MULTIVARIATE MODELLING OF EFFECTIVENESS OF LUBRICATION OF Ti-6Al-4V TITANIUM ALLOY SHEET USING VEGETABLE OIL-BASED LUBRICANTS

ABSTRACT

The article presents the results of modelling the friction phenomenon using artificial neural networks and analysis of variance. The test material was composed of strip specimens made of 0.5-mm-thick alpha-beta Grade 5 (Ti-6Al-4V) titanium alloy sheet. A special tribotester was used in the tests to simulate the friction conditions between the punch and the sheet metal in the sheet metal forming process. A test called the strip drawing test has been conducted in conditions in which the sheet surface is lubricated with six environmentally friendly oils (palm, coconut, olive, sunflower, soybean and linseed). Based on the results of the strip drawing test, a regression model and an artificial neural network model were built to determine the complex interactions between the process parameters and the friction coefficient. A multilayer perceptron with one hidden layer and eight neurons in this layer showed the best fit to the training data. The network training was conducted using three algorithms, i.e. Levenberg-Marquardt, back propagation and quasi-Newton. Taking into consideration both the coefficient of determination $R^2$ (0.962) and S.D. ratio (0.272), the best regression characteristics were presented by the network trained using the Levenberg-Marquardt algorithm. From the response surfaces of the quadratic regression model it was found that an increase in the density of lubricant at a specific pressure causes a reduction in the coefficient of friction. Low density and high kinematic viscosity of the oil leads to a high coefficient of friction.

Keywords: coefficient of friction; sheet metal; sheet metal forming; Ti-6Al-4V; titanium alloy

INTRODUCTION

The friction occurring during plastic working is a very complicated phenomenon because the real contact surface is not equal to the nominal [1]. The real contact area consists of many micro-areas of contact, the total area of which increases with increasing pressure [2]. Contact surfaces are covered with layers of oxides and so-called adsorption layers with a thickness of approx. $10^{-7}$–$10^{-6}$ mm that consist of atoms or molecules of substances existing in the earth's atmosphere held on material surfaces by the interaction of atomic forces [3, 4]. During the sheet metal forming (SMF) process, the properties of the surfaces of the tool and the workpiece in contact with each other may change. The temperature formed in the micro-areas of the contact
may lead to plasticisation of the roughness asperities and oxidation of the material [5, 6]. Tool wear and workpiece layer abrasion processes take place, generally with different intensity [7, 8]. In this way, wear products can disturb friction conditions and lower the surface finish of products. In the case of the forming of titanium and its alloys, the minimisation of friction is crucial because these sheets exhibit a great susceptibility to galling [9, 10].

The basic parameter that describes the phenomenon of friction in sheets subjected to plastic working is the coefficient of friction (COF). The COF should be treated as a certain proportionality factor between the tangential and normal stress on the area of contact surface in a specific forming process. Its value may vary widely depending on the type of lubricant, properties of the friction surfaces, sliding speed, lubrication method, unit pressure and processing temperature.

The basic way to ensure the good quality of the surface of tools is to apply coatings with appropriate functional properties. The effectiveness and durability of the coating depend on the method of its preparation. The adhesion of the lubricating coating, surface roughness and hardness of the substrate define the preliminary conditions in the tribological evaluation of the cooperating friction pair. The surfaces of the SMF tools are also subjected to surface treatment, such as polishing, grinding or texturing. Laser or photochemical texturing enables the control of the number of lubricant pockets constituting reservoirs of lubricant. By texturing the surface, the range of loads and sliding speeds for which hydrodynamic lubrication is extended. Due to the presence of different conditions with regard to the pressure forces in the individual areas of the drawpiece, a series of tribological tests were developed. Two main groups of tribological tests were developed. The tests simulating tribological conditions model the geometrical interactions of the friction pair. The process simulation tests are designed to manipulate plastic-forming operations while maintaining process kinematics. There are many friction tests simulating real contact conditions in SMF: strip drawing test, draw-bead test, strip-tension test, bending under tension and strip-reduction testing.

One of the most effective ways of reducing friction in SMF is to lubricate the sheet surface. In SMF various types of lubricants are used, which to a greater or lesser extent separate the surfaces of the tool and the shaped material from each other. The type of lubricant also has a decisive influence on the type of friction that occurs, i.e. boundary and mixed. The change of the COF value depends on the type of lubricant and the ratio of film thickness to roughness height and is expressed by Stribeck's curve [11]. As the industrial community moves towards green manufacturing processes, there is an increased demand for bio-degradable lubricants [12]. Apart from conventional synthetic lubricants, lubricants based on vegetable oils are more and more frequently used in SMF practice [13]. Due to high unit pressures and large friction displacements of materials, it is not always possible to maintain a continuous layer of lubricant, which results in the occurrence of various friction mechanisms in individual areas of the drawpiece.

