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Original Research

Application of Categorical Boosting to Modelling the Friction Behaviour of DC05 Steel Sheets in Strip Drawing Test

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Abstract

It is challenging to model the coefficient of friction, surface roughness, and related tribological processes during metal contact because of flattening, ploughing, and adhesion. It is important to choose the appropriate process parameters carefully when creating analytical models to overcome the challenges posed by complexity. This will ensure the production of sheet metal formed components that meets the required quality standards and is free from faults. This research analyses the impacts of nominal pressure, kinematic viscosity of lubricant, and lubricant pressure on the coefficient of friction and average roughness of DC05 deep-drawing steel sheets. The strip drawing test was used to determine the coefficient of friction. This work utilises the Categoric Boosting (CatBoost) machine learning algorithm created by Yandex to estimate the COF and surface roughness, intending to conduct a comprehensive investigation of process parameters. A Shapley decision plot exhibits the coefficient of friction prediction models via cumulative SHapley Additive exPlanations (SHAP) data. CatBoost has outstanding prediction accuracy, as seen by R^2 values ranging from 0.955 to 0.894 for both the training and testing datasets for the COF, as well as 0.992 to 0.885 for surface roughness.

Keywords: coefficient of friction, friction, sheet metal forming, steel sheet, surface roughness

1. Introduction

Sheet metal forming (SMF) is a metal processing technology that involves forming the material in the form of sheet metal in a way that allows obtaining a finished product with a given shape (Domitner et al., 2021; Venema et al., 2017). The use of the SMF processes allows for the quick and accurate production of components from sheet metal with a very complex shape, which is why it is widely used in many industries, including the automotive industry (Daniel el al., 2006; Spišák et al, 2016).

The deep drawing process involves forming the geometry of the finished product using a die and a punch, sometimes additionally at elevated temperature (Żaba et al., 2020). Therefore, an important phenomenon analyzed when designing metal processing using this method is the impact of selected process parameters on the surface quality of the finished product, energy consumption and tool durability (Çavuşoğlu et al., 2017). A phenomenon that has a direct impact on the nature of the deep drawing process is friction that occurs between the tools and the sheet metal surface, thereby causing wear of the mating surfaces (Bang et al., 2021).

The research carried out on the mapping of friction conditions in the sheet metal forming processes allows, using tribological tests, to simulate tribological phenomena in selected areas of the stamping piece (Groche et al., 2019; Sigvant et al., 2019). This is related to the diversified nature of friction conditions in different areas of the stamping piece (Gali et al., 2013; Le et al., 2002; Wang et al., 2017), resulting from various values of stresses, strains and displacements. However, regardless of the analyzed area of the drawpiece, in order to prevent the negative effects of friction in the deep drawing process, various techniques are used to reduce the value of the coefficient of friction (COF). The most frequently used method to reduce friction between mating surfaces is the use of lubrication (Szewczyk et al., 2022). The lubricating substances used, due to the various parameters they must meet, are selected appropriately depending on the type of oil (natural oil, mineral oil, synthetic oil). (Carcel et al., 2005; Trzepieciński et al., 2022) and its kinematic viscosity (Bay et al., 2008; Lee et al., 2002). Another way to reduce friction in the deep drawing process is to properly select the material from which the tools are made (Kim et al., 2008; Shisode et al., 2021). In addition to the direct selection of the appropriate material from which the tools are made, a common way to reduce friction between the mating surfaces is to coat the tool surfaces, which, in addition to reducing the COF, can improve properties such as resistance to abrasion and high temperatures (Guillon et al., 2001; Severo et al., 2009).

