SENSITIVITY ANALYSIS OF THE ARTIFICIAL NEURAL NETWORK INPUTS IN A SYSTEM FOR DURABILITY PREDICTION OF FORGING TOOLS

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Abstract

The paper presents the results of neural network sensitivity analysis used in prediction system of tool durability in die forging processes. Data collected during many experiments, tabulated in the form of knowledge vectors, has been used as a source of training data for artificial neural networks. The sensitivity analysis makes it possible to differentiate between the important variables and those which do not make a significant contribution to the results of the network operation. The obtained results of global sensitivity analysis, conducted for the elaborated network in the context of predicting the life of forging tools from the expert viewpoint, indicate general correctness and validity of the adopted model (solution), ascribing the highest sensitivity to the nitritiding input variable (related to hardness), which is in reality the main factor determining the tool resistance to the destructive effect of failure mechanisms.

Keywords: Artificial neural network, decision support system, durability of forging tools

1. INTRODUCTION

The forging dies and punches operate under difficult conditions: they are requested to have high strength, hardness and simultaneously - proper toughness. Additionally, they are constantly loaded by recurrent large temperature gradients. Through the optimum choice of process parameters one can significantly increase the life of tools, improve the quality of forgings and consequently, increase the productivity of the whole process. The main factors having an effect on the process of forging and a durability of forging tools are: tool and preform temperature, slug geometry, press settings, process speed, lubrication and cooling, and tool shape and quality [1]. The low durability of tools lowers the quality of forgings. During operation, forging tools and equipment are exposed to the effect of many destructive factors, which cause their wear. The most commonly occurring (and also the most extensively tested) destructive mechanisms are: plastic deformation and abrasive wear in warm forging [2] and hot forging [3], thermal fatigue cracking [4], [5], and thermo-mechanical fatigue [6]. Among them, the most frequently studied is the mechanism of wear, which prevails also in the process of cold forging [7]. For example, a comprehensive analysis of the major destructive mechanisms of tools in forging process of car steering system was presented in [8]. At present there are no clear criteria applicable in the evaluation or selection of methods to improve the life of tools [9]. In [11], based on own research and experiments carried out in cooperation with the forging industry, the author focuses on the selected methods, which provide the highest effectiveness in the improvement of the forging tool life and are currently used in the industrial processes of die forging. Various methods are being developed that are designed for analysis of the wear and tear of forging tools and prediction of 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. Efforts are also made to use decision support systems in optimization of the tools used in forging operations [20].

2. RESEARCH METHODOLOGY

Researches on improvement of the durability of forging tools were conducted in several stages. The first stage was focused on material and operational research carried out under industrial conditions in selected forging shops in Poland. The second stage of the research involved the use of a database derived from the material and in-service studies, to develop next a knowledge representation model for computer system to predict the durability of forging tools.

2.1. Material and operational tests

As part of experimental research and numerical modelling, the effect of specific forging parameters on the wear and tear of forging tools was measured and studied - **Figure 1** (INPUTS). As a result of performed simulations and material tests, a database has been created, which contains the results of the measurements of cases examined. Each database record contains fixed information on the following subjects - **Figure 1** (OUTPUTS):

- the size of material loss affecting in the specified area the tool geometry at the preset values of the forging process parameters,
- percent contribution to the die damage of the four basic wear mechanisms, i.e. thermo-mechanical fatigue, abrasive wear, plastic deformation and mechanical fatigue.

