Predicting of tool wear for hot metal forging - an overview and suggested new approach

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Abstract: The process of tool wear is a very complex phenomenon and as experience has shown, it is not easy to describe it mathematically either by phenomenological models or by empirical models, using classical statistical tools. Due to the complexity of the problem, predicting tool wear even today presents a great challenge. Better wear prediction would also mean lower production costs, since unexpected tool breakdowns (failures) can increase costs by up to 30 % per forging unit. An overview of wear models for predicting of tool wear in hot forging are presented in the paper and applications of the recently introduced new approach of tool wear prediction on industrial tools are given.

Key words: Hot forging, tool wear models, CAE Neural Networks, wear prediction.

1. Introduction

Due to their outstanding mechanical properties and a relatively low production cost, the forged products are still gaining in importance. They are used for products, which are exposed to high mechanical or/and thermal loads. A wish to reduce costs leads us to make use of all the resources, which may raise the production effectiveness. In the case of forging technologies, the latter is achieved by the tool life. However the major influence on the tool life (nearly 70 %) is attributed to its wear. Still today, wear prediction of the forging tool represents a major problem to tool designers and technologists in manufacturing, since the process of wear is a very complex one, and, as experience has shown, it is not easy to assess it mathematically. A better wear prediction would dramatically reduce production costs, since it would help us to avoid unexpected loss of tool during forging[1-9].

2. Influential parameters on tool wear

The parameters, which influence the tool wear the most (Figure 1) are surface hardness and toughness at elevated temperature (carbide-forming elements), workpiece deformation (contact surface traction), contact pressures, sliding lengths, sliding velocity, contact time, workpiece temperature, basic

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tool temperature, presence of the third particles in the interface (scale), lubrication (friction), method of tool surface cooling, etc. Their influence on wear is very complex and the relationship between wear and these parameters is highly non-linear and spatially very disordered [1-9, 37].

LUIG [7] systematized the influential sets of parameters, and within these, he recorded some parameters influencing the wear of the forging tools. BOBKE [9] presented vectors of influence of these parameters for three different stress states: a predominantly normal stress state, a predominantly shear stress state, and for the stress state, which exists (prevails) on the radii of curvature in the forging tools engravery of tools. It is evident that the influence of individual factors on wear, depending on the stress state, change drastically and that there are no linear, mutually independent parameters. There are different opinions regarding the most important tool parameter. Thus, e.g., HANSEN [3] claims that sliding lengths are the parameter most strongly influencing the wear. On the other hand, DOEGE ET AL. [5] claim that the temperature on the mass surface of the tool which causes a reducing of microhardness of its surface layer is the parameter which probably most strongly influences the wear during the hot die forging of steel. Thus, a higher temperature of the workpiece, a longer contact time, longer sliding distance and a higher

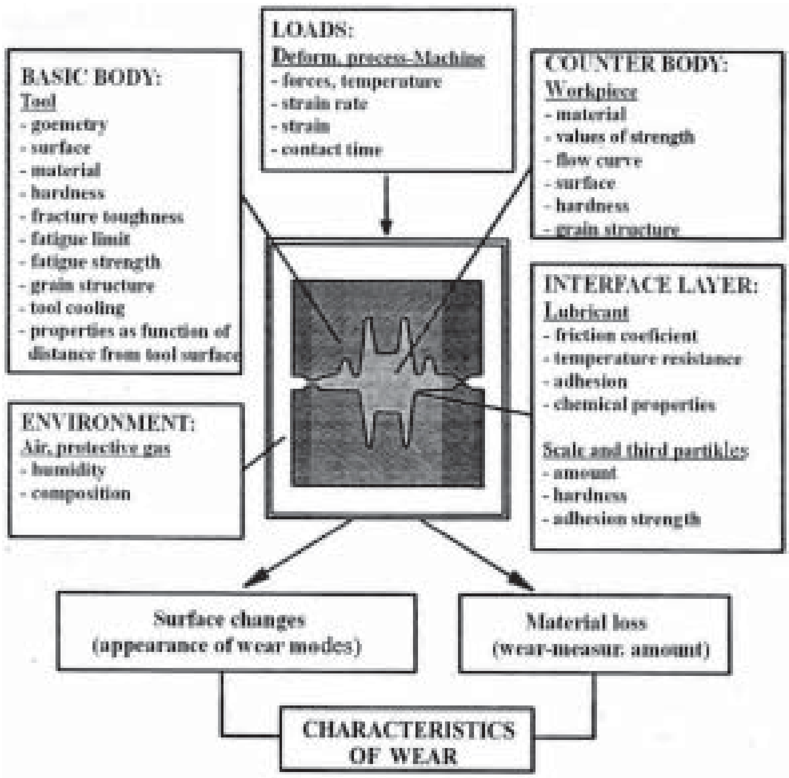

Figure 1. Influential parameters of tool wear [4, 7].

contact stress are increasing the temperature on the surface layer of the tool, while a thicker contact interface layer and better lubricant qualities are reducing it. Higher contact pressures influence the size of the contact surface and thus the transfer of heat from the workpiece to the tool. It is therefore necessary that the prediction models are also based on the system approach [34-36, 40].

