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Original Research

The Use of Artificial Neural Networks to the Analysis of Lubricating Performance of Vegetable Oils for Plastic Working Applications

Marek Szewczyk [1,*], Marwan T. Mezher [2,3], Tanya Abdulsattar Jaber [3]

[1] Department of Integrated Design and Tribology Systems, Faculty of Mechanics and Technology, Rzeszów University of Technology, ul. Kwiatkowskiego 4, 37-450 Stalowa Wola, Poland
[2] Departamento de Deseño na Enxeñaría, Universidade de Vigo, 36310 Vigo, Spain; marwantahir90@gmail.com
[3] Institute of Applied Arts, Middle Technical University, Baghdad 10074, Iraq; tanya.galxy@mtu.edu.iq

* Correspondence: m.szewczyk@prz.edu.pl

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Abstract

Sheet metal forming is the basic method of processing of deep-drawing quality steel sheets used in the automotive industry. A properly planned technological process of forming should include guidelines for friction conditions, or rather the coefficient of friction. Determination of the coefficient of friction is carried out using various methods. In this article, the strip drawing test was used to analyse the friction of low-carbon DC04 steel sheets. The tests were carried out at different contact pressures and with the use of different vegetable-oil based biolubricants. The most common edible and non-edible oils were selected for the tests: sunflower, rape-seed, moringa and karanja. The analysis of the experimental results was carried out using multilayer artificial neural networks (ANNs). Different learning algorithms and different transfer functions were considered in ANNs. Based on the analysis of experimental data, it was noticed that the coefficient of friction decreased with increasing contact pressure. The lowest values of the coefficient of friction, in the entire range of analysed pressures, were observed during lubrication with karanja oil. It was also found that Levenberg-Marquardt training algorithm with log-sigmoid transfer function provided the lowest values of performance errors and at the same time the highest value of the coefficient of determination $R^2 = 0.94719$.

Keywords: artificial neural networks, friction, lubrication, plastic working, steel sheets

1. Introduction

Sheet metal forming is the dominant technology in the automotive industry (Tisza et al., 2017). A car body consists of about 300–400 sheet metal parts (Tiefziehen, 2024). In order to optimally produce high-quality sheet metal parts for a given application, the forming process must be optimally designed. In the automotive industry, deep drawing is usually performed using rigid tools mounted on stamping presses (Tisza et al., 2017). The sheet metal thickness, the grade of the sheet metal material and the microstructure are the main variables influencing the forming process. The stamping machine influences the forming result through the stiffness of the press table, the precision of the punch guiding and the press-specific punch kinematics (Singer, 2019). The possibility of forming thin-walled components is primarily determined by mechanical properties, and more precisely, the tendency of the sheet metal to large deformations. The second important parameter responsible for the forming process is friction (Seshacharyulu et al., 2018). The description of the friction mechanisms occurring between the tool and the semi-finished product plays a noticeable role in the forming process. Friction limits the flow of the material and, under unfavorable conditions, causes deterioration of the surface quality of the drawpieces. The friction phenomenon, due to the continuous evolution of the sheet metal topography, changes during deep drawing and is therefore difficult to control and regulate (Folle et al., 2022).

Lubrication and tool texturing are currently considered to be the two basic economically viable methods of reducing friction. While texturing tool surfaces requires special tools, lubrication is a common way of changing friction conditions. Adamus et al. (2013) and Rao and Wei (2001) emphasize that an effective way of counteracting friction is to use anti-adhesive and anti-wear coatings that prevent direct contact of the workpiece with the tool. Currently, depending on the specificity of the formed materials, solid, liquid or gaseous lubricants are used (Losch, 2014). The lubricant should be appropriately selected for the processing temperature, the prevailing contact pressures and sliding speeds. In the last decade, attention has been paid to ensuring sustainable production in all aspects of production activities. This involves reducing or eliminating the use of lubricants and cooling agents produced from crude oil processing (Lovell et al., 2006). This restriction is intended, on the one hand, to reduce dependence on fossil fuels and, on the other hand, to increase the potential of oils to be easily recycled.