The mentioned possibilities of modifying the friction pair were investigated, among others, by Żaba et al. (2023), who analysed the influence of the material of the friction pair based on the sheet material and modifying the countersamples' material were made. The strip samples were made of aluminium alloy EN AW-6061-T4, Inconel 625 alloy and AISI 321 stainless steel. Four sets of countersamples were made of polyurethane resin, differing in the percentage content of aluminium powder and fiber roving. A direct relationship between the COF values and the countersamples' was indicated. Another interesting phenomenon influencing the SMF process was investigated by Masters et al. (2013), who analyzed the influence of pre-stretched sheet metal strips made of aluminium alloys on the phenomenon of friction. Three grades of aluminium alloys often used in the automotive industry (EN AW-5754, EN AW-6111, EN AW-6451) which were pre-stretched to 2%, 5%, 10%, and 15% were tested. The die was made of ductile iron EN-JS2070, and lubrication was performed using wax greases (ALO70, AlubVS) and oil (MP404). As a result of the tests, it was shown that plastically pre-stretched strip sheets have an impact on the phenomenon of friction and the surface roughness of the finished product, indicating that increasing the value of the initial deformation increases the surface roughness of the finished product.

Analyzing the results of experimental research on the impact of selected parameters of the deep drawing process on COF and the surface quality of the finished product is possible thanks to the use of tools for performing statistical analyzes, i.e. artificial neural networks or machine learning algorithms. These methods allowing for the processing and analysis of information, but also enabling the construction of neural models with the help of which it is possible to predict friction phenomenon and surface quality based on the indicated values of process parameters. This article utilises the Categorical Boosting (CatBoost) machine learning technique, which has been recently created by Yandex researchers and engineers. It serves as an open-source library for gradient boosting on decision trees.

2. Material and methods

2.1. Test material

The material used in the tests was low-carbon steel sheet DC05. The chemical composition of DC05 steel meets the requirements of the PN-EN 10130:2009 standard. Due to its properties, primarily high deformability, this steel is often used in production of components using the sheet metal forming processes. The basic properties of the tested steel were determined by uniaxial tension testing of sheet metal strips cut at an angle of 0° to the rolling direction using a Zwick Roell Z030 testing machine equipped with an extensometer. As a result of the uniaxial tensile test, the results were obtained in the form of a relationship between the engineering stress and the true strain (Fig. 1). The values of basic mechanical parameters are presented in Table 1. The value of Young's modulus was automatically determined (regression method) by the software of testing machine.

In order to check the influence of selected parameters of the friction process on the value of the COF and the surface quality of the sheets, the surface roughness of the DC05 sheet was measured. For this purpose, a stationary profilometer from Hommel-Etamic T8000RC was used. The values of the roughness parameters are presented in Fig. 2. This figure also shows an isometric view of the sheet metal surface. The material ratio curve of DC05 sheet metal is shown in Fig. 3.

Based on the material ratio curve and the values of the parameters presented in Fig. 3, it can be seen that the DC05 sheet in the as-received condition is characterized by a very concentrated material density distribution, having over 17% of the material ratio at a depth of approximately 8 μm.

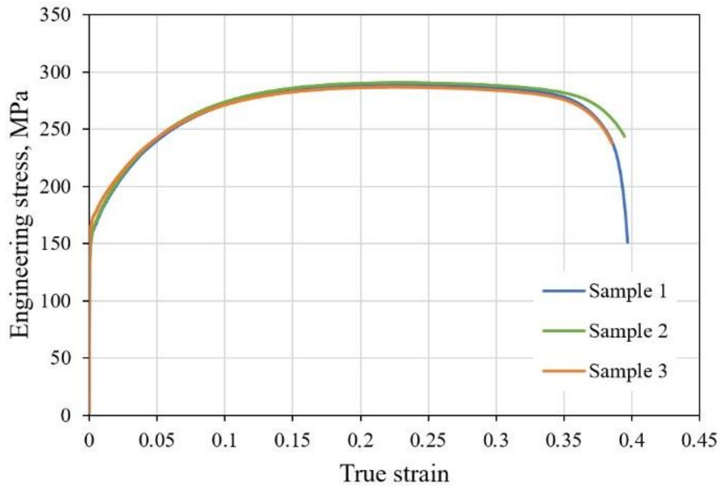

Fig. 1. The engineering stress - the true strain curve determined for samples made of DC05 sheet.