Friction between the workpiece and tool influences the flow of the deformed material and thus directly influences the tool wear. Modelling of the friction process in the interface layer between the tool and the workpiece is essential for the analysis of the hot die forging process [10-11, 25-28]. For determining friction, the conventional FEM programs have an installed model - either the

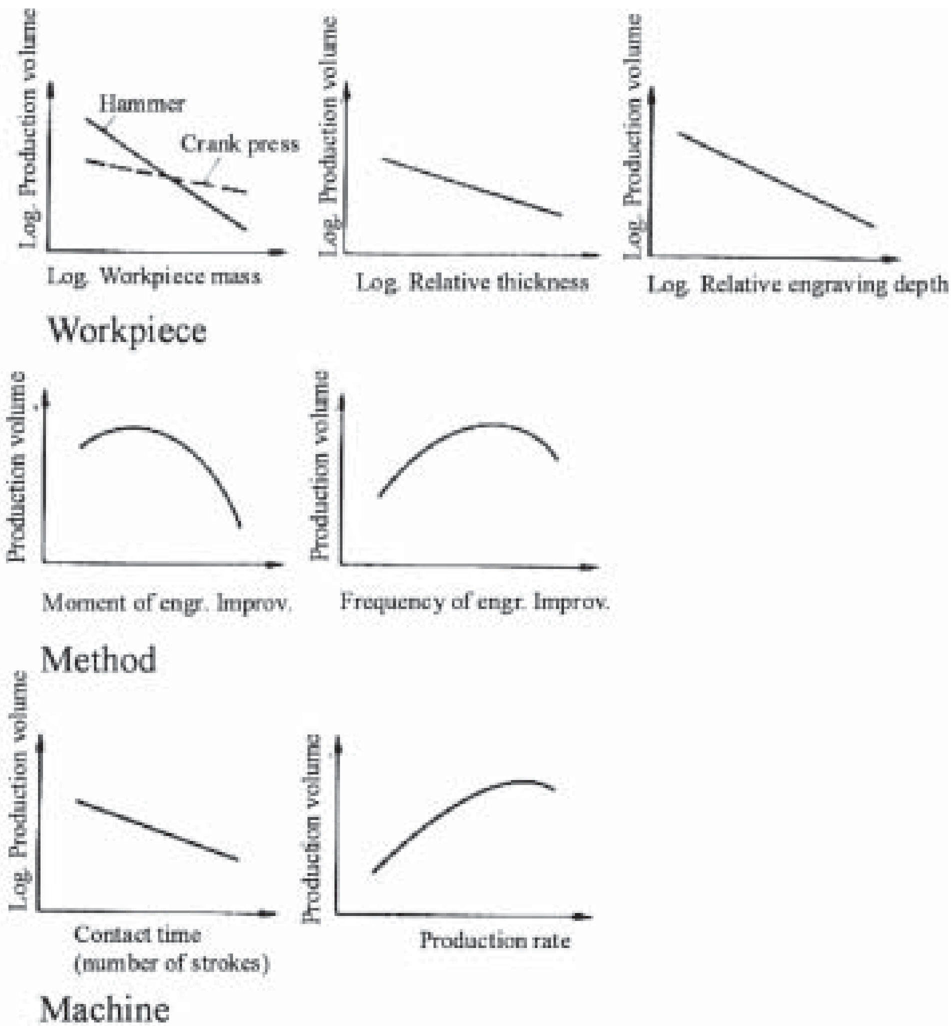

Figure 2. Dependence of tool life from various influential parameters [2].

Coulomb friction model or the model of a constant friction factor. As proved by some most recent research [28], in order to describe the friction conditions in the interface layer between the tool and the workpiece, it is reasonable, due to the complexity of the phenomena in this layer, to calculate with an adaptive friction factor as the function of material, roughness, a normal contact pressure, yield stress, a relative sliding velocity and the temperature**.** Due to the relationship and co-influence of all these parameters the authors have used the method of neural network to calculate the adaptive friction factor with which they simulated the material flow very precisely.

Figure 2 shows qualitatively the influence of various parameters on the tool life in the industrial process of hot forging. It can be realized that the phenomenon is highly nonlinear and very complex.

3. MODELS USED FOR PREDICTION OF TOOL WEAR

The surface layer on the hot die forging tool is due to simultaneous activity of mechanical, thermal, tribological and chemical loads and their complex interactive effects, very non-homogeneously structured and cannot be described mathematically with the presently available number of data from experiments or applications [6].

Wear prediction is based on identification and quantification of the phenomena which control this process. Due to the mentioned complexity of the tribological system and the simultaneous presence of different mechanisms subject to wear, the phenomenological approaches for prediction are still imperfect and too slow for a practical use. Model approaches have proved to be more useful. If we ignore purely empirical approaches, several semi-empirical approaches may very soon come into practice. These, as well, are relatively highly simplified, since some wear influence parameters, which are intermingled or have joint effects, are difficult to assess quantitatively [3, 6, 9].