The above-mentioned factors influencing the friction phenomenon show a synergistic effect and therefore it is very difficult to determine their influence on COF without statistical analysis. Multivariate methods are used to evaluate and collect the statistical data to clarify and explain relationships between different variables that are associated with this data [14]. Ikpambese and Lawrence [15] applied multiple linear regression and an artificial neural network (ANN) to predict the friction of brake pads. Both methods were found suitable for the prediction of the COF. Sudheer et al. [16] performed analysis of variance (ANOVA) to obtain the contribution of control parameters on the coefficient of friction of epoxy/glass/potassium titanate whisker composites in pin-on-disk tests. The results of the polynomial models developed by ANOVA agree well with the experimental values. ANOVA reveals the physically and statistically significant factors which influence the COF of AA6061/B₄C composites.
determined in a pin-on-disk type tribotester [17]. The tribological behaviour of fibre-reinforced epoxy composites predicted using ANN-single hidden layer and regression analysis has been studied by Egala et al. [18]. It was found that an ANN with multi-hidden layers predicts the tribological performance accurately and was then followed by the regression model. Yunus and Alsoufi [19] used ANOVA to evaluate the significance of each process parameter (sliding speed, applied pressure, sliding velocity) to minimise the COF of thermally sprayed industrial ceramic coatings.

In view of the above, it is evident that ANOVA and artificial neural networks are utilised to predict the friction of both metallic and composite sheets. Less work has been carried out on the study of the effect of the physico-chemical parameters of the lubricant on the value of the COF in SMF. Accordingly, this work is aimed at studying the performance of different synthetic and environmentally friendly lubricants using ANOVA and ANNs. The data set is comprised of the results of the strip drawing test (SDT) of alpha-beta Grade 5 (Ti-6Al-4V) titanium alloy sheet. The process parameters are lubricant type and nominal pressure.

**EXPERIMENTAL**

**Material**

Alpha-beta Grade 5 titanium alloy sheets with a thickness of 0.5 mm were used in the investigations. The chemical composition of the tested alloy is listed in Table 1. According to the ASTM B348 [20], some selected mechanical properties of Grade 5 titanium alloy are as follows: yield stress $R_{p0.2}$ = minimum 827 MPa, ultimate tensile stress $R_m$ = minimum 896 MPa, elongation $A = 10\%$.

Basic surface roughness parameters (Table 2) of the Grade 5 sheet surface are determined using Bruker Contour GT 3D optical measuring tool. Surface topography of the Grade 5 sheet surface is shown in Fig. 1.

| Table 1. Chemical composition of the Grade 5 titanium alloy (wt.%) [21] |
|---------------------------------|
| Al     | V      | C      | Fe     | O      | N      | H      | Ti     |
| 5.5-6.75 | 4.5-5.5 | <0.1   | <0.3   | <0.2   | <0.05  | <0.015 | bal.   |

| Table 2. Basic roughness parameters of Grade 5 titanium alloy sheet surface* |
|---------------------------------|
| Sa, $\mu$m | Sz, $\mu$m | St, $\mu$m | Sp, $\mu$m | Sv, $\mu$m |
| 0.23       | 2.03       | 2.24       | 1.14       | 1.10       |

* Sa - average height of the selected area,Sz - maximum height of the selected area,St - total height,Sp - maximum peak height and Sv - maximum valley depth.
Tribological test

COFs were determined using the strip drawing test as a friction simulator (Fig. 2). The frame of the friction simulator was mounted in the lower bracket of a Zwick/Roell Z100 uniaxial tensile testing machine. The specimens, in the form of strips with length $l = 200$ mm and width $w = 18$ mm, were mounted in an upper bracket of the testing machine. The pressure of the cylindrical countersamples with a radius of $R = 10$ mm was exerted on the specimen through a working spring and was achieved by a reduction of the height of the spring through a bolt. Based on the load-displacement linear characteristics of the spring, the values of the load have been determined and six levels of load between 50 and 200 N were considered. The average surface roughness of the set of rollers was $Ra = 0.32$ μm. Surface topography of the countersamples is shown in Fig. 3.

