inference system (ANFIS) in the context of forecasting the durability of forging tools from the point of view of an expert in the subject indicate the overall accuracy and validity of the adopted model (solution). It can be assumed that with the knowledge base expanded with further records, the correctness of the results will be even better.

4. SUMMARY AND CONCLUSIONS

Studies conducted by the authors concerning the analysis of the destructive mechanisms and methods to increase tool life confirm the high compatibility of the obtained theoretical results (based on the proposed adaptive neuro-fuzzy inference system (ANFIS)) with the technological practice. Only the results relating to the effect of pressure in the developed model are somewhat puzzling, since for high values of the pressure and a short path of friction, a weight gain in the tool material was observed, and not, as in the case of industrial forging processes, the loss of material according to a model of abrasive wear developed by Archard, where the loss is proportional, among others, to the pressure. For the long path of friction, the results are already compatible with reality.

The value of error with which the model is burdened is slightly higher than the value of error assumed for the first version of the system described in [10], but model developed in this article is valid for all the analyzed areas.

REFERENCES

[1] GRONOSTAJSKI Z. HAWRYLUK M, JAKUBIK J., KASZUBA M., MISUN G., SADOWSKI P, Solution examples of selected issues related to die forging, *Archives of Metallurgy and Materials* 60(4) (2016) 2767-2775.

[2] HAWRYLUK M., JAKUBIK J.: Analysis of forging defects for selected industrial die forging processes, *Engineering Failure Analysis* 59 (2016) 396-409, http://dx.doi:10.1016/j.engfailanal.2015.11.008

[3] HAWRYLUK M., KASZUBA M., GRONOSTAJSKI Z., SADOWSKI P.: Systems of supervision and analysis of industrial forging processes, *Maintenance and Reliability 2016*; is being printed in 2016-03_1

[4] WILK-KOŁODZIEJCZYK D, MRZYGŁÓD B, REGULSKI K, OLEJARCZYK-WOŻEŃSKA I, JAŚKOWIEC K, (2016), Influence of process parameters on the properties of austempered ductile iron (ADI) examined with the use of data mining methods, *Metalurgija* 55 (4), 849-851

[5] OPALIŃSKI A, GŁOWACKI M, OLEJARCZYK-WOŻEŃSKA I, MRZYGŁÓD B.,(2015), Prediction of technological process parameters based on experimental data, *Technical Transactions*, Issue 7, p203-210. 8p.

[6] MRZYGŁÓD B., OLEJARCZYK-WOŻEŃSKA .I, GŁOWACKI M., OPALIŃSKI A., (2015), Extracting knowledge from integrated experimental data on the ADI manufacture, *Computer Methods in Materials Science,* 15 (1), 85-93

[7] KATAYAMA T, AKAMATSU M, TANAKA Y (2004) Construction of PC based expert system for cold forging process design. *J Mater Process Technol* 155-156:1583-1589.

[8] SUBBA RAO AV, Pratihar DK (2007) Fuzzy logic-based expert system to predict the results of finite element analysis. Knowl-Based Syst 20:37-50.

[9] AZARI, A., POURSINA, M. I POURSINA, D. (2014). Radial forging force prediction through MR, ANN, and ANFIS models. *Neural Computing & Applications*, 25(3-4):849-858.

[10] GRONOSTAJSKI, Z., HAWRYLUK, M., KASZUBA, M., MARCINIAK, M., NIECHAJOWICZ, A., POLAK, S. i inni. (2015). The expert system supporting the assessment of the durability of forging tools. *The International Journal of Advanced Manufacturing Technology*, 82(9): 1973-1991.

[11] GRONOSTAJSKI, Z., HAWRYLUK, M., WALCZAK, S. I JABŁOŃSKI, D. (2011). Measuring & control systems in industrial die forging processes. *Eksploatacja i Niezawodność-Maintenance and Reliability,* 3:62-69.

[12] GRONOSTAJSKI, Z., HAWRYLUK, M., KASZUBA, M., NIECHAJOWICZ A. (2011). Application of the scanning laser system for the wear estimation of forging tools. *Computer Methods in Materials Science,* 11(2): 425-431.

[13] L.A. ZADEH, Fuzzy Sets, Inform Contr, 8 (1965), pp. 338-353

[14] PIEGAT A., „Modelowanie i sterowanie rozmyte". Akademicka Oficyna Wydawnicza EXIT, Warszawa19998.

[15] NAYAK PC, SUDHEER KP, RANGAN DM, et al. (2004), A neuro-fuzzy computing technique for modeling hydrological time series, *Journal of Hydrology*, 291(1-2), 52-66

[16] ALTUG S., CHOW M.Y., TRUSSELL H.J., (1999), Fuzzy inference systems implemented on neural architectures for motor fault detection and diagnosis, *IEEE Trans Ind Electron*, 46 (6), 1069-1079

[17] NAŁĘCZ M. I IN., „Biocybernetyka i inżynieria biomedyczna 2000. Tom 6: Sieci neuronowe", Akademicka Oficyna Wydawnicza EXIT, Warszawa 2000.

[18] Mathworks. Fuzzy Logic Toolbox User's Guide, 2014.