The basis for model prediction is the determination of influence parameters by laboratory physical simulations - their analysis, which may be numerically supported. The results of the analysis are then incorporated into equations by adequate statistical tools, which make the prediction possible. The basis for prediction is the experimentally verified database with data on the influence of wear-causing variables. In case of the laboratory study of wear, the simulation of tool wear has to be done at limiting conditions like the ones that exist in the applied technology - in our case it means in the tool operation during forging. It is therefore necessary to reproduce the same mechanical, thermal, tribological and chemical conditions as those existing in the intermediate layer between the tool and the workpiece [3-9].

Starting from the mechanical loads of wear surfaces, we have often used the Archard's model or its modifications, like FELDER AND MAHJOUB [13] (Equation 1):

$$\Delta h = \int_{Termomechanicalhistory} K_F \cdot K_W \cdot \frac{\sigma_N \cdot \Delta u}{H_V^m(microstructure(\Theta_s),\Theta_s)} \cdot f(\frac{H_v}{H_{va}}) \cdot dt \qquad (1)$$

Where:

- σ_N contact pressure,
- Δ_n relative sliding velocity,
- K_F constant dependent on interface (tool - workpiece),
- K_W constant dependent on chemical composition of applied tool,
- H_v microhardness,
- H_{va} microhardness of presented oxides,
- Θ_s temperature on tool surface,
- Δ_h wear.

Equation (1) is suggested by the authors for the calculation of wear on entire arbores of nitrided tools with greater radius.

Similar equations can also be found in STÖHLBERG ET AL. [15], PAINTER ET AL. [16], KANG ET AL. [12], BOBKE [9], HANSEN [3], etc. Various models are gradually including a number of influential parameters, and for their characterization they use FEM (e.g. sliding lengths).

VARDAN ET AL. [14] (Equation 2) take into account only the velocity of relative sliding, the temperature on the tool surface, and the contact pressure.

$$Z = \frac{\left(v^{\alpha} \cdot \theta_{1s}^{\beta} \cdot q^{\lambda}\right)}{10000} \qquad (2)$$

Where:

α, β, and λ exponents obtained by regression analysis,
v = relative sliding velocity,
Θ = temperature on tool surface,
q = contact pressure,
Z = wear.

Many outstanding papers are found in the published references, e.g. [4-6], for parameters controlling the wear procedure. The same is true for their mathematical linkage for the purpose of wear prediction. Main restrictions that occur here are the number of the included influence or variables, their weight, and the consideration of their mutual space interactions. The model of DOEGE ET AL. [5-6] (Equation 3) takes into account eight influential sets of parameters (the maximum number found in the available references), obtained using standard statistics, that enables calculation of the maximum wear.

$$H_i(x) = f(R_m)^{1.05} \times f(dT)^{1.10} \times f(F_p)^{0.96} \times f(L_w)_{0.66} \times f(R)^{1.10} \times f(l)^{0.54} \times f(A_i)^{0.63} \times f(x)^{0.29} \quad (3)$$

Where:

$H_i(x)$ = wear at point x in dependence of number of strokes,
$f(R_m)$ = factor dependent on tensile strength
$f(dT)$ = factor dependent on average temperature difference between workpiece and tool,
$f(F_p)$ = factor dependent on forging force,
$f(L_w)$ = factor dependent on chemical composition of applied tool,
$f(R_1/R_0)$ = factor dependent on tool macrogeometry (R= tool arbor radius),
$f(l)$ = factor dependent on sliding length,
$F(A_i)$ = factor dependent on tool laded surface,
$f(x)$ = factor dependent on number of strokes.

The authors claim that compatibility between the experimental and the calculated values is extremely high. The equation they used enabled calculation of wear on the points of tool arbor radii where maximum values of wear occur. All the factors and their exponents are obtained by the standard statistics.

Some other authors [17] also stress the importance of variable influential parameters (contact pressure, sliding lengths, etc.) along the sliding deformed material on the tool curvature (arbor radius). Consequently, non-uniform wear and deposition of materials can occur, especially on small tool radii [4-6, 9]. In such cases, primarily, the above-mentioned models are not always reliable in predicting wear on the entire arbor radius. Neural networks have been efficiently applied for wear prediction on cutting tools [29-30], and on samples in laboratory wear testing [31-32]. There have also been some attempts to apply neural networks to forming tools [33-36]. NAIDIM ET AL. [33] used this approach for prediction of tool wear in cold extrusion, while TERČELJ ET AL. [34-36] used a similar approach on hot forging tools. CZER ET AL. [19] combined expert know-how and data from numerical simulations, for better tool life prediction. FALK AND ENGEL [20] proposed a combined application of numerical simulations and neural networks for solving similar problems. Cases, where back-propagation neural networks (BP NN) were used to predict tool wear in various laboratory tribological applications, are presented in references [31-32].

