

Tomasz Trzepieciński^{1*}, Marwan T. Mezher^{2,3}, Valmir Dias Luiz⁴, Salah Eddine Laouini^{5,6}, Hirpa G. Lemu⁷

¹ Department of Manufacturing Processes and Production Engineering, Faculty of Mechanical Engineering and Aeronautics, Rzeszów University of Technology, 35-959 Rzeszów, Poland

² Departamento de Diseño na Enxeñaría, Universidade de Vigo, 36310 Vigo, Spain

³ Institute of Applied Arts, Middle Technical University, Baghdad 10074, Iraq

⁴ Department of Metallurgy and Chemistry, Centro Federal de Educação Tecnológica de Minas Gerais, Timóteo 35180-008, Brazil

⁵ Department of Process Engineering and Petrochemical, Faculty of Technology, University of El Oued, El-Oued 39000, Algeria

⁶ Laboratory of Biotechnology Biomaterial and Condensed Matter, Faculty of Technology, University of El Oued, El-Oued 39000, Algeria

⁷ Department of Mechanical and Structural Engineering and Materials Science, University of Stavanger, N-4036 Stavanger, Norway

* tomtrz@prz.edu.pl

APPLICATION OF FEED-FORWARD NEURAL NETWORKS FOR MODELING FRICTION PHENOMENA WITH PRESENCE OF VEGETABLE OIL-BASED BIO-LUBRICANTS

ABSTRACT

Reducing the use of petroleum-based oil lubricants in metal forming processes is a major task of modern sustainable industry. In order to meet the expectations of industry, this article presents the friction results of DC04 sheets in a friction pair with 145Cr6 tool steel tested with corn, sunflower, rapeseed, cottonseed and soybean vegetable oils. The friction process variables were also contact pressure and surface roughness of countersamples. The assessment of the lubricant efficiency was based on the friction coefficient value. Complex phenomena in the contact zone make the interpretation of results difficult. Therefore, feed-forward neural networks were used to analyse the relationship between input parameters and coefficient of friction. Different training algorithms and transfer functions were tested to find the optimal architecture of the neural network. The friction coefficient value, depended on the friction conditions and considering all tested oils, ranged between 0.155 and 0.181. The 3-10-1 neural network trained using the Levenberg-Marquardt algorithm and consisted of neurons with a radial basis transfer function provided the lowest mean squared error ($MSE = 2.2233 \times 10^{-6}$) and the root mean squared error ($RMSE = 0.001491$). The prediction quality of this network defined by the coefficient of determination was $R^2 = 0.9697$.

Keywords: feed-forward neural networks; coefficient of friction; friction; steel; training algorithm; transfer function; tribology

INTRODUCTION

In the face of growing environmental awareness and emphasis on sustainable development, biodegradability of raw materials used in industry is becoming a necessity. Challenges related to reducing the negative impact on the natural environment force the metal processing industry to intensively search for and implement solutions that are friendly to the earth [1]. The transition to biodegradable raw materials is a step towards increasing the

sustainability of production, which brings benefits to both the environment and manufacturers [2, 3]. In addition to changing the way energy is obtained to drive machines, there is a trend towards using highly biodegradable processing lubricants [4]. This is one of the ways to eliminate substances derived from fossil fuels. It is also important that raw materials are obtained in a sustainable manner, which means protecting natural resources and minimising the negative impact on ecosystems [5]. The introduction of biodegradable materials in metal processing technologies will significantly contribute to reducing the amount of waste ending up in landfills [6]. About 85% of lubricants being used around the world are petroleum based oils [7].

Friction is a phenomenon accompanying all metal plastic working processes. This phenomenon depends mainly on the topography and the mechanical properties of the tribological pair materials, the processing temperature, protective coatings on the tools and the contact conditions [8-10]. In the sheet metal processing industry, forming processes are usually carried out under lubrication conditions [11]. The purpose of the lubricant is to reduce friction, reduce forming forces and ensure the appropriate quality of the drawpiece surfaces [12]. The lubricant should be non-toxic, environmentally friendly to humans, adapted to the forming temperature, and should be easily removed from the surface of the formed components [13]. Temperature affects the friction phenomena in contact interface, specifically galling and tool wear is accelerated with the increase of temperature [14]. Friction reduction is possible by using hard tool coatings (i.e., TiN, TiCN, TiAlN) deposited through chemical and physical vapor deposition processes [15].

The progress in the field of alternative lubricants is also observed as a result of the introduction of new criteria that must be taken into account when forming the components, such as: biodegradability, bioaccumulation, toxicity and ecotoxicity [16]. Conventional synthetic lubricants are still widely used in sheet metal forming processes, but research results on the use of edible and non-edible oils in forming processes appear in the literature. According to Syahrullail and Afifah [17], vegetable oils have a great potential to replace the petroleum-based oils and they are characterized by strong adhesion to the metal surface. High-oleic vegetable oils are a prospective alternative to conventional mineral oil-based lubricants [18]. Szewczyk and Sz wajka [19] tested lubrication performance of non-edible and edible oils in strip drawing test. It was found that karanja and moringa oils achieved the lowest values of the coefficient of friction in DC04/145Cr6 steel friction pair. Więckowski et al. [20] tested effectiveness of pure rapeseed oil and rapeseed oil with additive of boric acid during experimental strip drawing tests of X20Cr13/X165CrV12 friction pair. The results revealed that the rapeseed oil with the additive of boric acid was the most effective bio-based lubricant. Bucur et al. [21] considered palm oil and rapeseed oil as biodegradable lubricants in metal forming. It was found that lubrication effectiveness is sensitive to the surface topography of the tools. Trzepieciński et al. [22] used karanja, rapeseed and sunflower oils to lubricate pre-strained DC04 steel sheets in flat die strip drawing test. The karanja oil provided the lowest values of friction coefficient. Prakash and Kumar [23] examined the effectiveness of jatropha, karanja and cottonseed oils in the deep drawing evaluating surface finish and the drawability. Cottonseed bio-lubricant is found to be the most effective in reduction friction than the other two oils. Trzepieciński and Szpunar [24] compared lubrication performance of palm and rapeseed oils and conventional synthetic oils. They found that in Ti-6Al-4V/NC6 tribological system, engine oil (SAE10W-40) ensured the most effective reduction of the friction. Potential of using vegetable-based lubricants in the automotive sector was analysed by Singh et al. [25]. Kandeve et al. [26] analysed the rapeseed oil with the addition of different amounts of metal-containing additive (1-5 wt.%) in a steel-bronze tribological system. It was found that bio-based oil reduced the wear, working temperature and coefficient

