MODELLING OF THE DRAW BEAD COEFFICIENT OF FRICTION IN SHEET METAL FORMING

Modelowanie współczynnika tarcia na progu ciągowym w procesie kształtowania blach

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A b s t r a c t: This paper presents the results of determining the value of the coefficient of friction on the drawbead in sheet metal forming. As the research material, steel, brass and aluminium alloy sheets cut at different directions according to the sheet rolling direction were used. Sheet strip specimens were tested under dry friction and lubrication of sheet surfaces using machine oil. Results of experiments were used to study the effect of process parameters on the coefficient of friction using artificial neural networks. Input data was optimized using genetic algorithm, forward stepwise selection and backward stepwise selection. The aim of the research was to determine the effect of the value of the unit penalty on the significance of individual input parameters of the neural network and the value of the error generated by the multilayer perceptron. It was found that in the case of all materials the value of coefficient of friction for specimen orientation 90° was greater than for the specimen orientation 0°. Friction tests also reveal that sheet lubrication reduced the frictional resistance by 12-39%, depending on the grade of sheet material. Among all input parameters that significantly affect the value of the coefficient of friction the most important are the lubrication conditions and the orientation of the sample.
K e y w o r d s: artificial neural networks, coefficient of friction, drawbead, friction, sheet metal forming

S t r e s z c z e n i e: W artykule przedstawiono wyniki wyznaczania wartości współczynnika tarcia na progu ciągowym w procesie kształtowania blach. Jako materiał badawczy wykorzystano blachy stalowe, mosiężne i ze stopu aluminium, które zostały wycięte w różnych kierunkach względem kierunku walcowania blachy. Pasy blachy badano w warunkach tarcia suchego oraz smarowania powierzchni blach olejem maszynowym. Wyniki eksperymentów posłużyły do zbadania wpływu parametrów procesu tarcia na wartość współczynnika tarcia za pomocą sztucznych sieci neuronowych. Dane wejściowe zostały zoptymalizowane przy użyciu algorytmu genetycznego, selekcji krokowej postępującej oraz wstecznej. Celem badań było określenie wpływu wartości kary jednostkowej na istotność poszczególnych parametrów wejściowych sieci neuronowej oraz wartość błędu generowanego przez perceptron wielowarstwowy. Stwierdzono, że w przypadku wszystkich materiałów wartość współczynnika tarcia próbek zorientowanych pod kątem 90° była większa niż dla orientacji próbek 0°. Testy tarcia wykazały również, że smarowanie blach zmniejszyło opory tarcia o 12–39% w zależności od gatunku materiału blachy. Spośród wszystkich parametrów wejściowych, które istotnie wpływają na wartość współczynnika tarcia, najważniejsze z nich to warunki smarowania oraz orientacja próbki.
S ł o w a k l u c z o w e: sztuczne sieci neuronowe, współczynnik tarcia, próg ciągowy, tarcie, kształtowanie blach

Introduction

The friction between the working surface of the tool and the plastically deformed material has a significant impact on the deformation process and the surface roughness of the drawpiece. External friction causes geometric and kinematic limitations in the implementation of plastic working processes [8, 13]. The type of friction (i.e., dry mixed, boundary) significantly affects the damage to the surface of the component. The frictional connections formed on the surface of the tool cause scratches and burrs on the surfaces of the drawpiece. The phenomenon of friction in plastic working processes differs significantly from friction in machine joints due to [11, 15, 18]:

– large deformations,
– continuous change of surface topography of the workpiece,
– high normal pressures greater than the yield point of the workpiece,
– low relative speeds.

Deep drawing is one of the basic operations of plastic working and consists in transforming a flat sheet into a drawpiece with an non-developable surface [14,17]. During deep-drawing in the bottom of the drawpiece and the cylindrical surface dominate tensile stresses [12, 16]. In the flange, apart from tensile stress, compressive stresses also occur. The sheet metal forming process is most often carried out on presses with tools consisting of a punch, die and blankholder. When forming drawpieces with complex shapes, different sliding speeds occur at different locations on the drawpiece [16]. Draw beads (Fig. 1) are used to limit the flow of material around the flange of the drawpiece [5, 10].