Recent research describes micro-mechanical models for prediction of friction and wear on tool surfaces. The authors agree that the models are still purely theoretical ones [21-24]. SADOWSKI developed a thermodynamical model for prediction of wear in tribological system. This approach is also purely theoretical [18].

4. New trends in predicting of tool wear

4.1 Basic characteristics of the new approach for tool wear prediction

A combination of two methods, i.e., the finite element method (FEM) and the neural network by conditional average estimator (CAE NN), to predict non-linear wear on the tool arbor radius has been applied recently [35-36]. Such an approach enables the whole observed tool arbor radius to be treated as an entity and also allows an increased number of influential parameters to be taken into account. Note that establishing a large database of tool wear is a time consuming process. This, however, is far beyond the scope of the present paper and is not a prerequisite for using the proposed method. The main contribution of the paper is, therefore, the application of FEM and CAE NN to modelling tool wear.

For the purpose of a model prediction for practical use, it is not necessary to know the entire physical background of the wear; it is enough to follow, with regard to a selected tool-workpiece pair, the time sequence of parameters of mechanical and thermal character on the tool surface at synchronous recording the wear-geometry changes in its contour. These facts have inspired us to use the CAE neural network method for wear prediction, since it is capable of taking into account, and processing a complex space dependence of influential parameters of any physical phenomena. The database for prediction was established by the FEM analysis of tribomechanical and tribothermical load states on the tool surface layer during the test simulation of hot die forging and a simultaneous measurement of wear on the replica. From the long-term point of view, the analysis of similar cases extends the database and increases the reliability of prediction.

Large amount of data on tool wear and influential parameters enables us to take into account (4) the majority of essential parameters and (5) their inter-dependence. The CAE NN method is one of the possible approaches for doing this. The basis of the new approach (CAE and FEM) for wear prediction has already been presented in [34-36]. A detailed description of CAE NN can be found in[38-41]; hence in this paper only the basic principles are given. Note, however, that CAE NN is not a typical neural network.

In a general approach of CAE NN, each of the output variables corresponding to the vector under consideration $\hat{\mathbf{x}}$ (i.e., a vector with known input variables p_i and output variables $\hat{\mathbf{r}}_k$ to be predicted)

$$\hat{\mathbf{x}} = (p_1,...,p_i,...,p_L,\hat{r}_1,...,\hat{r}_k,...)^T \tag{4}$$

can be estimated by the formula

$$\hat{r}_k = \sum_{n=1}^{N} C_n \cdot r_{nk} \tag{5}$$

where:

$$C_n = \frac{c_n}{\sum_{j=1}^{N} c_j} \tag{6}$$

and

$$c_n = \exp\left[\frac{-\sum_{i=1}^{L}(p_i - p_{ni})^2}{2w^2}\right] \tag{7}$$

Here $\hat{\mathbf{r}}_k$ is the k-th output variable to be predicted (corresponding to the vector $\hat{\mathbf{x}}$; in our case tool wear), r_{nk} is the same output variable corresponding to the n-th vector in the database, p_{ni} is the i-th input variable of (parameters that influence tool wear), p_i is the i-th input variable of $\hat{\mathbf{x}}$, N is the number of model vectors in the database, w is the smoothness parameter, and L is the number of input variables.

In general, the relevant processes regarding tool wear can be investigated at several levels, i.e., the nano-, micro- and macro-level, as well as at the external (visible) level. The higher the level, the more difficult it seems to be to obtain the data concerning the relevant processes during the wear process. These problems still occur at the micro level, whereas FEM analysis, the precision of which has advanced greatly in the recent years, can bring more reliable data at the macro level. However, the temperature calculated on the surface layer of the tool, is still an exception. This is the reason why only the measured temperature of the workpiece is taken into consideration. The database is thus formed by following the essential parameters (mechanical and thermal loads) at the macro level (the FEM analysis), which indirectly affect the processes at other levels. For each point determined on the observed tool curvature (arbor radius, Figure 3) the temporal course of the influential parameters must be calculated. This includes normal and tangential pressures, sliding velocity, sliding length, the temperature on the tool surface, their relative values along the contour in the direction of sliding, etc. The temporal course of sliding lengths on the mentioned arbor radius computed in this way (FEM) is shown on Figure 4. It can be clearly seen that sliding lengths increase in the first part of the arbor radius and rapidly decrease in the second part, which means that there is a low value of relative sliding between the tool and the deformed material. The FEM analysis of contact pressures also indicates that in the first part relatively high pressures occur, whereas they decrease in the second