Research on the use of vegetable oil-based biolubricants has become increasingly popular in recent years (Salih & Salimon, 2021). These oils are biodegradable substances and, due to the presence of long chain fatty acids, they provide good lubrication in boundary lubrication conditions. Dyja and Adamus (2014) proposed the use of sunflower and rape-seed oils and olive oil for lubricating the surfaces of Grade 2 titanium sheets and EN AW-2024 aluminium alloy. The results of the research showed that vegetable oils can be a base for the production of biodegradable technological lubricants for the processes of stamping difficult-to-deform sheets. Więckowski and Dyja (2017) investigated the suitability of rape-seed oil, olive oil and sunflower oil for lubricating Grade 2 titanium sheets. It was found that the use of biolubricants allowed for a reduction in the coefficient of friction. Abdulquadir and Adeyemi (2008) investigated the lubricating performance of vegetable oil-based lubricants (red palm oil, palm kernel oil and shea butter oil) using ring compression test. The results revealed promising performance of the red palm oil followed by shea butter oil and palm kernel oil. Idegwu et al. (2013) tested the suitability of non-edible oils water-melon, mango, avocado and African cherry) in metal forming processes. Avocado and mango oils show greatest potential of replacing SAE 40 mineral oil in the equal channel angular extrusion of EN AW-6063 aluminium alloy workpiece. Keshtiban et al. (2018) investigated the lubrication performance of vegetable base oils (i.e., sesame oil, walnut oil, peanut oil and olive oil relative to mineral SAE 10W oil. The results revealed that walnut oil leads to 22% reduction of coefficient of friction and preserves surface quality of 26% more than SAE 10W oil.

Due to the complexity of the friction phenomenon associated with the interaction between tool-workpiece surfaces, the interpretation of research results is often based on the technologist's intuition and general observations. Therefore, in addition to experimental research, artificial intelligence-based techniques, i.e., artificial neural networks and machine learning techniques (Walker et al., 2023) are developed. These methods enable the identification of patterns and trends that can be used to optimise manufacturing processes (Zhao et al., 2023). Artificial neural networks (ANNs) are a universal tool designed to solve various classes of tasks, such as regression, classification and forecasting of time series (Argatov, 2019). Currently, many architectures of unidirectional, multilayer, cellular and recurrent neural networks are known. Neural networks gain the ability to forecast and analyse data based on the learning process, which can take place with or without a teacher (Schmidgall et al., 2024).

Artificial neural networks show many advantages, that is, the ability to generalise the acquired knowledge or the possibility of problem solving despite the lack of familiarity with the analytical dependence between the inputs and the outputs (Muñoz-Zavala et al., 2024). The tribological behaviours are characterized by time evolution and multi-parameter coupling (Yin et al., 2024). Recent achievements in the application of artificial intelligence methods for the prediction of friction coefficient values were presented by Rosenkranz et al. (2021) and Paturi et al. (2023). In the present paper, multi-layer artificial neural networks were applied to analyse the influence of friction process parameters on coefficient of friction. The results of strip drawing tests of DC04 steel sheets against 145Cr6 steel flat countersamples were used for neural network training. The variable parameters were lubrication conditions and contact pressure values. ANN models included multiple learning algorithms to select the model with the best predictive quality.

2. Materials and methods

2.1. Test material

The deep-drawing quality DC04 steel sheets with thickness of 0.83 mm were used as test material. This is a sheet metal produced in the rolling process with the following contents of major elements: Mn ≤ 0.4, C ≤ 0.08, S ≤ 0.03, P ≤ 0.03 and Fe (balance). The hardness of the sheet metal was determined by the Vickers method using a Qness 60Evo hardness tester (load 49.03 N, loading time 15 s). The values of basic mechanical parameters of the test sheets were determined in a uniaxial tensile test with five repetitions and the average hardness was determined based on six repetitions. The tensile test was conducted at ambient temperature (24°C) in adherence to the EN ISO 6892-1 standard (International Organization for Standardization, 2019). The speed of the preload force was 1 mm/min. The reference length for the samples was 50 mm. Selected mechanical properties of the sheets determined using a Zwick/Roell Z100 tensile testing machine are presented in Table 1. Material ratio curve and basic surface roughness parameters of sheet metal in as-received state (Fig. 1) were determined using a T8000RC (Hommel-Etamic) profilometer.

Table 1. Selected mechanical parameters of DC04 steel sheet.

Yield stress $R_{p0.2}$, MPa	Ultimate tensile stress R_m, MPa	Elongation A_{50}, %	Hardness HV5
184.2	303.9	42	97