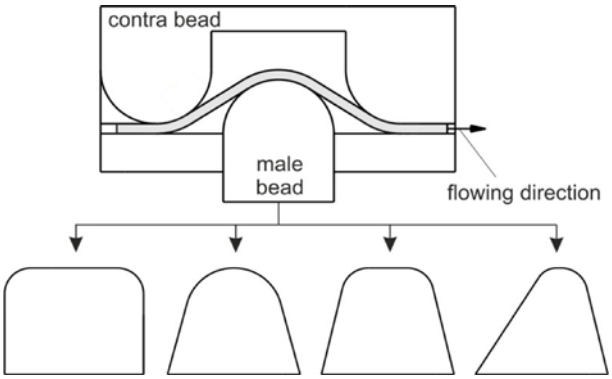


Fig.1. Design of the machined element

Due to the large number of factors influencing a given phenomenon, the development of analytical relationships for determining the response function for given process conditions is practically impossible. This task is successfully performed by artificial neural networks belonging to artificial intelligence methods. The condition for the proper operation of the neural network is the necessity to preselect the input data, which significantly affect the value of the variable explained by the use of the decomposition mechanism. The purpose of data decomposition is to find an answer to the question whether there is a relationship between the input variables and the dependent variable, or whether the relationship is completely random. Data processing systems allow for automatic analysis of a complex set of information and generating answers to the questions asked.

Due to the large number of factors influencing a given phenomenon, it is practically impossible to develop analytical relationships to determine the response function for given conditions of process implementation. This task is successfully performed by artificial neural networks belonging to artificial intelligence methods, whose structure and principle of operation are similar to information processing by living organisms [9]. The condition for the proper operation of the neural network is the necessity to preselect the input data, which significantly affect the value of the output variable by the use of the decomposition mechanism [3, 6]. The purpose of data decomposition is to find an answer to the question whether there is a relationship between the input variables and the dependent variable, or whether the relationship is completely random. Data processing systems allow for automatic analysis of a complex set of information and generating answers to the questions asked [1, 4].

Among the many methods of optimizing the number of training variables, one can mention the Hellwig method, the forward selection method, backward selection, stepwise selection, taboo-search and floating selection. The genetic algorithm searches combinations of features at random. In the next steps of the algorithm, sets of possible solutions (populations) are assessed. The rules governing mutation, crossing and selection ensure that a new population is generated randomly. Nevertheless, in the next steps of the algorithm, better and better individuals are obtained, i.e. sets of features with higher and higher ratings. Simulated annealing algorithm moves sequentially among all possible combinations of features. The rating of a subset of features after the step, i.e. after eliminating one feature, is compared with the rating before the step. There is some probability that the feature will be removed from the subset, even though the resulting subset is judged worse.

In this paper, methods of optimizing the number of input variables of a neural network using three different algorithms based on the results of friction testing. The draw-bead tribological test is used to model the friction phenomenon at the drawbead during sheet metal forming. Three grades of brass, steel and aluminium alloy sheets were tested. The aim of the investigations is to determine the effect of the value of the unit penalty function on (i) the significance of individual input variables of the neural network and (ii) the value of the error generated by the artificial neural network for the training set.

Material and methods

In the tests three grades of brass sheets M63 z4 (1/2 hard), M80 r (soft) and M90 z4 (1/2 hard), three grades of aluminium alloy sheets AA5251 r (recrystallised), AA5251 H14 (strain-hardened – 1/2 hard) and AA5251 H22 (strain-hardened and partially annealed - 1/4 hard), and deed-drawing quality steel sheets DC01, DC03 and DC04 were used. The samples for the friction test were prepared as strips approximately 200 mm long and 20 mm wide. The values of the basic mechanical parameters were determined in the uniaxial tensile test. Tensile tests were carried out using a universal testing machine with a constant crosshead speed of 5 mm/min at ambient temperature. The values of the strain hardening cefficient K and the strain hardening exponent n in the Hollomon equation are determined as follows:

$$\sigma_p = K \cdot \varepsilon^n \tag{1}$$

where σ_p – stress and ε – plastic strain are determined from the logarithmic true stress–true strain plot by linear regression.

The values of the roughness parameters were determined using the Surtronic 3+ Taylor Hobson surface roughness profilometer.