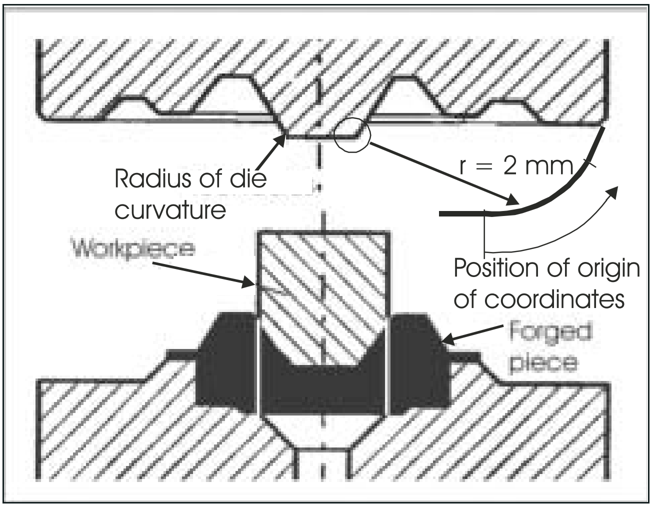

Figure 3. Applied tool with arbor radius and origin of coordinate system defined [5-6].

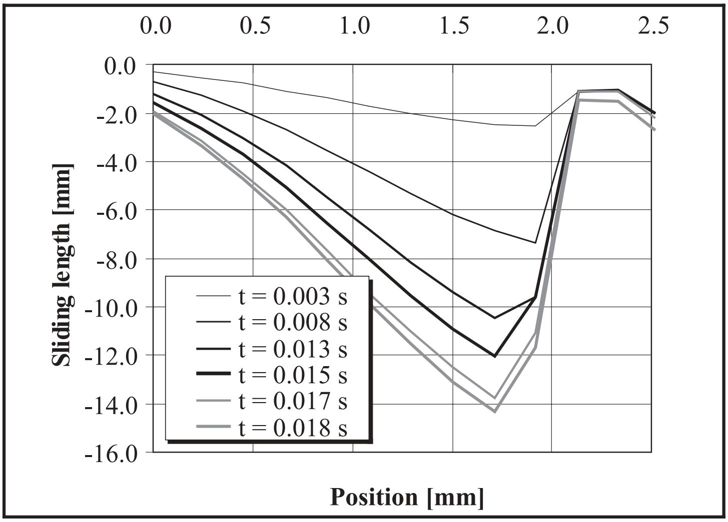

Figure 4. Temporal course of sliding lengths on the arbor radius.

Table 1. Variables - components of model vectors for description of wear.

$\sigma_{N(t,i)}$	Normal pressure at time *t* and on point *i*
$L_{(t.i)}$	Sliding length at time *t* and on point *i*
$v_{(t,i)}$	Relative velocity of slip at time t and on point *i*
N_s	Number of strokes
$W_{(Ns,i)}$	Wear at *Ns* on point *i*
$ó_{Nmax}/\sigma_{N(i)}$	Ratio of max. pressure on the whole die curvature to max. pressure on point *i*
$l_{max}/l_{max(i)}$	Ratio of max. sliding length on the whole die curvature to max. sliding length on point *i*
$v_{max}/v_{max(i)}$	Ratio of max. sliding velocity on the whole die curvature to max. sliding velocity on point *i*
$\Sigma\sigma_{N(t,i)}\Delta t$	Sum of products of normal pressure and time
υ	Temperature of forgings
i	Position of point on the curvature
t	Time
σ_s	Tensile strength
υ_{au}	Austenitising temperature
υ_t	Tempering temperature

part. Both cases explain why, on the one hand, the removal (wear) of material occurs in the first part of the arbor radius and, on the other hand, why deposition of material can be noticed on the second part (Figure 4). The database is furthermore formed by the physical properties of the tool materials (chemical composition, hardness, tensile strength, etc.), the expert knowledge, as well as wear data on the entire arbor radius at various number of strokes. In Table 1 all the applied influential parameters are given, except for parameters describing the chemical composition, which are given in Table 2.

Table 2. Allowed deviations (%) of chemical composition of tool steels used.

	C	Si	Mn	Cr	Mo	V	Ni	Co	Ti
W.Nr. 1.2344	0.37 0.43	0.90 1.20	0.30 0.50	4.80 5.50	1.20 1.50	0.90 1.10	- -	- -	- -
W.Nr. 1.2365	0.28 0.35	0.10 0.40	0.15 0.45	2.70 3.20	2.60 3.00	0.40 0.700	- -	- -	- -
W.Nr. 1.2714	0.50 0.60	0.10 0.40	0.65 0.95	1.00 1.20	0.45 0.55	0.07 0.12	1.50 1.80	- -	- -
W.Nr. 1.2799	0.01 0.05	- -	- -	- -	7.80 8.30	- -	11.80 12.20	7.85 8.25	0.45 0.55

The scattering of tool wear data can be caused by a variation of chemical composition (above all of the carbide-forming elements) of tools, though still within the allowed limits, by heat treatment of tool steels (a different temperature of austenitising and of tempering, etc.), by varying composition of the lubricant, and so on. Small variations in the chemical composition cannot simply be expressed in terms of other hardness data (tensile strength, etc.), but additionally by forming eight new vectors (parameters) for chemical composition. The number of parameters in such models can vary from 15 to 62, depending on the type of model.