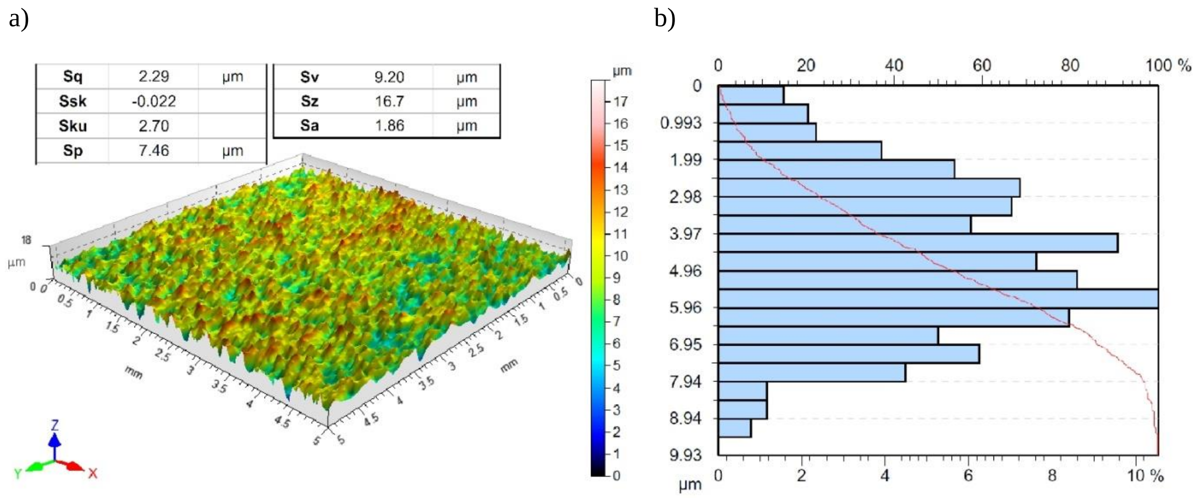

Fig. 1. a) surface topography and b) material ratio curve of DC04 steel sheet.

2.2. Samples

The length and width of the samples for the friction test were equal to 205 mm and 20 mm, respectively. Samples in as-received state and pre-strained samples with strains 7%, 14% and 21% were tested. The purpose of the pre-straining of the sheet strips was to change the surface topography and mechanical properties of the sheet as a result of the deformation reinforcement phenomenon. Pre-straining was performed on a Zwick/Roell tensile testing machine.

2.3. Friction tribotester and test conditions

A tribological tester was used to realise the strip drawing test of the sheet metal. The body of tester (Fig. 2) was fitted for mounting on a Zwick/Roell Z100 tensile testing machine. The test consists of pulling a strip sample clamped between two flat countersamples made of 145Cr6 steel (hardness 250 HV10). The hardness measurement of countersamples was carried out using a Vickers hardness tester from the Qness 60 EVO series. The load and loading time were, respectively, 98.07 N and 15 s. The basic surface roughness parameters of the countersamples were as follows: the kurtosis Sku = 3.76, the skewness Ssk = −0.544, the average roughness Sa = 0.636 µm. Flat samples with a width of 19 mm and a length of 130 mm were used in the tests.

The clamping force was recorded using a piezoelectric Kistler type 9345B force sensor, meanwhile, the pulling force was recorded by the measurement system of the tensile testing machine. The mean value of coefficient of friction was determined based on three replicates. Studies were realised at four contact pressures between 3 and 12 MPa. Such contact pressures correspond to the conditions of deep drawing of steel sheets (Severo et al., 2009; Vollertsen & Hu, 2006). The contact pressure analysed in this article refers to the nominal contact pressure resulting from the quotient of the clamping force and the nominal contact area of the countersamples with the sheet metal surface (285 mm^2).

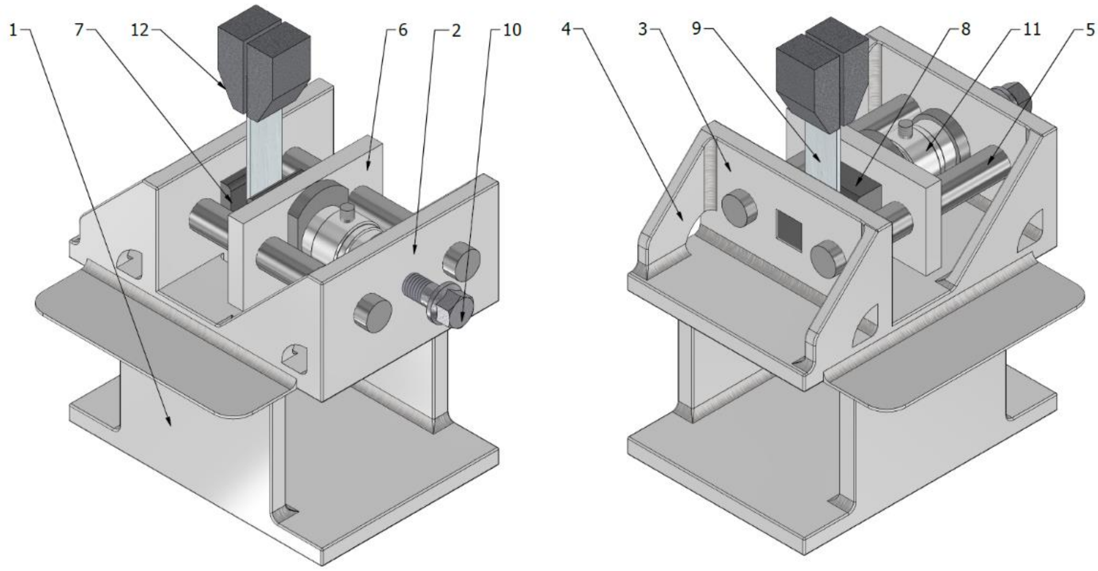

Fig. 2. Model of the tribotester: 1 – base; 2, 3 – support plates; 4 – rib; 5 – leading pin; 6 – bracket; 7, 8 – countersamples, 9 – sample, 10 – press bolt, 11 – Kistler type 9345B force sensor, 12 – gripper of tensile testing machine.