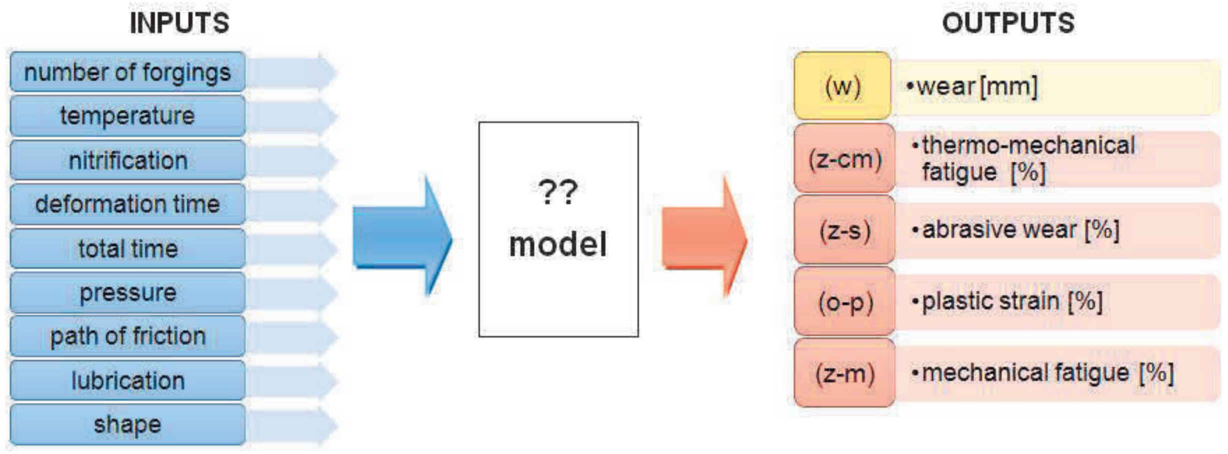

Figure 1 A pictorial diagram of the proposed system

More detailed information about the research has been provided in previous publications of the authors of this study [[15], [16]].

2.2. Development of a neural network

The second stage of the research involved the use of the developed database to design a knowledge representation model for computer system to predict the durability of forging tools. A pictorial diagram of the main assumptions adopted in the proposed system is shown in **Figure 1**. Looking for suitable forms of knowledge representation in the modelled system, numerous methods that allow for modelling of strongly nonlinear phenomena have been examined. The analysis of source data collected and developed in the form of knowledge vectors presents this data as incomplete information, because each vector represents only some selected cases; this data is also uncertain because it is burdened with numerous measurement errors. Attempts have been made to use fuzzy logic as a form of knowledge representation in the system [15]. Further studies have been undertaken to investigate and reduce predictive errors and to develop models based on the ANFIS algorithm [16].

The best results and the smallest prediction error, compared to earlier models, gave the system based on artificial neural network. The data collected from numerous experiments, tabulated as knowledge vectors, has been used as a source of training data for artificial neural networks. The characteristics of the developed network and the analysis of the results obtained using this network are presented in [17].

A simplified diagram of the selected network structure is presented in **Figure 2**. The network is of the MLP type and consists of one input layer (9 input variables/19 neurons), one hidden layer (25 neurons) and one output layer (5 neurons). The network marker was established as MLP 19-25-5.