4.2 Results of wear prediction by CAE NN

In the case of a small database a reasonable approach seems to be taking the wear data at a lower number of strokes. These data already indicate the direction of scattering of end wear data (above or below the average). This method of intermediate control of tool wear is regularly used in forges; usually, just the data on the point of maximum wear suffices. The accordance between the measured and CAE predicted wear values are estimated by the coefficient of determination (B):

$$B = 1 - \frac{\sum_{k=1}^{M} \left(\hat{r}_k - r_k\right)^2}{\sum_{k=1}^{M} \left(r_k - \bar{r}_k\right)^2} \tag{8}$$

$\bar{r}_k$ in equation 5 represents the mean value of r_k, and M is the number of model vectors tested.

4.3 Prediction of tool wear for other chemical compositions

In order to be able to predict tool wear by CAE NN, a minimal database had to be con-

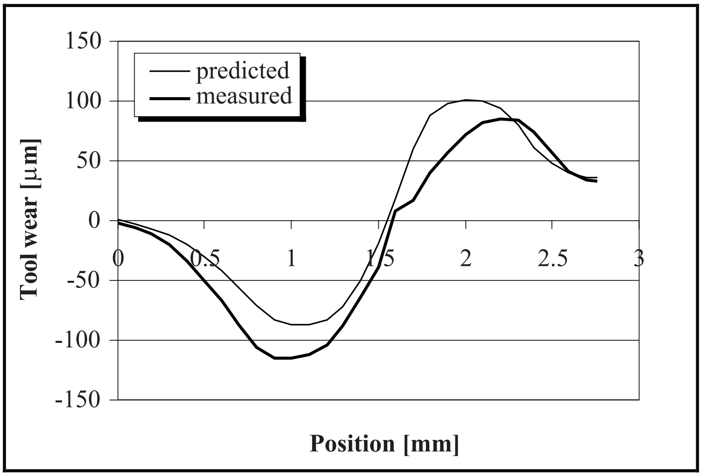

Figure 5. Comparison between measured and CAE predicted wear at 1000 strokes, W.Nr. 1.2799; tensile strength 1500 MPa, intermediate tool wear at 500 strokes is known, example 1.

structed. It was formed by means of FEM analysis of the forging process (temporal course of parameters), as well as by data characterizing the material properties (tensile strength, chemical composition, etc.). The database also includes the data on the tool wear of arbor radii at various number of strokes (100 and/or 200, 500 and 1000). The tools with tensile strength 1500 MPa were made of W.Nr. 1.2344, W.Nr. 1.2365 and W. Nr. 1.2714, having the same dimensions and austenitized at the same temperature (1100 °C). The workpieces (heated to 1100 °C) were made of C 45, their dimensions were Φ=30x40 mm, contact time 0.020 s, time of one cycle 13 s, the lubricant delta 31 (friction factor m=0.2), etc.[4-5, 9] The fourth tool (W.Nr. 1.2799) also had the same shape and dimensions (Figure 3), and knowing the intermediate data on tool wear (e.g., at 500 strokes), enabled us to predict (extrapolate) the tool wear of this fourth tool at a higher number of strokes, e.g., at 1000 strokes. The predicted CAE wear results for the fourth tool are shown in Figure 5 (Example 1).

It can be clearly seen that even a small database (wear data for only three tools) enables a relatively good estimate to be made of the

Table 3. Values of coefficients of determination *B* at smoothness parameter *w*=2.

	Example 1	Example 2	Example 3	Example 4
W.Nr.	1.2799	1.2365	1.2344	1.2714
Given data	0.862	0.941	0.945	0.994
Extrapolation	0.709	0.567	0.862	0.959

temporal course of wear on the entire arbor radius (*B*=0.709). In Table 3 the values of *B* for CAE predicted wear at 1000 strokes are given (Example 2-4) also for the other three tools (the same procedure as in Example 1). The *B* values for the given data set up (including the last measured wear data) can also be found in Table 3.

4.4 Prediction of the wear of a tool with different mechanical properties

By using different temperature for tempering the tool material, a different tensile strength can be achieved, which influences its wear resistance. Figure 6 shows the measured and CAE predicted values of wear obtained by interpolation from to the existing database and for the case of known wear data at 500 strokes (extrapolation). The database originally contains only wear data on the steel W.Nr. 1.2799, W.Nr. 1.2344, W.Nr. 1.2365 and W. Nr. 1.2714 with a tensile strength of 1500 Mpa. If data about the wear of tool steel material with tensile strengths of 1300 and 2000 MPa were added to the database, a CAE wear prediction at 1000 strokes for tool steel (1400 MPa) could be carried out (Example 5, interpolation). A coefficient of determination *B*=0.697 was obtained. If wear of a tool with a tensile strength of 1400 MPa at 1000 strokes was predicted by known wear data at 500 strokes, the value of *B* obtained was 0.649 (Example 6, extrapolation). It should be noted that the results for Example 5 were obtained using *w*=0.15 and for Example 6 using *w*=2. The different values applied for the smoothness parameter *w* were the consequence of the larger size of the databases and of the mathematical description of the model. In Example 5 the database was relatively extensive (approximately 500 model vectors), but in Example 6 only five model vectors were used.