Table 1. Basic mechanical properties of DC05 steel.

Ultimate Tensile Stress R_m, MPa	Yield Stress $R_{p0.2}$, MPa	Young's Modulus E, GPa	Elongation A_{50}, %
289.1	162.5	163.2	25.9

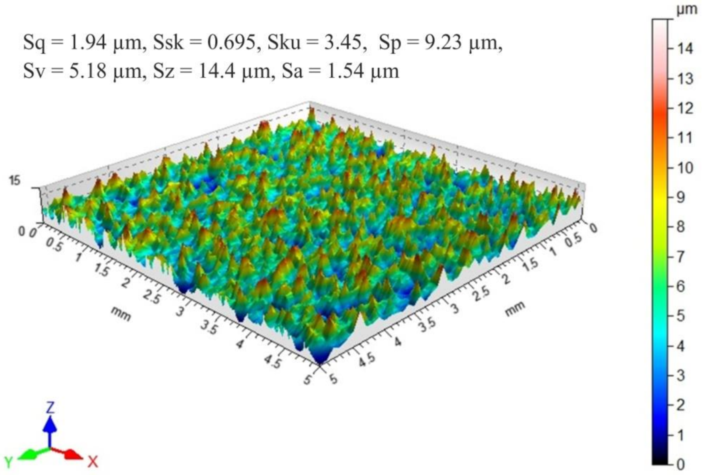

Fig. 2. Isometric view of the topography of the DC05 steel sheet in the as-received state.

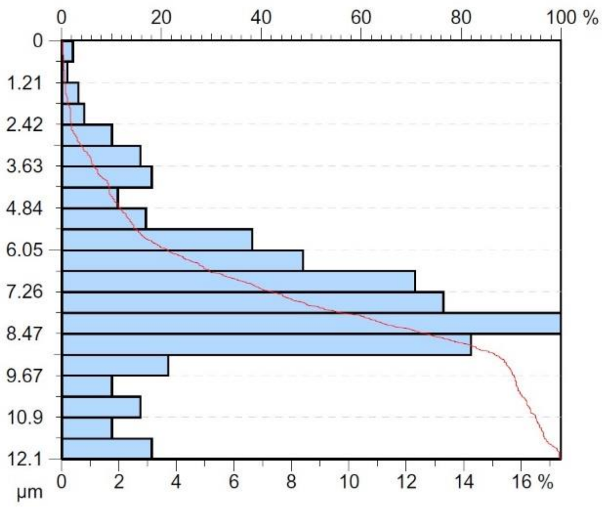

Fig. 3. The material ratio curve of DC05 sheet metal in the as-received state.

2.2. Experiment procedure

Research on the influence of process parameters such as nominal pressure, kinematic oil viscosity and lubrication pressure on coefficient of friction μ and surface quality of the finished product was carried out using a tribometer that allows to determine the COF, especially of sheet metals. The tribometer allows to simulate phenomena characteristic of the deep drawing process occurring in the area of the blankholder.

The friction tests were carried out using the test stand shown in Fig. 4. The presented test stand consisted of two measurement tracks. Measuring system of the Zwick Roell Z100 testing machine was used to recorded the force necessary to move the sheet metal strip. In turn, the second measurement track recorded the values of the clamping force, lubrication pressure and displacement of grip of tensile testing machine. The specimens for friction test were cut along the rolling direction of the sheet metal. The diagram of the test stand used in the research is shown in Fig. 5.

Fig. 4. Research stand.