The friction phenomenon arising in the drawbead region of the stamping die have been determined using a drawbead simulator. The model of the simulator is shown in Fig. 2. The device is designed to allow the separation of the deformation resistance of the sheet and the frictional resistance from the total resistance of the sheet metal deformation at the drawbead. Counter-samples in the form of rollers with a diameter of 20 mm and a width of 22 mm were made of cold work tool steel. The surface roughness of rollers was Ra = 0.32

Table. 1. Mechanical properties and roughness parameters of the tested sheets *

Material	Grade	$R_{p0.2}$, MPa	R_m, MPa	A_{50}, %	K, MPa	n	Ra, µm		Rq, µm		Rt, µm	
							0°	90°	0°	90°	0°	90°
Brass	M63 z4	313	397	0.36	589	0.15	0.17	0.2	0.31	0.4	2.5	4.8
	M80 r	120	280	0.48	594	0.37	0.14	0.16	0.18	0.18	1.4	1.9
	M90 z4	346	352	0.12	426	0.04	0.40	0.6	0.58	0.94	6.1	9.9
Aluminium alloys	AA5251 r	68	203	0.18	252	0.28	0.58	0.59	1.14	0.93	6.9	7.0
	AA5251 H14	212	234	0.04	254	0.06	0.22	0.28	0.29	0.35	2.4	2.5
	AA5251 H22	111	201	0.19	370	0.24	0.48	0.49	0.64	0.64	4.1	4.1
Steel	DC01	193	351	0.36	554	0.17	0.23	0.28	0.28	0.41	2.5	4.7
	DC03	196	336	0.42	557	0.19	0.45	0.35	0.62	0.49	3.1	6.4
	DC04	162	310	0.42	54	0.21	0.62	0.51	0.84	0.72	4.1	8.2

* $R_{p0.2}$ – yield stress, Rm – ultimate tensile stress, A_{50} – elongation, K – strain hardening coefficient, n – strain hardening exponent, Ra – average surface roughness, Rq – root mean square deviation of the profile under assessment, Rt – total height of the profile

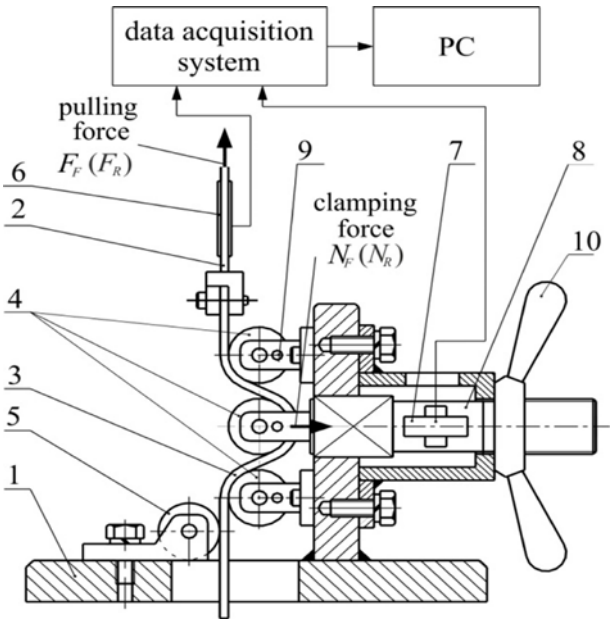


Fig. 2. Cross-section of a drawbead simulator: 1 – frame; 2 – upper tension member; 3 – specimen; 4 – working rollers; 5 – support roller; 6 and 7 – load cells; 8 – horizontal tension member; 9 – pin; 10 – wing nut

µm, measured parallel to the shaft axis. The tests were carried out at the wrap angle of the middle roller equal to 180°. Friction tests were carried out at dry friction and lubrication conditions using LAN 46 machine oil (Orlen Oil, Kraków, Poland). The properties of this oils provided by the manufacturer are listed in Table 2. Prior to testing, both sides of the specimen were oiled by a roller system that permits one to obtain a uniform oil coating between 1.5 and 2 $g \cdot m^{-2}$, which is comparable with the conditions of the stamping process. Specimens for tests were cut along (0°) and transversely (90°) to the rolling direction of the sheet. The drawing speed of strip specimens was 0.002 m/s.

Table 2. Selected properties of LAN 46 machine oil

Parameter	Value
Kinematic viscosity at 40°C	43.9 mm2/s
Viscosity index	94
Ignition temperature	232°C
Flow temperature	−10°C

The method of determining the coefficient of friction (COF) requires two tests of drawing a sheet metal strip over rotating and fixed rollers. Drawing the specimen over a set of rotating rollers allows one to minimise the frictional resistance. The drawing force in this case is mainly associated with overcoming the deformation resistance of the sheet metal strip. A set of fixed rollers represents the total resistance of drawing the specimen through the drawbead.