The literature analysis indicates the potential of very many species of edible and non-edible oils in reducing friction in metal forming processes. However, for the studies covered in the present work, the most commonly available two species of edible oils and two species of non-edible oils were selected. Sunflower oil (viscosity η = 58 mm^2/s, density ρ = 9200 kg/m^3) rape-seed oil (η = 51 mm^2/s, density ρ = 9140 kg/m^3) were selected from among edible oils. Karanja and moringa oils were characterized by viscosities of 75 mm^2/s and 73 mm^2/s, respectively. The density of karanja and moringa oils is 9360 kg/m^3 and 8970 kg/m^3, respectively.

During the friction test, the value of the clamping force F_C and the pulling force F_P of the sample were recorded. On this basis, the value of coefficient of friction was determined according to the relationship (Szewczyk, 2023):

$$\mu = \frac{F_P}{2F_C} \tag{1}$$

The average value of the coefficient of friction was determined for the stabilised range (Fig. 3).

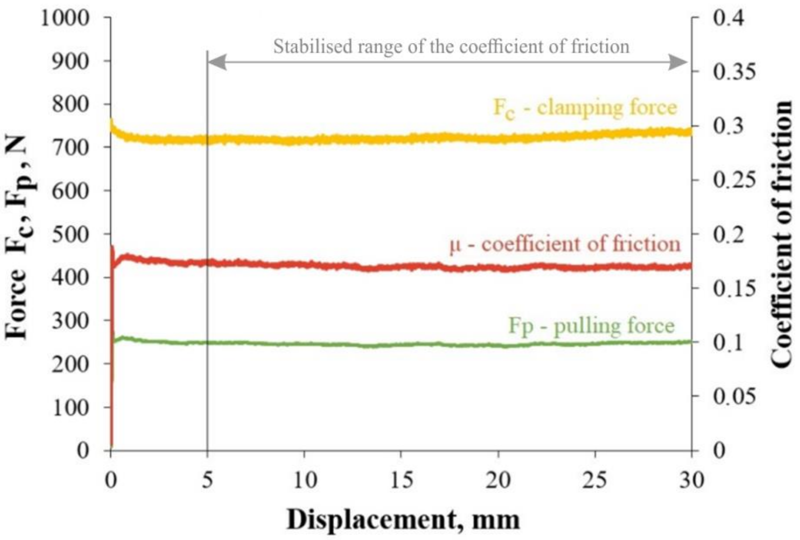

Fig. 3. Variation of the coefficient of the friction during strip drawing test (samples pre-strained at 14%, contact pressure 3 MPa, caranja oil).

The technical details of the friction test can be found in the previous work of the authors (Szewczyk, 2023), whereas this paper focuses on the analysis of the friction test results with the aid of artificial neural networks.

2.4. Artificial neural networks

2.4.1. Training and transfer functions

A multilayer neural network consists of at least three layers (input layer, hidden layer and output layer). Each of these layers contains neurons, but the number of neurons in the input layer is determined by the number of input parameters (Szewczyk & Szwajka, 2023). Similarly, the number of neurons in the output layer corresponds to the number of explained variables. The designer's task is to select the appropriate number of neurons in the hidden layer. Training a neural network is a critical stage in building an optimal ANN model adapted to the specifics of a given problem. During the training stage, the weights of the connections between neurons are modified (Mezher et al., 2024a). The input data were contact pressure, oil viscosity and the pre-strain value of samples. The explained parameter was the value of the coefficient of friction. Table 2 presents the training algorithms used in the research and their acronyms – these are the most commonly used algorithms for training multilayer ANNs. The task of the transfer function is to calculate the value of the output signal of neurons based on the value of the total excitation for each of the neurons in the ANN architecture. The activation function is used to calculate the output value of the neurons of the neural network. The hyperbolic tangent sigmoid function, log-sigmoid transfer function and pure linear function were used in the research (Table 3).

Table 2. Training functions used in the ANN models

Algorithm	Description
Trainlm	Levenberg-Marquardt
Trainscg	Scaled conjugate gradient
Traincgf	Conjugate gradient with Fletcher-Reeves updates
Traincgb	Conjugate gradient with Powell-Beale restarts
Traincgp	Conjugate gradient with Polak-Ribiere updates
Trainbfg	BFGS Quasi-Newton
Trainrp	Resilient backpropagation

Table 3. Transfer functions used in the ANN models

Function	Description
Tansig	Hyperbolic tangent sigmoid function
Logsig	Log-sigmoid transfer function
Purelin	Pure linear function

2.4.2. Data distribution

The training dataset consisted of input data sets and corresponded values of coefficient of friction at ANN output for 48 experiments. These data were used to train and validate the ANN. The datasets are divided into three groups: training set, test set and validation set. The choice of data assigned to individual sets can significantly affect the obtained network quality results (Mezher & Shakir, 2023). In this study, a split ratio of 80% was used for training data and 20% for test data. The experimental data were randomly assigned to individual sets. According to Mezher et al. (2024b, 2024c), 70% of the data was assigned to the training set, 15% was assigned to the test set and 15% was used to the validation set.