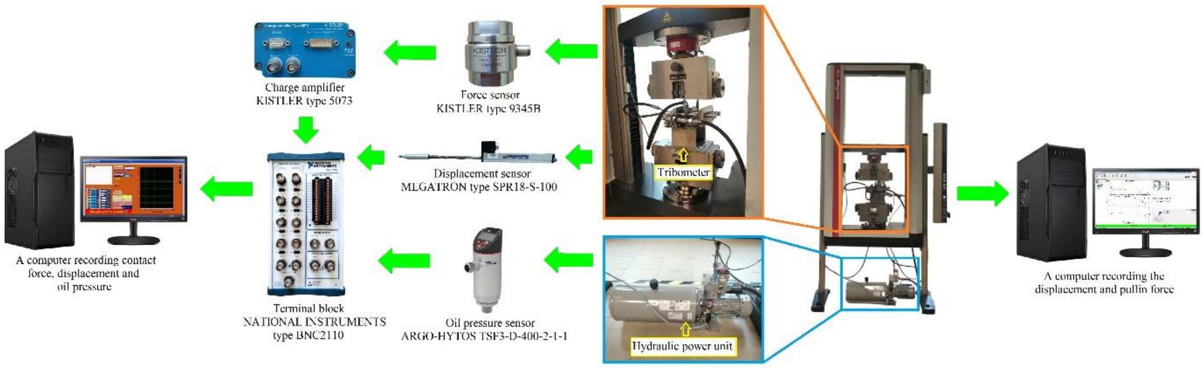

Fig. 5. Diagram of the research stand.

When carrying out the strip drawing tests, variable values of the normal force were used. A Kistler force sensor type 9345B was used to measure the normal force, the value of which was selected in such a way as to correspond to the nominal pressures (p_n) of 2, 4, 6, 8 MPa. Lubrication with oils of different kinematic viscosity (η_k) values was considered. The influence of lubrication on COF and surface quality was also studied without the use of lubricant. The oils used in the tests were selected to have significantly different kinematic viscosity values, so it was decided to use two oils from the same manufacturer (Naftochem), with the commercial names S100 Plus and S300. Due to the fact that the oil manufacturer did not provide the kinematic viscosity value at the temperature at which the tests were carried out (20°C), additional tests were performed to determine the value of kinematic viscosity of oils at 20°C. The tests were carried out using an Ostwald viscometer. The kinematic viscosity of 360 mm^2/s for S100 Plus oil and 1135 mm^2/s for S300 oil was determined. Lubrication was carried out using variable oil pressure (p_o) of 0.6, 1.2, and 1.8 MPa generated using an Argo-Hytos hydraulic power unit. The values of the applied oil pressure were selected in such a way that there was no oil leakage from the contact zone.

As a result of the tests carried out using variable values of the process parameters, graphs of the changes in normal force (F_N) and the force needed to pull the sheet metal strip (F_T) were obtained (Fig. 6). The comparison of the values of these forces in accordance with the relationship presented in Fig. 6 allowed for the determination the changes in COF during the test (Fig. 7). The values of the COF for further analysis were determined as the average value from the stabilised values of forces, in accordance with the diagram shown in Fig. 7.

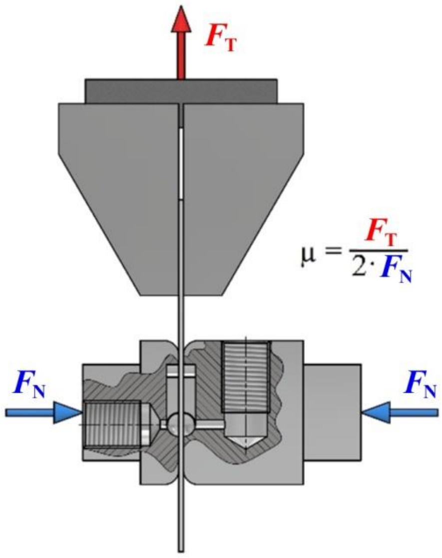

Fig. 6. Diagram of drawing a strip of sheet metal.