of friction. Ahmad et al. in paper [27] discussed vegetable oil-based approaches for enhancing tribological characteristics in metal forming operations. The way to further increase the efficiency of biolubricants is to use optimal protective coatings [28], add extreme pressure and anti-wear additives to oils [29] and texturise tools to enhance lubrication [30]. To summarize the literature review, most studies have focused on the analysis of the lubrication performance of some lubricants, such as, sunflower oil [22], boric acid [31], palm pressed fiber [32], rapeseed oil [21], palm stearin and palm oil [33] and combination of canola oil and boric acid [34]. Due to the presence of polar groups and long fatty acid chains and in the structure of vegetable oils, they support the occurrence of boundary lubrication [35]. Compared with mineral oils, bio lubricants exhibiting higher flash point and higher viscosity index [36].

The novelty of this article is that corn, sunflower, rapeseed, cottonseed and soybean vegetable oils were used as alternative to petroleum-based oil lubricants for DC04/145Cr6 steel contacts in metal forming. The research was conducted using a strip drawing test used to analyse friction phenomenon in sheet metal forming processes. Due to the complexity of the friction phenomenon, feed-forward artificial neural networks with different transfer functions were used to analyse the effect of friction process parameters on the coefficient of friction. Furthermore, different training algorithms were considered.

MATERIALS AND METHODS

In the tests, one of the basic grades of deep-drawing steel sheets DC04 was used. The sheet thickness was 0.8 mm. Chemical composition of the DC04 steel sheet according to the EN 10130 [37] standard is shown in Table 1. The mechanical properties of the sheets meet the criteria of the EN 10130 [37] standard. Selected mechanical properties (Table 2) were determined in a uniaxial tensile test according to the [38] standard. The parameters (strength coefficient – 481 MPa and strain hardening exponent – 0.18) in the Hollomon power equation defining the character of material flow were also determined.

Table 1. Chemical composition of the DC04 steel sheet (wt.%)

C	Si	P	S	Al	Fe
max. 0.08	max. 0.10	max. 0.025	max. 0.02	0.015–0.07	balance

Table 2. Basic mechanical properties of the DC04 steel sheet

Yield stress, MPa	Ultimate tensile strength, MPa	Elongation, %
185	302	22

The tested sheet is characterized by the following roughness parameters measured using a CCI Lite profilometer: average roughness $S_a = 1.32 \mu\text{m}$, root mean square deviation $S_q = 1.54 \mu\text{m}$, maximum profile peak height $R_p = 10.48 \mu\text{m}$, maximum height of profile $S_z = 20.79 \mu\text{m}$, kurtosis $S_{ku} 2.11$ and the skewness $S_{sk} = -0.12$. SEM micrograph of the DC04 sheet metal in as-received state is presented in Fig. 1.

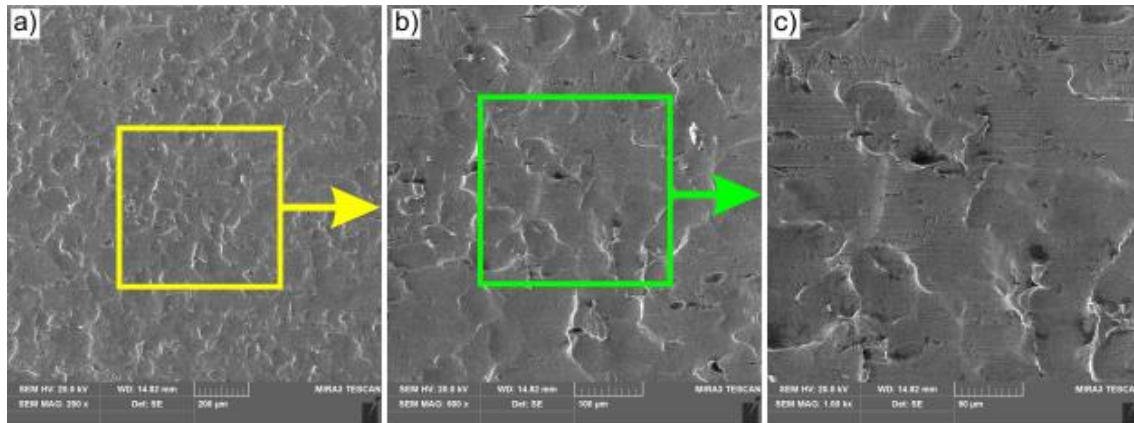


Fig. 1. a) SEM micrograph of the DC04 steel sheet in as-received state; subfigure b) shows the enlarged area marked in a) and subfigure c) shows the enlarged area marked in b)

EXPERIMENTAL PROCEDURE

The tests of determining the coefficient of friction of the sheets were carried out using the strip drawing test. This test is commonly used to study the friction conditions under the blankholder in the deep-drawing processes. The specially designed device consists of two main working elements – cylindrical countersamples (Fig. 2). During the test, the sample in the form of an 18 mm wide sheet metal strip was clamped between the countersamples with the specific normal force F_N (Fig. 2). One of the ends of the sheet metal strip was fixed in the grip of the testing machine. The tribotester body was attached to the second (lower) grip of the testing machine.