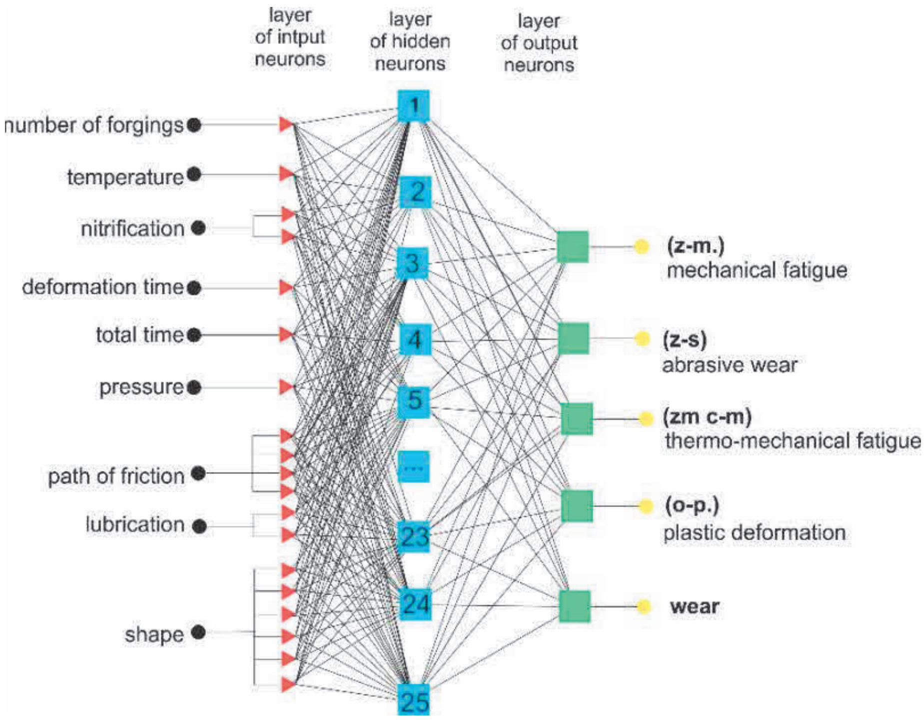

Figure 2 Diagram of the elaborated MLP 19-25-5 network [17].

- 19 - is the value which corresponds to the number of input neurons. For the analysis, the network has 9 input variables, of which five are continuous in character, and they are counted as separate inputs. Four initial variables are discrete in character (nitrification, path of friction, lubrication, shape) and for these networks one calculates the sum of their possible input values (e.g. the lubrication variable can assume the value of 'yes' or 'no' and the latter ones are two possible inputs for the network). And so, the network has 19 neurons at the input.
- 25 - is the number of neurons in the hidden layer.
- 5 - is the number of neurons in the output layer.

Summary of the training process of selected neural networks for each output variable and the specific characteristics are given in **Table 1**.

Table 1 Parameters of the MLP 19-25-5 neural network [17]

Name of network	**MLP 19-25-5**	**Name of network**	**MLP 19-25-5**
Error (training)	0.039309	Quality (testing)	0.842213
Error (validation)	0.127667	Training algorithm	BFGS (56 epoch)
Error (testing)	0.090174	Error function	SOS
Quality (training)	0.937455	Activation (hidden)	Tanah
Quality (validation)	0.828000	Activation (output)	Logistic

In this network, the BFGS (Broyden-Fletcher-Goldfarb-Shanno) method was used for training. In the case of the selected MLP 19-25-5 network, the assumed minimal approximation error was not achieved; the training process was terminated in 56 epoch, when the validation error started to grow.

3. SENSITIVITY ANALYSIS OF INPUT VARIABLES ADOPTED FOR THE MLP 19-25-5 NETWORK

Sensitivity analysis is the tool widely used in various fields of science [19]. This analysis is conducted after the neural network training process has been completed and shows which input data is most relevant. We learn this by analyzing a network error in the event of elimination of individual variables from the input data. When removing individual variables from the input data, it is necessary to carry out the network training process from the beginning and re-calculate its $Error_i$ every time. The analysis shows what loss is incurred by rejecting a particular variable - **Figure 3**.

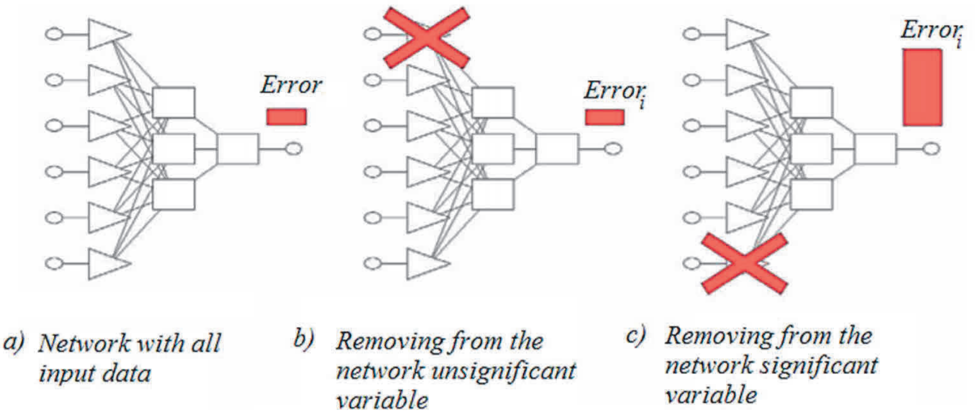

Figure 3 Schematic diagram of the significance analysis of input variables in neural networks [[19]]