![Surface topography of the Grade 5 sheet surface](image)

Fig. 1. Surface topography of the Grade 5 sheet surface

![Schematic diagram of friction simulator](image)

Fig. 2. Schematic diagram of friction simulator: 1 – bottom grip of testing machine, 2 – base, 3 – upper grip of testing machine, 4 – specimen, 5 – spring, 6 – bolt, 7 – mandrel, 8 – fixing pin, 9 – teflon insert, 10 – working rollers
The value of the coefficient of friction was estimated according to the following equation

$$\mu = \frac{F_t}{2F_c}$$  \hspace{1cm} (1)

where $F_t$ is the tangential (friction force), $F_c$ is the normal (clamping) force.

The nominal contact pressure in the contact of the cylindrical countersample and strip sheet metal has been calculated according to formula [2]:

$$p = \frac{0.418^2 \cdot F_c \cdot E}{w \cdot R}$$  \hspace{1cm} (2)

where $E = 115$ GPa is the Young’s modulus of Grade 5 titanium alloy, $w$ is the specimen width and $R$ is the radius of the countersample.

The countersamples and strip specimens were cleaned with acetone. The friction test was carried out in lubricated conditions. Six vegetable oils, i.e. palm oil, coconut oil, olive oil, linseed oil, soybean oil, and sunflower oil, were selected according to the relevant literature [13, 22-25]. The basic physical properties of these oils are listed in Table 3. The sheet metals were lubricated using a teflon shaft. The lubricant was applied in an amount of 2 g/m².

| Oil type   | Density $\rho$, kg/m³ | Kinematic viscosity $\eta$, mm²/s |
|------------|------------------------|----------------------------------|
| olive      | 892                    | 4.52                             |
| linseed    | 890                    | 3.74                             |
| sunflower  | 878                    | 4.45                             |
| palm       | 875                    | 5.72                             |
| soybean    | 885                    | 4.05                             |
| coconut    | 805                    | 2.75                             |

ANOVA analysis

Quadratic multivariate ANOVA analysis was performed based on the results of the SDT. The nominal pressure, oil density, and kinematic viscosity parameters of the oil were included in the regression model (Table 4). The explained variable was the coefficient of friction.
Based on backward elimination regression analysis, explanatory variables A, B, C were introduced into the model with the assumed significance level of $\alpha = 0.05$. The backward elimination method, using the analysis of variance in regression, allows for the selection of statistically significant variables, i.e. those whose influence on the dependent variable being analysed is the strongest. At each step, the independent variable with the highest probability corresponding to Fisher's parameter $F$ is removed from the model, if the probability ($P$-value) is sufficiently high (in this research not less than 0.10). The significance of the regression coefficients obtained was assessed on the basis of the $F$-test.

**ANN modelling**

In the research included in this paper, the feedforward multilayer perceptron is applied. It consists of an input layer, a hidden layer, and an output layer. In each of these layers there is a specific number of neurons. The number of neurons in the input and output layers is determined by the number of explanatory and explained variables, respectively. There are no connections between neurons inside the layers. A set of data, both the input data and the corresponding output data, is called the training set. The load pressure and physical parameters of vegetable oil-based lubricants were used as the training set, i.e. kinematic viscosity and density. The output parameter was the COF. The min-max function was used to normalise the training data:

$$D = \frac{(D - \text{min})}{\text{max} - \text{min}} (N_{\text{max}} - N_{\text{min}}) + N_{\text{min}}$$

where $D$ - value of the variable subjected to normalisation, and $(\text{min}, \text{max})$ is the interval in which the original data are contained and $(N_{\text{min}} = -1, N_{\text{max}} = 1)$ is the new interval.

The results of the experimental tests have been assigned to the training set. In order to independently check the convergence of the training algorithm, 20% of the data included in the training set was assigned to the verification set.

The network training process was carried out using back propagation (BP), the Levenberg-Marquardt (LM) algorithm and the quasi-Newton (qN) algorithm.

The back propagation learning cycle consists of the following stages:
- determination of the response of the output layer neurons and hidden layers to a given input signal,
- determining the error made by neurons located in the output layer and sending it towards the input layer,
- adaptation of weights.

The back propagation algorithm defines the procedure of weight correction in a multilayer network using gradient optimisation methods. The correction of the net weight vector is based on the minimisation of the error measure function (objective function), which was defined as the sum of squared errors at the network outputs. If the weights of learned neurons are updated after each element is presented, then the objective function has the form:
\[
E = \frac{1}{2} \sum_{k=1}^{m} (z_k(t) - y_k(t))^2
\]  
(4)

where \( E \) is the loss for the output, \( z_k(t) \) is an output and \( y_k(t) \) is the target.