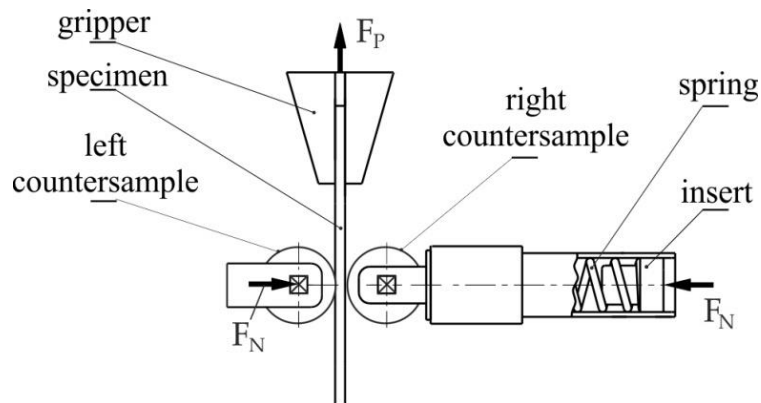


Fig. 2. Schematic diagram of the strip drawing test

The force of pressing the countersamples was applied by means of a spring with the following force characteristic $F_N = f(\text{deflection } x)$: $F_N = 10.154x + 0.66$ ($R^2 = 0.999$). This relationship was determined based on the uniaxial compression test of the spring on a testing machine. The pressing forces were applied by shortening the spring resulting from the above equation so as to obtain contact pressures between 1.8 and 5.1 MPa. The value of the contact pressure based on the normal force was determined according to the relationship [39]:

$$p = \frac{\pi}{4} \sqrt{\frac{F_N / wE}{2\pi R}} \quad (1)$$

where

$$E = \frac{2E_1E_2}{E_1(1 - \nu_2^2) + E_2(1 - \nu_1^2)} \quad (2)$$

where w is sample width, R is the radius of the countersample; E_1 (186.9 GPa) and ν_1 are the Young's moduli and Poisson's ratio of the sheet metal, respectively; E_2 (210 GPa) [40] and ν_2 are the Young's moduli and the Poisson's ratio of countersample materials, respectively.

The pulling force F_P was measured using a measuring system of a testing machine. For each contact pressure, the friction path was about 40 mm. The sliding speed was 5 mm/min. Friction tests were performed at room temperature (23°C). The coefficient of friction was determined based on three repetitions according to the relationship:

$$\mu = \frac{F_P}{2F_N} \quad (3)$$

Five vegetable oils were tested: corn, sunflower, rapeseed, cottonseed and soybean with kinematic viscosity of 46.3, 58, 51, 50.1 and 65.4 mm²/s, respectively. Lubrication strategy was adopted according to [41].

Countersamples were made of 145Cr6 cold-work tool steel. Due to the method of manufacturing cylindrical countersamples (turning and grinding), surface roughness was measured to obtain average roughness R_a of 0.32(±0.025) µm, 0.63(±0.031) µm and 1.25(±0.049) µm measured along the countersamples generatrix. Furthermore, average roughness S_a was measured using Alicona InfiniteFocus instrument, which was equal to 0.44(±0.035) µm, 0.56(±0.033) µm and 1.35(±0.045) µm for countersamples characterised by average roughness 0.32(±0.025) µm, 0.63(±0.031) µm and 1.25 (±0.049) µm, respectively. Detailed characteristics of countersamples' surface can be found in [42].

Artificial Neural Networks

A feed-forward artificial neural network (ANN) 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. 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 or hidden layers. Training a neural network involves presenting the network with data and modifying the weights of the neurons in the network so that the network error is reduced to a minimum. The following training functions were used to train ANNs: scaled conjugate gradient algorithm (Trainscg), Levenberg-Marquardt (Trainlm), conjugate gradient with Polak-Ribiere updates (Traincgp), conjugate gradient with Powell-Beale restarts (Traincgb) and conjugate gradient with Fletcher-Reeves updates (Traincgf).

The input parameters used were contact pressure, lubricant viscosity and the average surface roughness of countersamples. The output variable was the coefficient of friction. The entire data set contained 90 training sets. To increase the efficiency of the learning algorithm, the experimental data set should be randomly divided into three data sets: the main (training) set, the validation set and the test set. According to previous studies [43], 80% of the data was assigned to the training set, and 20% for testing. The training dataset was divided into validation and test subsets to ensure that the model learnt from and assessed all data samples. The training dataset, comprising 80% of the whole dataset, was then partitioned as follows: 70% for training, 15% for validation, and 15% for testing. The testing dataset, comprising 20%, was reserved for final evaluation and was excluded from the training datasets. The ANN model is initially fit on a training data set, which is a set of examples used to fit the weights of connections between neurons in ANN [44]. Finally, the test data set is a data set used to

provide an unbiased evaluation of a final model fit on the training data set [45]. The data in the test data set were not used in training. The fitted model is used to predict the responses for the observations in the validation data set. This set provides an unbiased evaluation of a model fit on the training data set while tuning the model's hyperparameters [45]. The validation set is also used to determine when to stop the training process to prevent overfitting [46].

The neuron activation function allows for determining the output value of the neuron based on the aggregated input value (total neuron excitation). Based on the excitation of all neurons in the neural network, the value of the output parameter (coefficient of friction) was determined. The following transfer functions were used in the analyses: pure linear function (Purelin), log-sigmoid transfer function (Logsig), hyperbolic tangent sigmoid function (Tansig), Softmax and the radial basis (Radbas) transfer function.

The quality of a neural network's forecasting is assessed based on many indicators and parameters. In our research, the following metrics were utilized to validate the neural model: the root mean squared error (RMSE), the coefficient of determination (R^2) and the mean squared error (MSE) [47]:

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

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_v - \bar{y})^2}{\sum_{i=1}^n (y_r - \bar{y})^2} \quad (5)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_v - y_r)^2 \quad (6)$$

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.

RESULTS AND DISCUSSION

Experiments

Fig. 3 shows the influence of contact pressure and type of lubricant on the friction coefficient value. In the case of corn oil, the influence of countersample roughness on the coefficient of friction is not clear (Fig. 3a). Although there is a clear tendency to reduce friction with increasing pressure, the friction coefficient values determined for individual contact pressures differ by about 0.05-0.07. Friction with sunflower oil of much higher viscosity than corn oil revealed a clear influence of countersample roughness on the coefficient of friction. The countersample with the highest analysed average roughness $R_a = 1.25 \mu\text{m}$ showed a clearly higher friction coefficient value (Fig. 3b). The influence of countersample roughness on the friction coefficient should be considered together with the oil viscosity because for rapeseed oil the highest friction coefficients were recorded for the countersample with average roughness $R_a = 0.63 \mu\text{m}$ (Fig. 3c).