With the rejection of some variables, the network error is expected to increase (**Figure 3c**), and therefore the basic measure of network sensitivity will be the quotient *W* of $Error_i$ obtained for the network startup with a data set without one variable and *Error* obtained with the full set of variables (1).

$$W = \frac{Error_i}{Error} \tag{1}$$

The larger is the network error with one variable rejected relative to the original error (for a network with all input variables), the more sensitive is the network to the absence of this variable. If the error quotient is 1 or less, then removing the variable does not affect the quality of the network or even tends to improve it. Once a sensitivity analysis has been performed for all analyzed variables, they can be ranked in terms of their significance.

The results of the sensitivity analysis for the developed MLP19-25-5 network are summarized in **Table 2**. It can be seen that all 9 explanatory (input) variables have a significant effect on the result of inference. The most significant variables are those for which the error quotient exceeds 5, i.e. nitrification, shape, lubrication, and path of friction.

Table 2 Global sensitivity analysis for the MLP19-25-5 network

RANGE	INPUT	W
1	nitrification	15.98
2	shape	8.07
3	lubrication	5.68
4	path of friction	5.57
5	number of forgings	2.90
6	deformation time	2.63
7	pressure	2.32
8	total time	1.98
9	temperature	1.39

The obtained results of global sensitivity analysis, conducted for the MLP19-25-5 network in the context of the forging tool life prediction from the point of view of the subject matter expert, indicate general correctness and validity of the adopted model (solution), given the fact that the highest sensitivity has been ascribed to the input variable called *nitriding* (related to hardness), which is actually the main factor determining the tool resistance to the destructive effect of failure mechanisms. The general use of thermal-chemical treatment in the form of nitriding hardens the working surface of forging tools to a depth of up to 0.3 mm and thus increases the surface hardness from 550 HV for untreated tools to 1100 HV. This has also been confirmed by numerous studies and observations, which clearly demonstrate that the life of nitrided tools is much longer after the treatment than before. However, if this issue is considered in the context of hardness alone, it can be stated that higher hardness of the tool can enhance the risk of mechanical fatigue. Additionally, after approximately 18,000 forgings, serious material losses are observed due to the presence of single large and very hard particles, which are detached from the nitrided layer and act next as an abrasive material [17].

As regards the second, in terms of the sensitivity, variable, i.e. shape, the results obtained are consistent with the generally accepted knowledge and experience of blacksmiths and technologists. The shape of the die largely determines the critical areas where a given destructive mechanism is likely to operate. Tribological conditions, i.e. the third in the sequence input variable, are also important, since, as shown in [21], the mechanisms that govern the damage of tools lubricated and cooled are completely different than the mechanisms that operate in tools used without lubrication and cooling. Research conducted in the field of durability (materials testing, etc. [9,15-17] on other input variables and their order are correct and the resulting hierarchy only concerns the analyzed input variables. In the developed network, only the result obtained for the variable called *pressure* is a bit puzzling, because in the case of abrasive wear described by Archard model, the volume of the worn out material is proportional to, among others, pressure. On the other hand, Archard model is primarily valid for lubricant-free contacts. Moreover, as indicated above, the input variables are generally the dependent variables, which is the main reason why even for experienced researchers, some of the results examined separately must raise doubts.

4. SUMMARY AND CONCLUSIONS

The analysis of the destructive mechanisms conducted by the authors and studies of the 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. The sensitivity analysis carried out for the adopted input variables indicates the high logical consistency and validity of the adopted model. It is important to take into account the extreme values of the input variables, as their change may cause changes in the established order. This analysis also indicates the possibility of reducing the number of input variables and selecting only the most relevant ones, the operation which can in consequence simplify the model. Further work aiming at model improvement will be related to the process of optimizing the network and introducing a larger amount of training data obtained from the consecutive experimental data. The presented results are of a distinctly application character, because based on the analysis of the destructive mechanisms, appropriate methods can be applied or preventive measures can be taken that will allow increasing the durability of forging tools. The solutions developed are mainly addressed to the staff of the die forges.

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