2.4.3. Performance metrics

Selecting appropriate performance metrics enables an objective assessment of the quality of ANNs. These metrics allow determining the quality of the model forecast in relation to the actual experimentally recorded data. The following metrics were utilized to validate the predictive ANN model: mean squared error (MSE), root mean squared error (RMSE), mean error (ME), mean absolute error (MAE), and the coefficient of determination (R^2) (Mezher et al., 2024b):

$$\mathrm{ME} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{y_v} - \mathrm{y_r}) \tag{2}$$

$$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{y_v} - \mathrm{y_r})^2 \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{y_v} - \mathrm{y_r})^2} \tag{4}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(|\mathrm{y_v} - \mathrm{y_r}|) \tag{5}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{\mathrm{i}-1}^{\mathrm{n}}(\mathrm{y_v} - \bar{\mathrm{y}})^2}{\sum_{\mathrm{i}-1}^{\mathrm{n}}(\mathrm{y_r} - \mathrm{y_r})^2} \tag{6}$$

where n is number of observation, y_r is the target value, y_v is the predicted value and $\bar{y}$ is the average target value.

For a very good model, the value of coefficient of determination is close to 1. Low values of other metrics mean minimal ANN error. RMSE is more sensitive to errors compared to MAE, ME and MSE. However, MAE is not sensitive to instabilities in the data.

3. Results and discussion

3.1. Coefficient of friction

Figure 4 shows the influence of sample pre-strain and oil type on the coefficient of friction. The general relationship is the decrease of the coefficient of friction with the increase of contact pressure. Increased pressure causes the generation of higher pressure in valleys of the surface topography. In these conditions, the oil enclosed in the so-called ‘oil pockets’ transfers part of the load. The remaining part of the load is transferred by the peaks of the surface topography which are in contact with the much harder tool surface. At some contact pressures and oils, it can be seen that with the increase of pre-strain of samples, the coefficient of friction decreases. Pre-straining of samples causes a change in the topography of the sample surface, but also its mechanical properties resulting from the work hardening phenomenon. The influence of only sample pre-straining on coefficient of friction is not unequivocal because this influence should be considered simultaneously with the value of contact pressure and oil properties. During the tests with the highest pressure value (12 MPa), karanja oil provided the lowest value of the coefficient of friction (Fig. 4d). Taking into account all analysed oils, the determined friction coefficients were in the range between 0.126 (contact pressure 12 MPa, moringa oil, sample pre-strain 21%) and 0.184 (contact pressure 3 MPa, sunflower oil, sample pre-strain 21%). The highest friction coefficients, above 0.18 for all sample pre-strains, were observed for lubrication with sunflower oil at a contact pressure of 3 MPa (Fig. 4a).

Interpretation of friction phenomenon based on experimental results is very difficult due to many parameters (amount of pre-strain, oil viscosity, contact pressure) and phenomena (flattening and ploughing of surface topography, work hardening phenomenon), which synergistically affect the coefficient of friction. Therefore, artificial neural networks were used to model the friction phenomenon.

3.2. Neural networks

To determine the proper artificial neural network model providing the best prediction of the coefficient of friction of DC04 steel sheets, different network structures with different training algorithms and transfer functions were tested. Table 4 presents the values of the obtained network quality metrics, which are explained in the ‘Performance metrics’ section.