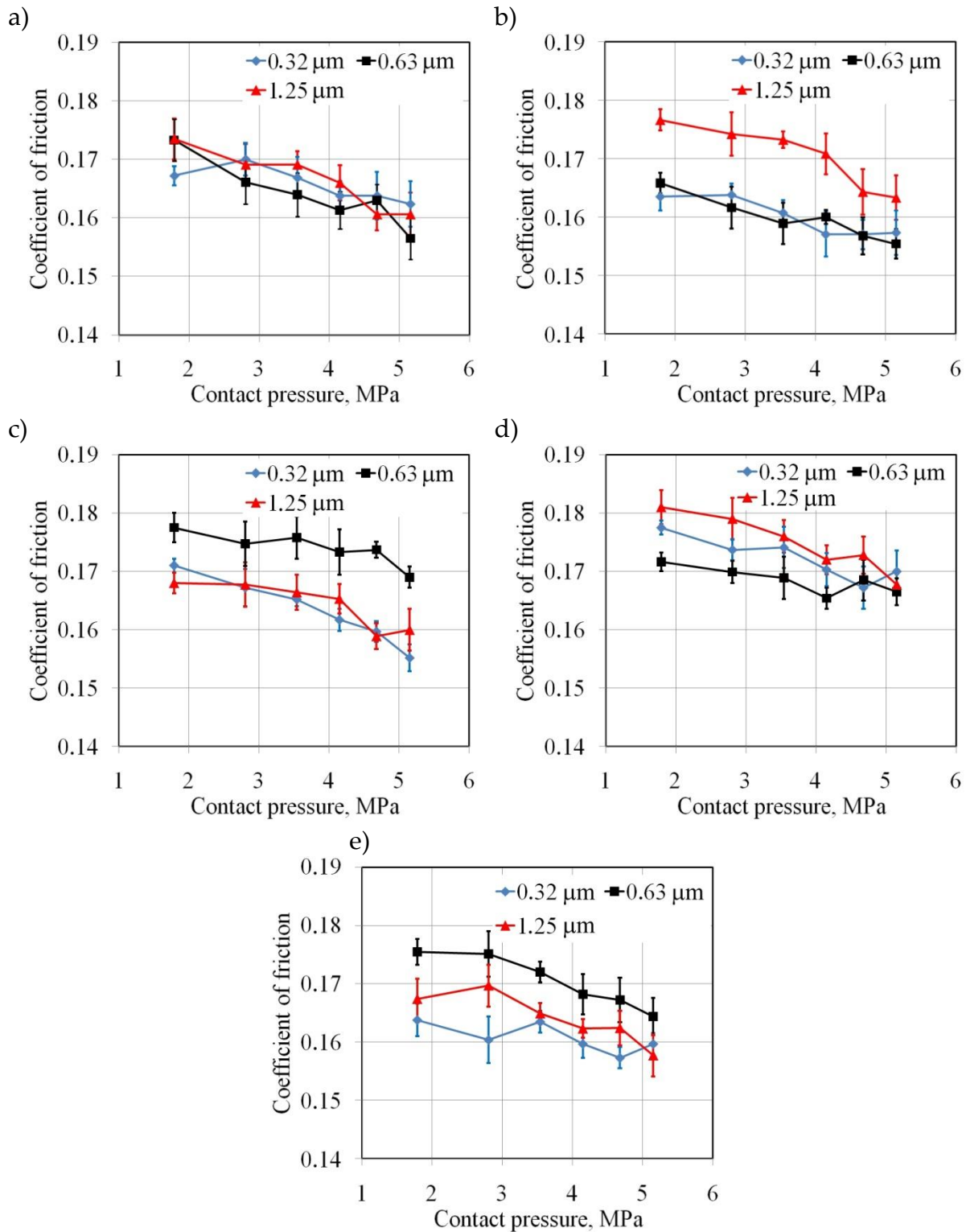


Fig. 3. Effect of contact pressure on the coefficient of friction for: a) corn, b) sunflower, c) rapeseed, d) cottonseed and e) soybean oil

The friction coefficient values for this roughness were higher by about 0.07-0.12 in relation to the other two countersamples' roughnesses. The friction coefficient values for cottonseed oil varied in the range of 0.165-0.181, but higher friction coefficients were recorded for lower contact pressures (Fig. 3d). Friction with the oil of the highest analysed viscosity showed that the highest friction coefficient occurred for the countersamples with

average surface roughness $R_a = 0.63 \mu\text{m}$ (Fig. 3e). The influence of the countersample roughness should be considered together with the contact pressure and oil viscosity. At low countersamples roughness, there is a relatively large real contact area. However, at a high surface asperities, mechanical interaction of the asperity summits and deep grooves in the sheet metal surface dominate. High contact pressure with low surface roughness of the countersample favours the phenomenon of flattening of asperities and the formation of closed valleys, so called closed lubricant pockets (Figs. 4, 5).

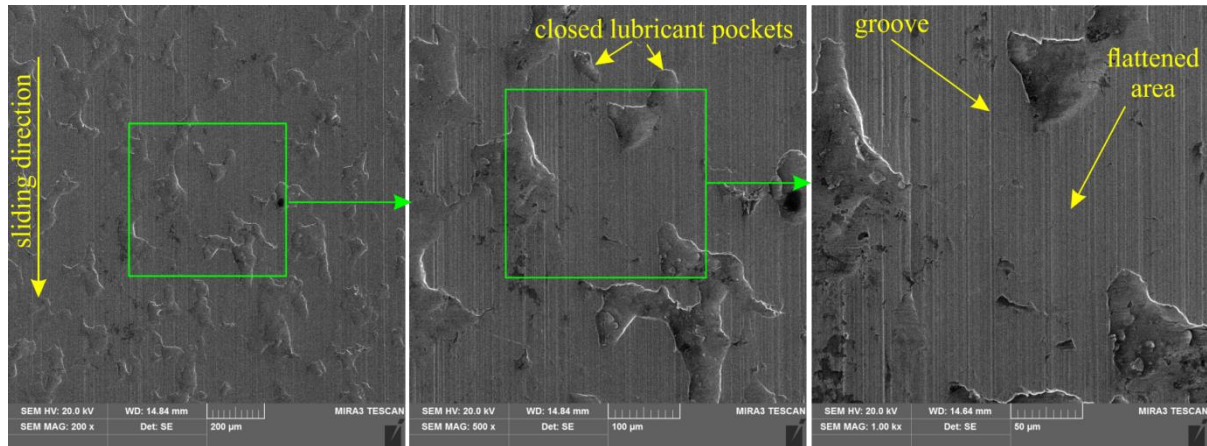


Fig. 4. SEM micrographs of DC94 steel sheet after friction test under the following conditions: lubricant – sunflower oil, contact pressure – 4.1 MPa, R_a of countersamples – $0.32 \mu\text{m}$