The weights were corrected after the presentation of the entire learning sequence. In order to minimise the mean square error, the steepest descent rule was used:

\[
\Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}}
\]  
(5)

where \( \Delta w_{kj} \) is the new weight, \( E \) is the loss for the output, \( \eta \) is the training coefficient and \( \frac{\partial w_{kj}}{} \) is the old weight.

The LM second-order optimisation algorithm is currently one of the most commonly used methods for training unidirectional neural networks. This is mainly due to its simple implementation, quick convergence, and not very high computational complexity. It is based on solving the nonlinear problem using the least squares method. The qN algorithm is an alternative to the LM algorithm. The idea behind the method is to approximate Hessian or its reciprocal using first derivatives.

The following parameters were adopted as network quality indicators: root mean square (RMS) error and determination coefficient \( R^2 \):

\[
RMS = \sqrt{\frac{1}{n} \sum_{i=1}^{n} |a_j - p_j|^2}
\]  
(6)

\[
R^2 = 1 - \left( \frac{\sum_{i=1}^{n} (a_j - p_j)^2}{\sum_{i=1}^{n} (p_j)^2} \right)
\]  
(7)

where \( p \) is the predicted value, \( a \) is the actual value and \( n \) is the number of vectors in training sets.

RESULTS AND DISCUSSION

Results of ANOVA

High levels of the factors are coded as +1, while low levels are coded as −1. Then the quadratic regression equation in terms of coded factors is as follows:

\[
\text{COF} = 0.2344 - 0.0158A + 0.0125B - 0.0179C - 0.0228AB + 0.0012AC - 0.0014BC + 0.0005A^2 + 0.0208B^2 - 0.0028C^2
\]  
(8)
The F-value of 26.85 (Table 5) implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise. The total coefficient of determination $R^2$ of the regression model is 0.9131 (Table 6). The predicted $R^2$ of 0.8303 is in reasonable agreement with the adjusted $R^2$ of 0.8791 because the difference is less than 0.2. An adequacy precision greater than 4 indicated an adequate regression model.

Table 5. Results of ANOVA for the response surface reduced quadratic model

| Source      | Sum of squares | Mean square | F-value | p-value | Meaning  |
|-------------|----------------|-------------|---------|---------|----------|
| Model       | 0.0070         | 0.0008      | 26.85   | < 0.0001 | significant |

Table 6. Fit statistics of the quadratic regression model

| Parameter                          | Value  |
|------------------------------------|--------|
| Std. Dev.                          | 0.0054 |
| Mean                               | 0.2257 |
| Coefficient of variation %         | 2.38   |
| $R^2$                              | 0.9131 |
| Adjusted $R^2$                     | 0.8791 |
| Predicted $R^2$                    | 0.8303 |
| Adequacy precision                 | 20.4776|

The relationship between the predicted and actual values of the COF lies along a straight line (Fig. 4a). The proportional distribution of the COF values along the regression line prove a good correlation of data across the entire range of variability of input parameters. The normal probability plot of residuals is also represented by a straight line (Fig. 4b). The analysis of the distribution of regression residuals is one of the most important steps in regression analysis. The residuals are a series of negative and positive differences between the observed dependent variable and the analytical observations obtained from the regression model. The proportional distribution of studentised residuals along the baseline (Fig. 5) confirms the normal distribution of the data. The normal distribution of the residuals is necessary for the performance of the $F$-test, depending on the assumption of the normal distribution.

Fig. 4. (a) predicted versus actual values of COF and (b) normal probability plot.
As the nominal pressure increases, the value of the COF decreases (Figs. 6a and 6c). In the SDT the tangential (friction) force does not change proportionally with the normal force. This phenomenon is also observed in a previous papers of the authors [2, 13]. Therefore, the COF value determined from Eq. (1) is not constant over a wide range of clamping force changes. According to the well-known classic Amontons-Coulomb friction law, the COF does not depend on the area of contact. In SMF, where the tool comes into contact with a relatively soft body (workpiece), the pressures may exceed the yield point of the sheet material many times over. Under these conditions, the value of the COF depends on the mechanical interactions between surface asperities of the bodies in contact.

An increase in the density of the lubricant at a specific pressure reduces the value of the COF (Fig. 6a). Denser oil provides a suitable lubricant pad that effectively separates the contacting surfaces. If oil is deposited in the closed valleys of the surface topography, favourable conditions are created for the formation of "oil pockets" [2, 26]. The highest values of COF were observed during lubrication with vegetable oil-based lubricants with low density and high kinematic viscosity. By contrast, the lowest values of COF are produced with oils with high density and medium kinematic viscosity (Fig. 6b). This requirement is met by olive oil. The relationship between the kinematic viscosity of oil and pressure takes a saddle shape (Fig. 6c). The optimal range of changes in the kinematic viscosity value to ensure effective lubrication over the entire range of applied pressures is between 3.41 and 4.07 mm²/s. The tests conducted on the dry friction of the test sheets in the same pressure range found values of the COF in the range 0.28-0.34 depending on the pressure applied.