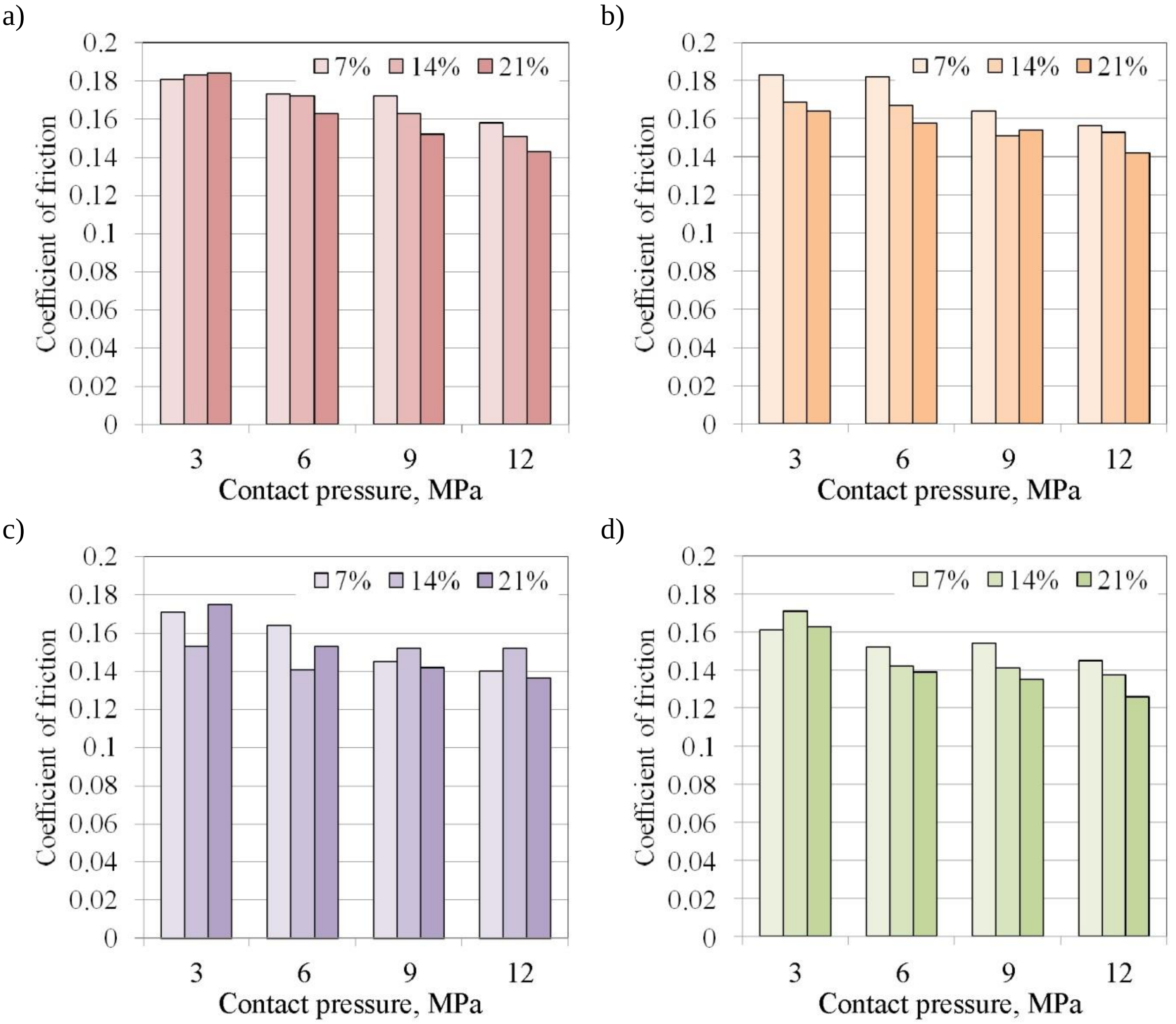

Fig. 4. Effect of contact pressure on the coefficient of friction at lubricated conditions with oils: a) sunflower, b) rape-seed, c) moringa and d) karanja.

Table 4. Validation metrics of ANN model for analysing the coefficient of friction.

Training function	Transfer function	MSE	RMSE	R^2	ME	MAE
Trainlm	Tansig	3.1501×10^{-5}	0.005612	0.92197	7.91906×10^{-5}	0.003614
	Logsig	2.1766×10^{-5}	0.004665	0.94719	5.87449×10^{-5}	0.003397
	Purelin	5.0784×10^{-5}	0.007126	0.87001	6.16322×10^{-5}	0.005435
Trainscg	Tansig	4.6074×10^{-5}	0.006787	0.92197	−0.000832351	0.004615
	Logsig	4.0272×10^{-5}	0.006346	0.90038	0.000853815	0.004992
	Purelin	5.3951×10^{-5}	0.007345	0.86495	−0.000418044	0.005390
Traincgf	Tansig	3.3915×10^{-5}	0.005823	0.91519	0.000214465	0.004149
	Logsig	3.8472×10^{-5}	0.006202	0.90462	-5.8701×10^{-6}	0.004625
	Purelin	5.4383×10^{-5}	0.007374	0.87078	0.001666045	0.005664
Traincgb	Tansig	3.0711×10^{-5}	0.005541	0.92446	−0.000640952	0.003776
	Logsig	4.6867×10^{-5}	0.006846	0.88195	−0.000486623	0.005061
	Purelin	5.2381×10^{-5}	0.007237	0.86689	−0.000254137	0.005528
Traincgp	Tansig	3.3944×10^{-5}	0.005826	0.91602	0.000632601	0.004477
	Logsig	3.4944×10^{-5}	0.005911	0.9044	0.000642702	0.004567
	Purelin	5.1371×10^{-5}	0.007167	0.86906	0.000603342	0.005601
Trainbfg	Tansig	3.80921×10^{-5}	0.006172	0.9071	−0.001079029	0.004677
	Logsig	4.8988×10^{-5}	0.006999	0.8766	0.000563815	0.005382
	Purelin	5.0991×10^{-5}	0.007141	0.87009	0.000586272	0.005585
Trainrp	Tansig	3.8075×10^{-5}	0.006171	0.90556	0.000129846	0.004820
	Logsig	4.6953×10^{-5}	0.006852	0.88092	0.000440025	0.005027
	Purelin	6.1396×10^{-5}	0.007835	0.86287	0.001353808	0.006295