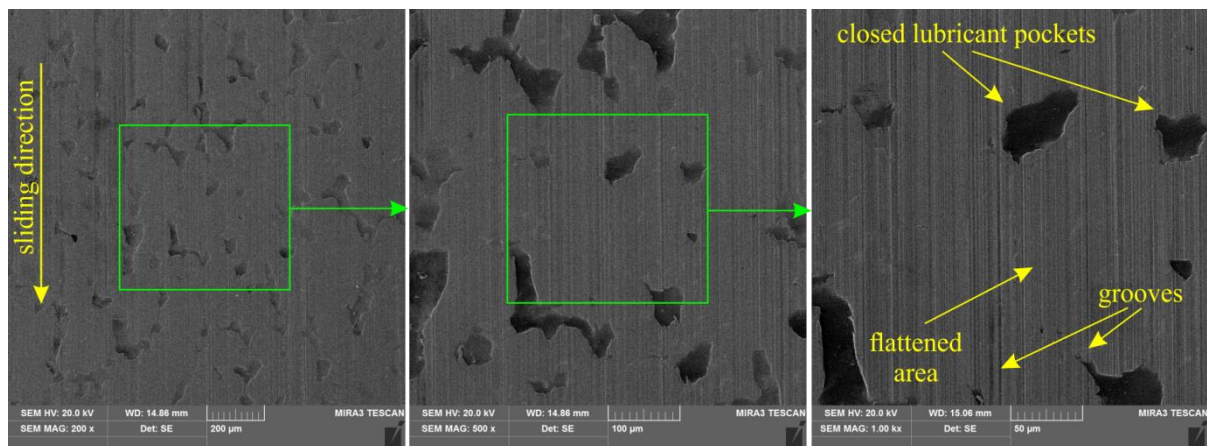


Fig. 5. SEM micrographs of DC04 steel sheet after friction test under the following conditions: lubricant – soybean oil, contact pressure – 5.1 MPa, R_a of countersamples – $0.63 \mu\text{m}$

The formation of such pockets is beneficial because the lubricant enclosed in such pockets transfers part of the load, limiting the mechanical contact of the rubbing surfaces. The wear mechanism that is abrasive and fatigue-induced delamination leading to pocket formation. Generally, the phenomenon of flattening of asperities presented in Figs. 4 and 5 occurred during friction with the participation of all oils and all contact pressures. Of course, the greater the contact pressure, the more intense the phenomenon was. Quantitative analysis of tribological phenomena occurring during friction of a soft sheet metal and a hard tool is very difficult without the use of analytical tools such as artificial neural networks.

The primary goal of the authors was to carry out tribological examination of the sheets in the conditions of the real forming process/ therefore, the strip sheets were tested in the as-

received state (Fig. 1). The surface of as-received sheets has not been polished, so it also affects the wear mechanism, and probably all non-uniformities act as a third body in abrasive wear.

Artificial Neural Networks

Table 3 shows the values of the obtained network quality metrics. The 3-10-1 neural network trained using the Levenberg-Marquardt algorithm (Trainlm) and with a radial basis (Radbas) transfer function provided the lowest mean squared error ($MSE = 2.2233 \times 10^{-6}$) and the root mean squared error ($RMSE = 0.001491$), and at the same time the highest R^2 -value (0.9697). The worst prediction defined by the coefficient of determination was obtained for the Trainlm training algorithm with the Purelin transfer function ($R^2 = 0.62821$). The highest mean squared error ($MSE = 2.29903 \times 10^{-5}$) was characterised by the network trained using the conjugate gradient algorithm with Powell-Beale restarts (Traincgb) and with a pure linear transfer function. Regardless of the type of training algorithm, the lowest values of the coefficient of determination were obtained for networks containing neurons with Purelin transfer function. This means that the experimental data are characterised by nonlinearity of the influence of friction process parameters on the coefficient of friction and pure linear transfer function is not effective enough.

Table 3. Validation metrics for analysing the coefficient of friction neural network model

Training function	Transfer function	MSE	RMSE	R^2
Trainlm	Radbas	2.2233×10^{-6}	0.001491	0.9697
	Tansig	2.31803×10^{-6}	0.001522	0.96854
	Softmax	6.50842×10^{-6}	0.002551	0.90942
	Logsig	1.43319×10^{-5}	0.003785	0.88167
	Purelin	2.25651×10^{-5}	0.004750	0.62821
Trainscg	Radbas	1.33703×10^{-5}	0.003656	0.80556
	Tansig	1.45335×10^{-5}	0.003812	0.78231
	Softmax	1.33174×10^{-5}	0.003649	0.80255
	Logsig	1.51809×10^{-5}	0.003896	0.77056
	Purelin	2.26746×10^{-5}	0.004761	0.63144
Traincgf	Radbas	3.06506×10^{-6}	0.001750	0.89753
	Tansig	1.01683×10^{-5}	0.003188	0.8531
	Softmax	1.48374×10^{-5}	0.003851	0.77602
	Logsig	1.16673×10^{-5}	0.003415	0.8289
	Purelin	2.25605×10^{-5}	0.004749	0.62961
Traincgb	Radbas	1.20618×10^{-5}	0.003473	0.82334
	Tansig	9.84491×10^{-6}	0.003137	0.85819
	Softmax	2.0461×10^{-5}	0.004523	0.67742
	Logsig	1.57331×10^{-5}	0.003966	0.76335
	Purelin	2.29903×10^{-5}	0.004794	0.63002
Traincgp	Radbas	1.11194×10^{-5}	0.003334	0.83937
	Tansig	1.67091×10^{-5}	0.004087	0.76239
	Softmax	1.6442×10^{-5}	0.004054	0.74769
	Logsig	1.43319×10^{-5}	0.003785	0.78582
	Purelin	2.24726×10^{-5}	0.004741	0.63152