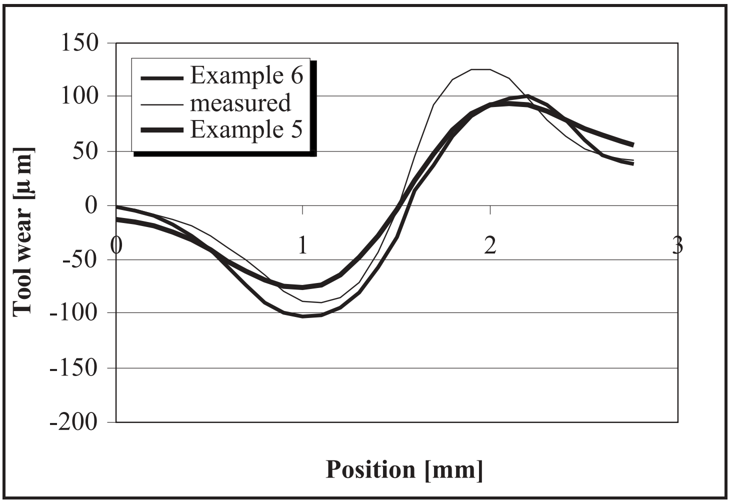

Figure 6. Comparison between measured and CAE predicted wear at 1000 strokes, W.Nr 1.2365, tensile strength 1400 MPa (Example 5, interpolation; Example 6, extrapolation, known wear at 500 strokes).

4.5 Wear prediction of a tool austenitized at a different temperature

The temperature of austenitising has great influence on the dissolution of carbides and consequently on the wear resistance of tool steels. The Figure 7 shows the measured and CAE predicted values at 1000 strokes of a tool austenitized at 1050 °C. Example 7 shows the CAE predicted wear obtained by interpolation (known wear data at 1100 °C and 1000 °C). Example 8 again shows the predicted value, considering the known wear data at 500 strokes (extrapolation). In Example 7 the value of *B* is 0.657, while in Example 8 the value of *B* is 0.924, indicating good agreement, as is also shown in Figure 7. In this case, there is also an agreement between the measured and predicted values.

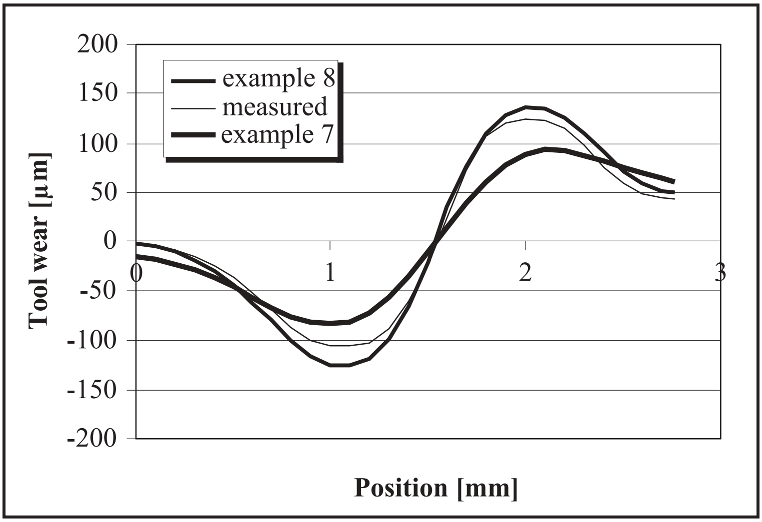

Figure 7. Comparison between measured and CAE predicted wear at 1000 strokes, W.Nr. 1.2365, temperature of austenitising (1050 °C); Example 7, interpolation; Example 8, extrapolation.

4.4 Wear prediction of a tool at a different forging temperature

If the temperature of the workpiece is changed, the mechanical and thermal loads are also changed (at lower temperature the contact pressures are increased and the temperature on the tool surface decreases, and vice versa). As known from the literature [4-5, 9, 37], lower thermal loads on the tool surface also mean lower wear values, since the temperature is the most influential wear parameter. Mechanical loads increase at lower workpiece temperatures.

From an existent database on the temporal course of the influential parameters and wear data on all the mentioned types of materials at a workpiece temperature of 1100 °C, the wear on W.Nr. 1.2365 at a workpiece temperature of 900 °C was predicted.