The difference in the pulling force for the rotating and fixed rollers can be attributed to the friction process and used to calculate the value of the coefficient of friction according to the relationship:

$$\mu = \frac{1}{\pi}\frac{F_F - F_R}{N_F} \tag{2}$$

where N_F is the normal force obtained with fixed beads, F_F is the pulling force obtained with fixed rollers and F_R is the pulling force obtained with the freely rotating rollers.

As a result of the experimental friction tests, 36 different training sets (TSs) were obtained (6 grades of sheets × 2 sample orientations × 2 lubrication conditions). On the basis of the received sets of input signals and the corresponding values of the COF, regression models were built using the Statistica program and the impact of the applied methods of optimizing the input signals on the quality of the neural network was assessed. For the analysis, the model of a multilayer perceptron (MLP) was adopted, which, with a properly selected structure, can model any regression problem [2, 7]. From all training pairs (input signals and the corresponding output signal), 10% of cases were randomly selected and included in the validation set (VS). Data from this group was used for independent control of the training algorithm. The remaining number of cases was assigned to the training set.

Data preprocessing

The following set of variables was selected as input parameters in MLP:

- mechanical parameters $R_{p0.2}$, R_m, A_{50}, K and n,
- surface roughness parameters of sheets, Ra, Rq and Rt,
- lubrication conditions,
- sample orientation.

The input data was optimized with a genetic algorithm, forward stepwise selection, and backward stepwise selection. The aim of the genetic algorithm is to find a solution for which the value of the fitness function reaches the maximum. The algorithm worked on the initial population of 300 individuals with the crossing coefficient c_k = 0.5, the mutation rate r_m = 0.1 and different values of the unit penalty ρ = 0.0005, ρ = 0.001, ρ = 0.002, ρ = 0.004, ρ = 0.01, ρ = 0.03. The unit penalty is multiplied by the number of input variables selected in each mask, and then added to the validation error value. The task of the genetic algorithm was to check the quality of the network implementing the generalized regression for a given set of input variables resulting from the reproduction mechanism of the initial population.

Results

• Coefficient of friction

Table 2 presents the values of the friction coefficient of the tested sheets, determined in the conditions of dry friction (μs) and in the conditions of lubricating the sheet surface with oil (μ_o). For the specimen orientation 0°, the values of the coefficient of friction under lubricated conditions were lower by about 22-28% for brass sheets, 19-20% for aluminium alloy sheets and 23-39% for steel sheets. For the specimen orientation 90°, the values of the coefficient of friction under lubricated conditions were lower by about 12-22% for brass sheets, 23-37% for aluminium alloy sheets and 32-37% for steel sheets. In the case of all materials the value of COF for specimen orientation 90° was greater than for the specimen orientation 0°.

Table 2. Values of COFs for tested materials

Specimen orientation	Coefficient of friction					
	μs	μo	μs	μo	μs	μo
Material	**M63 z4**		**M80 r**		**M90 z4**	
0°	0.23	0.17	0.18	0.14	0.25	0.18
90°	0.25	0.22	0.19	0.15	0.27	0.21
Material	**5251 r**		**5251 H14**		**5251 H22**	
0°	0.24	0.19	0.2	0.16	0.21	0.17
90°	0.26	0.2	0.26	0.18	0.29	0.18
Material	**DC01**		**DC03**		**DC04**	
0°	0.24	0.18	0.17	0.13	0.23	0.14
90°	0.27	0.17	0.25	0.16	0.28	0.19

• Artificial neural networks

The results of the optimization analyzes carried out to determine the input signals to the neural network are presented in Tables 3-5. Parameters that significantly affect the value of the coefficient of friction and their removal will worsen the explanation of the value of the coefficient of friction are the lubrication conditions and the orientation of the sample - these variables were selected by each method, regardless of the value of the unit penalty. Among the parameters of sheet surface roughness, the parameters Ra (0°) and Rt (0°) have the most important influence on the value of the friction coefficient.

In terms of the unit penalty values for each of the tested algorithms, the local minimum network error value for the training set is observed. The high error value with a large number of variables can be explained by the noise introduced by the variables, which can be correlated with each other. For further analysis, set of input variables were selected for which the network error value was the smallest, i.e. 0.018 (Table 3).