Table 4 presents additional regression metrics for the best network ($R^2 = 0.9697$): the mean absolute error (MAE), the mean error (ME) and the mean relative error (MRE) [47]:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n (|y_v - y_r|) \quad (7)$$

$$\text{ME} = \frac{1}{n} \sum_{i=1}^n (y_v - y_r) \quad (8)$$

$$\text{MRE} = \frac{1}{n} \sum_{i=1}^n \left(\left| \frac{y_v - y_r}{y_r} \right| \right) \quad (9)$$

Table 4. Evaluation of the best neural network model (Trainlm with Radbas) based on the validation metrics

Validation metric	MSE	R^2	ME	MAE	RMSE	MRE
Value	2.2233×10^{-6}	0.9697	-8.5776×10^{-6}	0.001222	0.001491	5.7219×10^{-7}

MAE provide a more precise assessment compared to other validation measures [47]. There are no a substantial difference between the MAE (0.001222) and RMSE (0.001491) errors which indicates no important discrepancies in the error distribution. The predicted data of the artificial neural network is more consistent with the actual value when R^2 is closer to one and the mean relative error is closer to zero. The tests obtained $\text{MRE} = 5.7219 \times 10^{-7}$ (Table 2), which is a very low value in relation to the friction coefficient value usually given with an accuracy of two significant digits.

The regression lines for the best neural network found with respect to the training set, validation set, and test set are shown in Fig. 6a-6c. Fig. 6b compares the predicted and experimental friction coefficient values for the cumulative data set. The data represented by circles are distributed proportionally along the regression lines, which indicates that the data is normally distributed. This distribution is one of the most important probability distributions, playing an important role in statistics. The slope of the regression line indicates that in the range of small coefficients of friction, the neural network model slightly overestimates the data and vice versa in the range of large coefficients of friction, the model slightly underestimates the value of this coefficient. However, the prediction is at a satisfactory level ($R^2 = 0.96741$). 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 0.97383 and 0.9797, respectively. Therefore, the quality of the cumulative prediction of the neural network model for all data ($R^2 = 0.9697$) is in very good agreement with the prediction for the training set ($R^2 = 0.96741$). Furthermore, Fig. 7 showed a significant positive correlation between the predicted and actual coefficient of friction findings of the best ANN model using the Trainlm training algorithm with the Radbas transfer function.

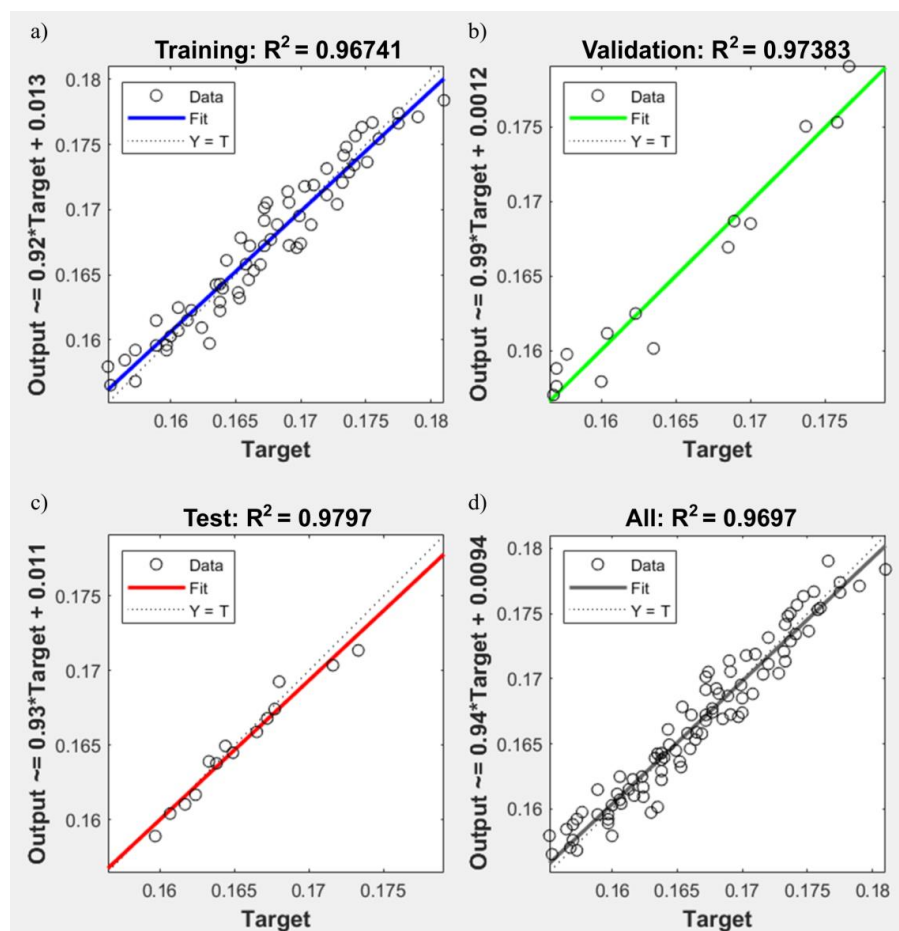


Fig. 6. Regression curves of the best ANN model of coefficient of friction using Trainlm training algorithm with Radbas transfer function for a) training set, b) validation set, c) test set and d) all data

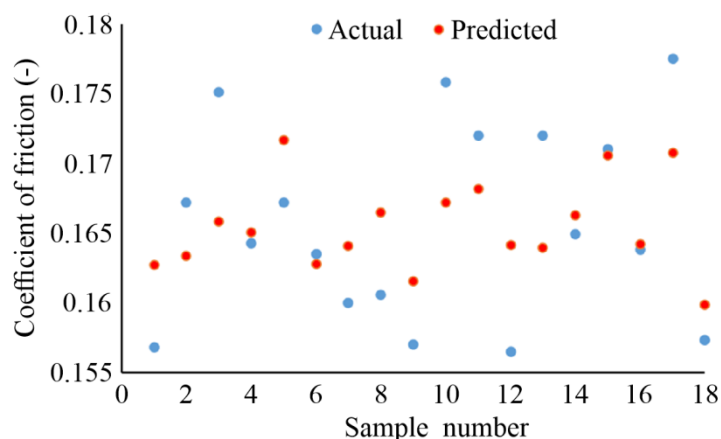


Fig. 7. Actual and predicted coefficients of friction for the test set of the best ANN using the Trainlm training algorithm with the Radbas transfer function