An FEM analysis was again carried out. It is worth mentioning that in this case there were no known wear data for any of the materials in the existing database at lower temperature. Again, the method of input of a single wear data at 500 strokes was applied. *B* obtained in this case was 0.789 (Figure 8, Example 9). By increasing the number of the wear data at lower temperature, interpolation in the problem space can be used. If the wear data are known at lower temperature (900 °C) for at least one of the above mentioned tool materials (W.Nr. 1.2714), the wear data of W.Nr. 1.2365 can be predicted much more reliably (Example 10, interpolation). The value *B* in this case is even higher than in the previous example where it amounts to *B* = 0.864, (*w*=0.075).

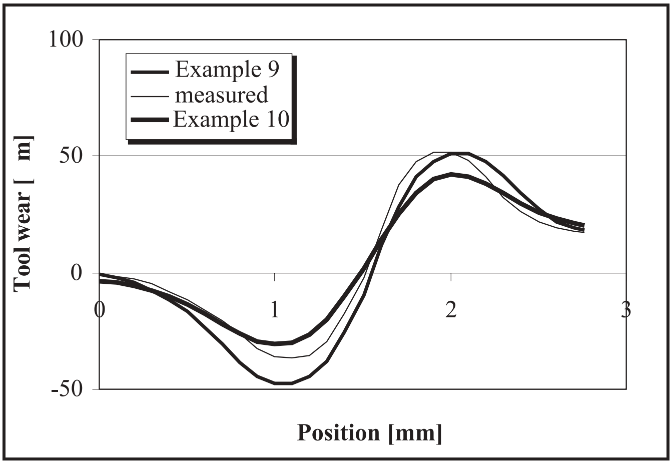

Figure 8. Comparison between measured and CAE predicted wear at 1000 strokes, W.Nr. 1.2365, temperature 900 °C, (Example 9, extrapolation; Example 10, interpolation).

A similar approach was used for predicting tool wear when using other lubricants; the results met our expectations.

The values for the coefficient of determination (*B*) in particular cases show that by increasing the size of the database the CAE predicted wear results improve, too. This can be observed for both models and also for both predicting modes (interpolation and extrapolation). Namely, increasing the amounts of data (model vectors) fills the vectors of problem space, which, due to the complexity of the wear process, is very extensive. Having a large enough database, the CAE NN approach will represent only an interpolation in the problem space. In this case it can be expected with a high degree of certainty that the description even of such a non-linear problem as wear is going to be very precise.

5. CONCLUSIONS

Accurrate predicting of tool wear in hot forging is a very important economical factor and today still represents a great challenge for technologists in the industry. Due to complexity of the phenomenon, it is not easy to describe mathematically, thus a new approach for a better solution of this problem is desired. An overview of the models for tool wear predicting and application of the recently introduced approach are given in the paper.

In this paper a procedure is described for systematically enlarging the database (a time consuming process) and how to utilize this limited data for predicting wear. The examples presented in this paper are adapted to the actual conditions in forges. Though most forges possess extensive databases, obtained in the many years of forging programs, this data could not be used to the best effect due to the use of rigid mathematical tools, i.e., prediction of tool wear on the basis of known wear data. This paper offers a new approach for better usage of such databases. Depending on the extensiveness of the database, the procedures of extrapolation and interpolation by CAE NN may be applied. Extrapolation was carried out on the basis of known individual wear data at a lower number of strokes and this enables reliable predictions of wear on the entire arbor radius at a higher number of strokes. In the case of a smaller database, the input of expert knowledge can be of great help. A sufficient amount of data also promises an even more reliable prediction of tool wear.

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Napovedovanje obrabe na orodjih za toplo kovanje - pregled in predlagan nov pristop

Povzetek: Proces obrabe na orodjih za toplo kovanje je zelo kompleksen fenomen. Kot kažejo dosedanje izkušnje process obrabe zelo težko opišemo matematično tako z fenomenološkimi kot tudi z empiričnimi modeli pri čemer pri slednjem uporabljamo klasična statistična orodja. Napovedovanje obrabe zaradi omenjene kompleksnosti problema tako še danes predstavlja velik izziv tako za raziskovalce v akademski sferi kot tudi za tehnologe v industriji. Boljša napoved obrabe bi znatno znižala proizvodne stroške (tudi do 30 % na enoto proizvoda), ki nastanejo kot posledica nepričakovanih izpadov orodja iz proizvodnje, in zato so želje po izboljšavah na tem področju z ekonomskega vidika zelo tehtne. V prispevku so podani dosedanji najpomembnejši modeli za napovedovanje obrabe orodij pri tolem kovanju ter aplikacija novega pristopa, ki je bil predlagan pred kratkim. S pomočjo umetne inteligence (CAE Neural Networks) lahko na osnovi znane obrabe majhnega števila orodij napovedujemo obrabo na obravnavanem orodju in sicer na osnovi metode extrapolacije (znan podatek o obrabi pri nižjem številu udarcev) ter na osnovi extrapolacije (znani podatki o obrabi orodij s podobnimi mehanskimi lastnostmi kot obravnavano). Ujemanja med izmerjenimi in napovedovanimi rezultati o obrabi je zelo visoko, ki pa se z večanjem baze podatkov še povečuje.