When assessing the regression model, particular attention should be paid to the ratio of the standard deviation of errors and the standard deviation of the value of the explained variable (S.D. ratio), and the Pearson correlation coefficient R^2. These parameters are determined independently for each of the data sets.

Table 6 shows the regression statistics of the network with input the parameters presented in Table 3 that ensure the lowest value of the network error. Multiple analyzes have been performed with MLPs containing varying numbers of neurons in hidden layer 5-15. The highest value of the Pearson correlation coefficient with the lowest value of S.D. ratio provided a network with a structure of 6:6-11-1:1 (Fig. 3). Selected regression statistics of this network are presented in Table 6. The value of the correlation

Table 3. The influence of the value of the unit penalty on the selection of input variables by genetic algorithm

Variable / Unit penalty	R_{p02}	R_m	A_{50}	C	n	Ra (0°)	Ra (90°)	Rq (0°)	Rq (90°)	Rt (0°)	Rt (90°)	Lubrication conditions	Specimen orientation	ANN error for set TS
0.0005	-	-	-	-	+	+	-	+	-	-	-	+	+	0.0036
0.001	+	+	-	+	-	-	+	+	-	-	-	+	+	0.0028
0.002	+	+	+	+	+	-	-	-	-	-	-	+	+	0.0031
0.004	-	+	+	-	-	-	+	-	-	+	-	+	+	0.0018
0.01	-	-	+	-	+	-	-	-	+	+	-	+	+	0.0029
0.03	-	-	-	-	-	-	-	-	-	-	+	+	+	0.0045

Table 4. The influence of the value of the unit penalty on the selection of input variables by backward stepwise selection

Variable / Unit penalty	R_{p02}	R_m	A_{50}	C	n	Ra (0°)	Ra (90°)	Rq (0°)	Rq (90°)	Rt (0°)	Rt (90°)	Lubrication conditions	Specimen orientation	ANN error for set TS
0.0005	+	-	+	+	-	-	-	-	-	-	-	+	+	0.0033
0.001	-	-	+	+	-	-	+	-	-	-	-	+	+	0.0043
0.002	+	-	+	+	+	-	-	+	-	-	-	+	+	0.0029
0.004	-	+	+	-	+	-	-	-	+	+	-	+	+	0.0041
0.01	-	+	+	-	-	+	-	+	-	+	-	+	+	0.0045
0.03	-	-	-	-	-	+	-	+	-	+	+	+	+	0.0051

Table 5. The influence of the value of the unit penalty on the selection of input variables by forward stepwise selection

Variable / Unit penalty	R_{p02}	R_m	A_{50}	C	n	Ra (0°)	Ra (90°)	Rq (0°)	Rq (90°)	Rt (0°)	Rt (90°)	Lubrication conditions	Specimen orientation	ANN error for set TS
0.0005	+	+	+	-	+	+	-	+	-	-	+	+	+	0.0042
0.001	+	+	-	+	-	+	+	-	-	+	-	+	+	0.0031
0.002	-	-	-	-	-	+	-	-	-	-	-	+	+	0.0023
0.004	-	+	+	-	+	-	+	-	-	-	+	+	+	0.0019
0.01	+	+	+	+	+	+	-	-	-	+	-	+	+	0.0028
0.03	-	+	+	-	-	-	-	-	-	-	-	+	+	0.0061