The ANN 3-10-1 with Levenberg-Marquardt (Trainlm) training algorithm with log-sigmoid transfer function provided the lowest MSE (2.1766×10^{-5}), RMSE (0.004665), ME (5.87449×10^{-5}) and at the same time the highest coefficient of determination R^2-value (0.94719). The worst prediction defined by the coefficient of determination was obtained for the resilient backpropagation (Trainrp) training algorithm ($R^2 = 0.86287$) with the Purelin transfer function.

The smallest mean error value ($ME = -5.8701\times10^{-6}$) was characterized by the network trained using the conjugate gradient algorithm with Fletcher-Reeves updates (Traincgf) with the Logsig transfer function. However, the coefficient of determination for this ANN was not satisfactory ($R^2 = 0.90462$) compared to ANN trained with Trainlm algorithm.

For all the ANN training algorithms tested, which had neurons with pure linear function (Purelin), the mean squared errors (MSEs) values were the highest among all transfer functions. The same conclusion can be drawn for the root mean squared errors (RMSEs), the value of which was the highest for networks containing neurons with pure linear function. This means that the experimental data are characterized by the nonlinearity of the influence of friction process parameters on coefficient of friction. Therefore, it can be concluded that the Purelin transfer function is not suitable for use in ANNs predicting the value of the coefficient of friction based on the conducted experimental studies.

Fig. 5 shows regression curves for training, validation and test sets. Additionally, a comparison of experimental data and predicted data, taking into account the cumulative sets, is presented. The value of the coefficient of determination for the data included in the training set is $R^2 = 0.94701$. The experimental data are distributed proportionally along the regression line, which indicates the distribution of data according to the normal distribution also called Gaussian distribution. The slope of the regression line indicates that in the range of small coefficients of friction, the ANN model overestimates the data and vice versa in the range of large coefficients of friction, the model underestimates the value of this coefficient.