CONCLUSIONS

The article presents the results of the research on the potential of using vegetable oils in sheet metal forming processes. The test material used was deep-drawing DC04 steel sheet, commonly used in the automotive industry. Experimental studies using strip drawing test

have shown a similar potential to reduce the friction coefficient by the tested oils. The friction coefficient value, dependent on the friction conditions and considering all tested oils, ranged between 0.155 and 0.181. In the range of contact pressures analysed, corresponding to real forming conditions in deep-drawing processes, the basic friction mechanism was flattening of surface asperities. The intensity of this phenomenon depended mainly on the contact pressure and the surface roughness of the countersamples. Based on the obtained set of 90 experimental data sets, a feed-forward neural networks were built to predict the friction coefficient value. Among the many applied training algorithms and different transfer functions of neurons, the 3-10-1 network trained using the Levenberg-Marquardt algorithm and consisted of neurons with a radial basis transfer function provided the lowest mean squared error ($MSE = 2.2233 \times 10^{-6}$) and the root mean squared error ($RMSE = 0.001491$). The high prognostic ability of this network was confirmed by the value of the coefficient of determination $R^2 = 0.9697$. Depending on the type of data set, the value of the determination coefficient varied between $R^2 = 0.96741$ (training set) and $R^2 = 0.9797$ (test set). Artificial neural networks containing neurons with Purelin transfer function showed the lowest coefficients of determination.

The results of the experimental studies meet the need for the development of sustainable manufacturing, in which the sheet metal forming process is carried out without the participation or with a minimal participation of substances derived from the processing of crude oil. Both the studies presented in this article, as well as the results of the authors' previous works, indicate similar or better lubricating properties of environmentally friendly vegetable oils. The results of the studies and the methodology used in the studies can be used by designers of deep-drawing processes. Although the article focuses mainly on the application of neural networks to modeling the friction phenomenon, the discussion of the experimental results allows for a better understanding of the complexity of tribological phenomena accompanying the sheet metal forming process. The presented research results, after extending the training set, can be the basis for the use of other statistical algorithms, including machine learning, support vector machines or gradient boosting to model the friction phenomenon of deep-drawing quality sheet metals.

REFERENCES

1. Hami N., Muhamad M.R., Ebrahim Z. The impact of sustainable manufacturing practices and innovation performance on economic sustainability. *Procedia CIRP* 26 (2015) 190-195.
2. Malik M.A.I., Kalam M.A., Multaba M.A., Almomani F. A review of recent advances in the synthesis of environmentally friendly, sustainable, and nontoxic bio-lubricants: Recommendations for the future implementations. *Environmental Technology & Innovation* 32 (2023) 103366.
3. Pichler J., Eder R.M., Besser C., Pisarova L., Dörr N., Marchetti-Deschmann M., Frauscher M. A comprehensive review of sustainable approaches for synthetic lubricant components. *Green Chemistry Letters and Reviews* 16(1) (2023) 2185547.
4. Das R. Eco-friendly Lubricants for Tribological Application. In: Martínez, L., Kharissova, O., Kharisov, B. (Eds.) *Handbook of Ecomaterials*. Springer, Cham, 2019.
5. Berman, D. Plant-based oils for sustainable lubrication solutions—Review. *Lubricants* 12 (2024) 300.

6. Hermewan A.N., Masudin I., Zulfikarijah F., Restuputri D.P., Shariff S.S.R. The effect of sustainable manufacturing on environmental performance through government regulation and eco-innovation. *International Journal of Industrial Engineering and Operations Management* 6(4) (2024) 299-325.
7. Chandrakar J.K., Suhane A. The prospects of vegetable based oils as metal working fluids in manufacturing application – A review. *Industrial Journal of Engineering Research & Technology* 3(5) (2014) 2196-2203.
8. Tomków J., Czapryński A., Fydrych, D. The abrasive wear resistance of coatings manufactured on high-strength low-alloy (HSLA) offshore steel in wet welding conditions. *Coatings* 10 (2020) 219.
9. Sirohi S., Pandey S.M., Świerczyńska A., Rogalski G., Kumar N., Landowski M., Fydrych D., Pandey C. Microstructure and mechanical properties of combined GTAW and SMAW dissimilar welded joints between Inconel 718 and 304L austenitic stainless steel. *Metals* 13 (2023) 14.
10. Janeczek, A., Tomków, J., Derazkola, H. A., Łyczkowska, K., Fydrych, D. Effect of underwater friction stir welding parameters on AA5754 alloy joints: Experimental studies. *The International Journal of Advanced Manufacturing Technology* 134(11) (2024) 5643-5655.
11. Lachmayer R., Behrens B.-A., Ehlers T., Müller P., Althaus P., Oel M., Farahmand E. Gembarski P.C., Wester H., Hübner S. Process-integrated lubrication in sheet metal forming. *J. Manuf. Mater. Process.* 6 (2022) 121.
12. Szpunar M., Trzepieciński T. Prediction of the coefficient of friction in the single point incremental forming of truncated cones from a Grade 2 titanium sheet. *Tribologia - Finnish Journal of Tribology* 40(1–2) (2023) 4–17.
13. Domhof A.T.M., Waanders D., Hol J., Sigvant M. Friction and lubrication modelling in sheet metal forming: Influence of local tool roughness on product quality. *IOP Conference Series: Materials Science and Engineering* 1284 (2023) 012087.
14. Özkan D., Yilmaz M. A., Karakurt D., Szala M., Walczak M., Bakdemir S. A., Türküz C., Sulukan E. Effect of AISI H13 Steel Substrate Nitriding on AlCrN, ZrN, TiSiN, and TiCrN Multilayer PVD Coatings Wear and Friction Behaviors at a Different Temperature Level. *Materials* 16 (2023) 1594.
15. Niemczewska-Wójcik M., Madej M. Surface topography and tribological properties of cutting tool coatings. *Advances in Science and Technology Research Journal* 17(6) (2023) 39-48.
16. Zajezińska A. *Biodegradowalne smary plastyczne*. Instytut Nafty i Gazu – Państwowy Instytut Badawczy, Kraków 2016.
17. Syahrullail S., Afifah A.N. Bio-lubricant for metal forming. *Mytribos Symposium* 2 (2017) 54-56.
18. Aiman Y., Syahrullail S., Kameil A.H. Tribological in metal forming process and the use of bio lubricant as metal forming lubricant: A review. *Jurnal Teknologi (Sciences & Engineering)* 86(1) (2023) 95-114.
19. Szweczyk M., Szwajka K. Assessment of the tribological performance of bio-based lubricants using analysis of variance. *Advances in Mechanical and Materials Engineering* 40 (2023) 31-38.
20. Więckowski W., Adamus J., Dyner M. Sheet metal forming using environmentally benign lubricant. *Archives of Civil and Mechanical Engineering* 20 (2020) 51.
21. Bucur A., Lazarescu L., Pop G.M., Achimas G., Gebhardt A. Tribological performance of biodegradable lubricants under different surface roughness of tools. *Academic Journal of Manufacturing Engineering* 17(1) (2019) 172-178.