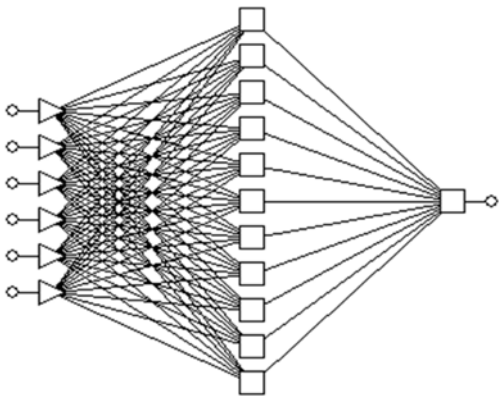


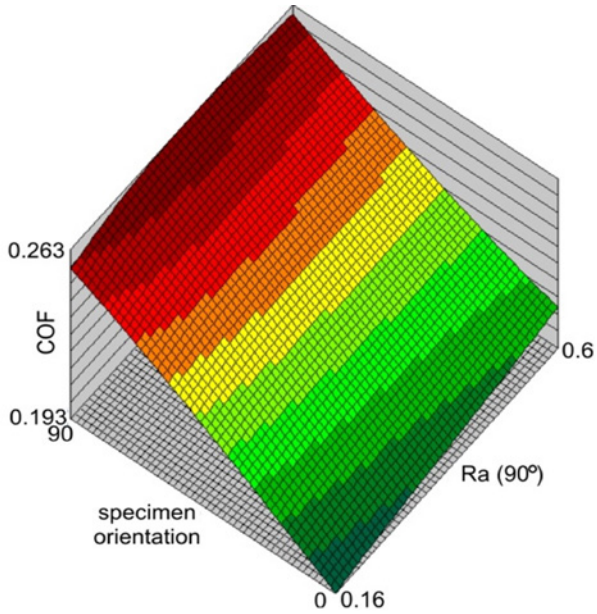
Fig. 3. Structure of MLP 6:6-11-1:1

Table 6. Regression statistics of MLP 6:6-11-1:1

Parameter	TS	VS
Data Mean	0.2117	0.1814
Data S.D.	0.0428	0.0452
Error S.D.	0.0018	0.0106
Abs E. Mean	0.0084	0.0250
S.D. ratio	0.247	0.696
Correlation	0.968	0.795

coefficient for the training set R2 = 0.968 proves a good convergence of the training algorithm. The value of the correlation coefficient for the validation set is much smaller, but it should be emphasized that this set contained only 10% of the training data. With an increasing number of input data in the validation set, the statistics values for that set will approach the corresponding statistics specified for the training set.

As the sample orientation angle changes from 0° to 90°, the value of the friction coefficient increases (Fig. 4). The change of the roughness parameter Ra (90°) in a lesser extent affects the change of the friction coefficient. A different relationship can be observed for the influence of the sample orientation and the roughness parameter Ra (90°) on the value of COF (Fig. 5). When the Rt (0°) parameter increases, the value of the friction coefficient decreases, but only for small values of the sample orientation angle. For the sample orientation of 90°, the value of the friction coefficient depends to a small extent on the value of the Rt (0°) parameter.



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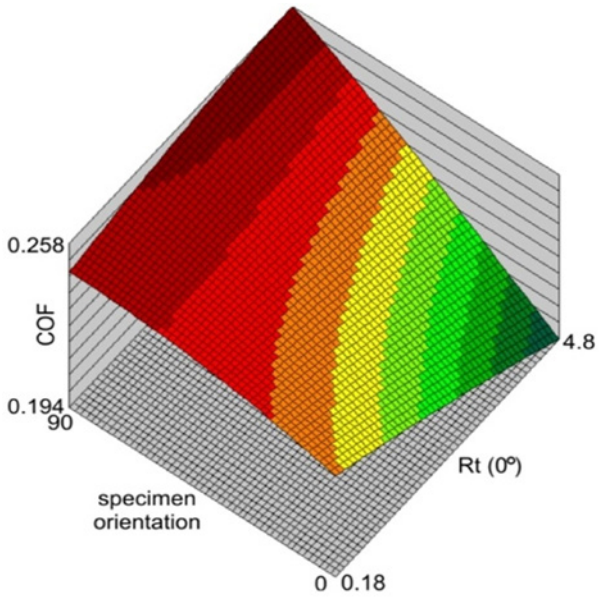

Fig. 3. Structure of MLP 6:6-11-1:1

Conclusions

An approach to integration genetic algorithms and stepwise selection of input variables in the working process of neural networks to calculate the friction coefficient in sheet metal forming is demonstrated in this article. Proper selection of input variables is found to be crucial task to ensure proper quality of the MLPs. This process allows avoiding the time-consuming testing of MLPs with different structure in order to find the optimum network for specific task. The following conclusions are drawn from the research:

- in the case of all materials the value of COF for specimen orientation 90° was greater than for the 0° orientation,
- lubrication reduced the coefficient of friction by 12-39%, depending on the grade of sheet material,
- optimisation of the number of input parameters shown that surface roughness parameters Ra (0°) and Rt (0°) have the most important influence on the value of the COF,
- parameters that significantly affect the value of the COF are the lubrication conditions and the orientation of the sample,
- results of ANN modelling shows that as the sample orientation angle changes from 0° to 90°, the value of the COF increases,
- the change of the roughness parameter Ra (90°) in a small extent affects the change of the COF.

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