Results of ANNs

Due to the lack of universal guidelines for the selection of the network architecture for modelling a specific problem, a number of experiments were carried out in the Statistica program to find the network structure producing the lowest value of network error and the highest value of determination coefficient. For this purpose, the automatic algorithm built into the Statistica program performs many experiments to select the network structure on the basis of the set of input data presented and the corresponding COF values. As a result of searching for the optimal network, the ANN with the architecture 3:3-8-1:1 (Fig. 7) with eight neurons in the hidden layer was selected.
Fig. 6. Surface responses for COFs: effect of (a) pressure and oil density, (b) kinematic viscosity of oil and oil density and (c) kinematic viscosity of oil and pressure on the value of the COF

Fig. 7. Architecture of a neural network 3:3-8-1:1
Graphs of changes in the network training errors are presented independently for the training set (blue line) and validation set (red line) in Fig. 8. To prevent overlearning, the training process was completed after observing no further decrease in error for the training set (Fig. 8a and 8c) or when the network training error value for the validation set was greater than for the training set (Fig. 8b). For all learning algorithms, the value of the training error for the validation set was lower than for the training set. This testifies well to the convergence of the learning process based on the training set.

During the learning process using the BP algorithm, large fluctuations in the error value were observed (Fig. 8a). This is typical for this algorithm because the error is minimised from the last layer to the input layer in the direction opposite to the information flow in the network. The trend of network error for the training set is very stable and only minimally decreases with an increasing number of epochs (blue line in Fig. 8a).

The best convergence is provided by the qN algorithm for which only about 160 epochs were sufficient to reach the minimum $RMS$ error for the training set (Fig. 8c) equal to 0.1441 (Table 7). The LM algorithm required more epochs to complete the learning process (Fig. 8b), but at the same time the $RMS$ error value for the training set is the smallest among all the algorithms ($RMS = 0.1378$).

![Graphs of changes in the network training errors](image)

**Fig. 8.** Variation of network training errors vs. number of epochs during network training with the BP (a), LM (b) and qN (c) algorithms.
Table 7. Values of RMS errors of the networks trained using different algorithms

| Source                  | Training algorithm |
|-------------------------|--------------------|
|                        | BP                | LM      | qN      |
| RMS error (training set)| 0.1920            | 0.1378  | 0.1441  |
| RMS error (validation set)| 0.1025         | 0.1376  | 0.1526  |

The network with the minimum RMS error for the training set is the network trained using the LM algorithm. This network also provided the highest coefficient of determination for the training set (Fig. 9b). However, it should be emphasised that the remaining networks had a similar $R^2$-value. The $R^2$-values for the networks trained with BP and qN algorithms were higher by 1.86% (Fig. 9a) and 0.4% (Fig. 9c), respectively. Apart from the coefficient of determination, an important parameter of ANN performance is the standard deviation ratio (S.D. ratio), which defines the quality of the network as the ratio of the standard deviation of the error of the explained variable (Error S.D.) to the standard deviation of the data (Data S.D.). A value of this parameter which is lower than 0.3 demonstrates a very good quality of ANN model [27]. The smallest value of this parameter is provided by the network learned with the Levenberg-Marquardt algorithm (Fig. 9b).

Fig. 9. Basic regression statistics of the ANNs investigated which were trained using the BP (a), LM (b) and qN (c) algorithms

CONCLUSIONS

The ANN experiments conducted confirmed that it was possible to use them for modelling the COF of Grade 5 titanium alloy sheets in lubricated conditions. The coefficients of determination of all the networks investigated were higher ($R^2 > 0.94$) than that of the regression model ($R^2 = 0.9131$). Taking into account both the coefficient of determination $R^2$ and S.D.
ratio, the best regression characteristics were presented by the network trained using the Levenberg-Marquardt algorithm. An increase in the density of lubricant at a specific pressure reduces the value of the COF. The highest values of COF were observed during lubrication with vegetable oil-based lubricants with low density and high kinematic viscosity. The change in the value of the COF for all the oils tested in the pressure range 75-151 MPa was in the range of approx. 0.19-0.26. This gives a positive premise for the use of vegetable oil-based lubricants in SMF, taking into account that the COF of the titanium sheets tested, determined under dry friction conditions, was 0.28-0.34 depending on the pressure applied.

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