22. Trzepieciński T., Szewczyk M., Sz wajka K. the use of non-edible green oils to lubricate DC04 steel sheets in sheet metal forming process. *Lubricants* 10 (2022) 210.
23. Prakash V., Kumar D.R. Performance evaluation of bio-lubricants in strip drawing and deep drawing of an aluminium alloy. *Advances in Materials and Processing Technologies* 8(1) (2022) 1044-1057.
24. Trzepieciński T., Szpunar M. Assessment of the effectiveness of lubrication of Ti-6Al-4V titanium alloy sheets using radial basis function neural networks. *Acta Polytechnica* 61(3) (2021) 489-496.
25. Singh Y., Garg R., Kumar S. Aspects of non-edible vegetable oil-based bio-lubricants in the automotive sector. *Green* 5(1-6) 1-14.
26. Kandeva M., Kalitchin Z., Zadorozhmaya E., Vend A. Performance characteristics of lubricant based on rapeseed oil containing different amounts of metal-containing additive. *Industrial Lubrication and Tribology* 74(3) (2022) 309-315.
27. Ahmad N.A., Samion S., Rahim E.A., Jamir M.R.M. Environmentally approach for enhancing tribological characteristics in metal forming: A review. *Jurnal Tribologi* 26 (2020) 37-59.
28. Trzepieciński T. Approaches for preventing tool wear in sheet metal forming processes. *Machines* 11 (2023) 616.
29. Monetti C., Ilo S., Lebersorger T. Characterization of lubricants for metal forming by means of an oscillating tribo-test-rig. *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology* 223(5) (2009) 817-826.
30. Sulaiman M.H., Christiansen P., Bay N. Influence of tool texture on friction and lubrication in strip reduction. *Procedia Engineering* 207 (2017) 2263-2268.
31. Rao K.P., Wie J.J. (2001). Performance of a new dry lubricant in the forming of aluminum alloy sheets. *Wear* 249 (2001) 86–93.
32. Hafis S.M., Ridzuan M.J.M., Mohamed A.R., Farahana R.N., Fatin B.N., Syahrullail, S. Properties of palm pressed fibre for metal forming lubricant applications. *Procedia Engineering* 68 (2013) 130-137.
33. Syahrullail S., Kamitani S., Nakanishi K. Experimental evaluation of refined, bleached, and deodorized palm olein and palm stearin in cold extrusion of aluminum A1050. *Tribology Transactions* 55(2) (2012) 199-209.
34. Lovell M., Higgs C.F., Deshmukh P., Mobley A. Increasing formability in sheet metal stamping operations using environmentally friendly lubricants. *Journal of Materials Processing Technology* 177(1–3) (2006) 87-90
35. Biresaw G. Elastohydrodynamic properties of seed oils. *Journal of the American Oil Chemists' Society* 83 (2006) 559–566
36. Alves S.M., Barros B.S., Trajano M.F., Ribeiro K.S.B., Moura E. Tribological behavior of vegetable oil-based lubricants with nanoparticles of oxides in boundary lubrication conditions. *Tribology International* 65 (2013) 28–36.
37. EN 10130; Cold rolled low carbon steel flat products for cold forming—Technical delivery conditions. European Committee for Standardization: Brussels, Belgium, 2009.
38. ISO 6892-1:2009; Metallic Materials—Tensile Testing—Part 1: Method of Test at Room Temperature. ISO: Geneva, Switzerland, 2009.
39. Ter Haar R. Friction in sheet metal forming, the influence of (local) contact conditions and deformation. Universiteit Twente: Enschede, Holland, 1996.

40. SIHARD 2063 Steel. Available online: <https://steelselector.sij.si/steels/MERILOSP.html> (Accessed on 2 December 2023).
41. Carcel A.C., Palomares D., Rodilla E., Puig M.A.P. Evaluation of vegetable oils as pre-lube oils for stamping. *Materials and Design* 26(7), (2005) 587-593.
42. Trzepieciński T. The comparison of the multi-layer artificial neural network training methods in terms of the predictive quality of the coefficient of friction of 1.0338 (DC04) Steel Sheet. *Materials* 17 (2024) 908.
43. Mezher M. T., Shakir R. A. Modelling and evaluation of the post-hardness and forming limit diagram in the single point incremental hole flanging (SPIHF) process using ANN, FEM and experimental. *Results in Engineering* 20 (2023) 101613.
44. Gareth J. *An Introduction to Statistical Learning: with Applications in R*. Springer New York, NY, 2013.
45. Brownlee, J. What is the Difference Between Test and Validation Datasets?. Retrieved 2025-02-12. <https://machinelearningmastery.com/difference-test-validation-datasets/>
46. Prechelt L. Early Stopping — But When?. In G. Montavon; G. B. Orr, K. R. Müller (eds.). *Neural Networks: Tricks of the Trade*. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2012, pp. 53–67.
47. Mezher M. T., Pereira A., Shakir R. A., Trzepieciński T. Application of machine learning and neural network models based on experimental evaluation of dissimilar resistance spot-welded joints between grade 2 titanium alloy and AISI 304 stainless steel. *Heliyon* 10(24) (2024) e40898.