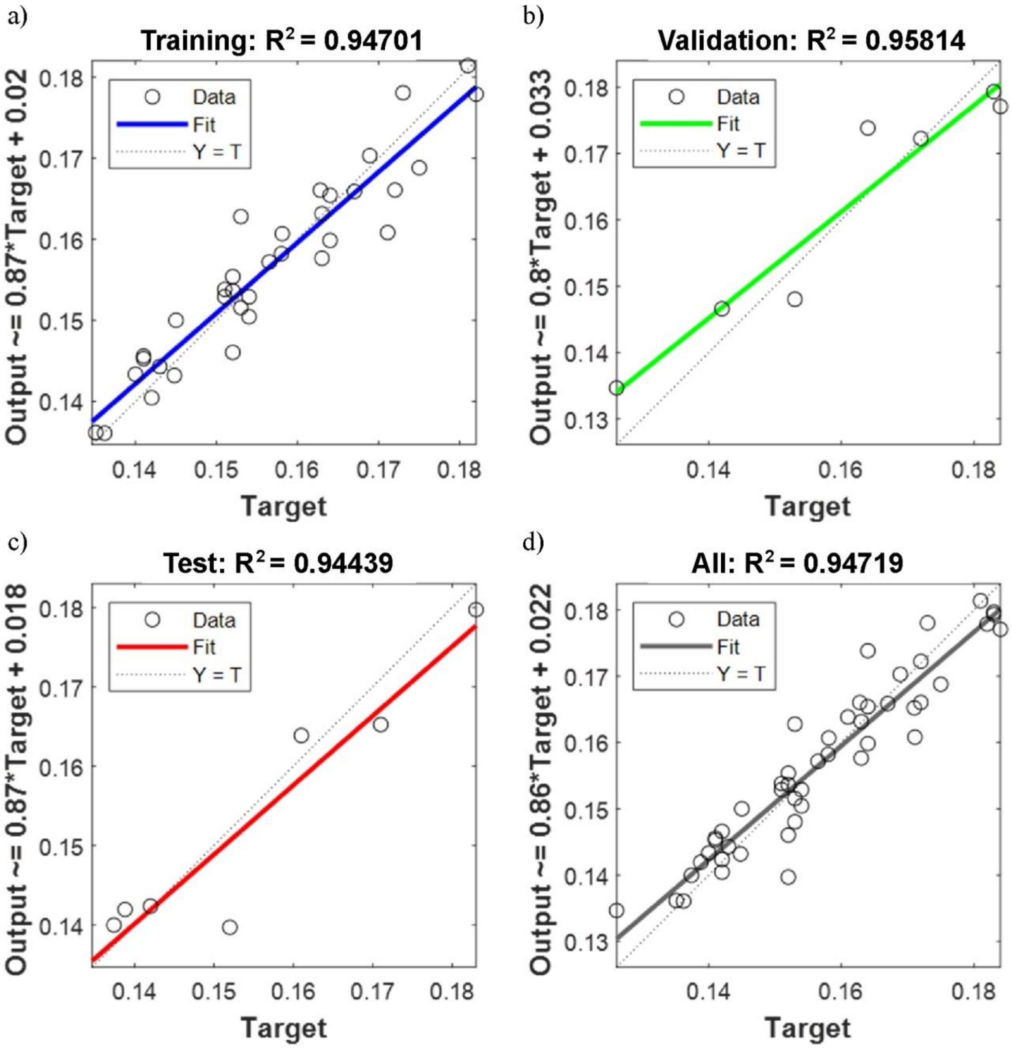

Fig. 5. Regression curves of the best ANN model using Trainlm with Logsig for a) training set, b) validation set, c) test set and d) all data.

However, the prediction is at a satisfactory level ($R^2 > 0.94$). Despite the fact that there was much less data in the validation and test sets (15% each), the prediction for these sets is at a similar level as for the training set. The values of the coefficients of determination for the validation and test sets are 0.95814 and 0.94439, respectively. Therefore, the quality of the cumulative prediction of the ANN model for all data ($R^2 = 0.94719$) is in very good agreement with the prediction for the training set ($R^2 = 0.94701$).

4. Conclusions

The use of highly biodegradable natural oils on the one hand limits the use of lubricants produced on the basis of fossil fuels, and on the other hand is consistent with the policy of sustainable development of the industry. This article presents the results of pilot studies on the use of bio-oils in sheet metal forming. Based on the results of experimental studies and modeling using artificial neural networks, the following conclusions can be drawn:

- an increase in contact pressure caused a tendency to reduce the value of the coefficient of friction,
- for contact pressures between 6 and 12 MPa and lubrication with sunflower and karanja oils, a clear tendency to reduce the coefficient of friction is visible with an increase in the sample pre-strain value,
- in the range of contact pressures between 6 and 12 MPa, karanja oil reduced the coefficient of friction most effectively,
- the ANN 3-10-1 with Levenberg-Marquardt (Trainlm) training algorithm with log-sigmoid transfer function provided the lowest MSE (2.1766×10^{-5}), RMSE (0.004665), ME (5.87449×10^{-5}) and at the same time the highest coefficient of determination R^2-value (0.94719),
- for all the ANN training algorithms tested, which had neurons with pure linear function (Purelin), the MSE and RMSE values were the highest among all transfer functions,
- the high cumulative coefficient of determination $R^2 = 0.94719$ indicates the good quality of the developed ANN model for predicting the friction coefficient value based on the friction process parameters (contact pressure, oil viscosity and the pre-strain value of samples).

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Zastosowanie Sztucznych Sieci Neuronowych do Analizy Wydajności Smarowania Olejów Roślinnych w Przeróbce Plastycznej Metali

Streszczenie

Kształtowanie blach stalowych głębokotłocznych jest podstawową metodą obróbki blach stosowanych w przemyśle motoryzacyjnym. Prawidłowo zaplanowany proces technologiczny formowania powinien uwzględniać wytyczne dotyczące warunków tarcia, a właściwie współczynnika tarcia. Wyznaczanie współczynnika tarcia przeprowadza się różnymi metodami. W tym artykule do analizy tarcia blach ze stali niskowęglowej DC04 wykorzystano test przeciągania pasa blachy. Testy przeprowadzono przy różnych naciskach kontaktowych i z wykorzystaniem różnych biosmarów na bazie olejów roślinnych. Do testów wybrano najpopularniejsze oleje jadalne i niejadalne: słonecznikowy, rzepakowy, moringa i karanja. Analizę wyników eksperymentów przeprowadzono z wykorzystaniem wielowarstwowych sztucznych sieci neuronowych. W sieciach neuronowych rozważano różne algorytmy uczenia sieci i różne funkcje przejścia. Na podstawie analizy danych eksperymentalnych zauważono, że współczynnik tarcia zmniejszał się wraz ze wzrostem nacisku kontaktowego. Najmniejsze wartości współczynnika tarcia, w całym zakresie analizowanych nacisków, zaobserwowano podczas smarowania olejem karanja. Stwierdzono również, że algorytm uczenia Levenberga-Marquardta z logarytmiczno-sigmoidalną funkcją przejścia zapewnił najmniejsze wartości błędów sieci neuronowej i jednocześnie największą wartość współczynnika determinacji R^2 = 0,94719.

Słowa kluczowe: sztuczne sieci neuronowe, tarcie, smarowanie, przeróbka plastyczna, blachy stalowe