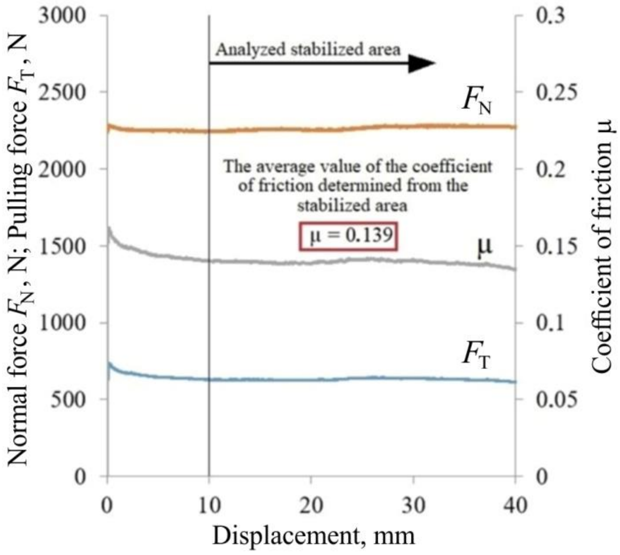

Fig. 7. Change of the COF and force values during friction test (F_N = 4 MPa, p_o = 0.6 MPa, η_k = 1135 mm^2/s).

2.3. CatBoost

Categorical Boosting (CatBoost) is a sophisticated open-source programme created by Yandex researchers and engineers (Dorogush et al., 2018). Its purpose is to enhance decision tree gradients. One of its notable benefits is its ability to smoothly handle categorical data, avoiding the requirement for preprocessing or encoding such data into numbers (Ibragimov et al., 2019). In addition, CatBoost provides precise forecasts using its default settings, eliminating the need for customers to manually alter parameters (Nabipour et al., 2017). By default, CatBoost builds a total of 1000 trees. Each tree is totally symmetrical and binary, with a depth of six and two leaves. The learning rate is dynamically calculated by considering the properties of the dataset and the number of repetitions, with the goal of selecting an ideal value. Decreasing the number of iterations helps speed up the training process, but it requires increasing the learning rate for maximum performance.

3. Results and discussion

CatBoost has expertise in accurately anticipating a wide range of objectives using its default settings. The analysis demonstrated that CatBoost accurately predicted the COF, achieving R^2 values of 0.955 and 0.894 for the training and testing datasets, relative mean square error (RMSE) 0.004 and 0.005 respectively. Moreover, when it comes to predicting average roughness *Sa*, CatBoost demonstrated remarkable performance with R^2 values of 0.992 for the training dataset and 0.885 for the testing dataset, 0.017 and 0.053 as RMSE values respectively.

The coefficient of determination R^2 value was determined according to the following relationship (Najm & Paniti, 2023):

$$R^2 = \frac{SS_{\text{tot}} - SS_{\text{res}}}{SS_{\text{tot}}} \tag{1}$$

where SS_{tot} is the total sum of squares:

$$SS_{\text{tot}} = \sum_{i=1}^{n} \left(y_i^{\text{target}} - \bar{y}\right)^2 \tag{2}$$

$$\bar{y} = \frac{1}{n} \sum_{i=1}^{n} \left(y_i^{\text{target}}\right) \tag{3}$$

and SS_{res} is the sum of the squares of residuals:

$$SS_{\text{res}} = \sum_{i=1}^{n} \left(y_i^{\text{target}} - y_i^{\text{predict}}\right)^2 \tag{4}$$

After substituting equations (2) and (4) into equation (1), we get (Najm & Paniti, 2023):

$$R^2 = \frac{\sum_{i=1}^{\text{n}} \left(y_i^{\text{target}} - \bar{y}\right)^2 - \sum_{i=1}^{\text{n}} \left(y_i^{\text{target}} - y_i^{\text{predict}}\right)^2}{\sum_{i=1}^{\text{n}} \left(y_i^{\text{target}} - \bar{y}\right)^2} \tag{5}$$

Figures 8a and 8b illustrate the impact of each data point on the model's predictions. The X-axis displays SHAP values, representing the influence of each input features. The Y-axis depicts all the features, where red indicates high levels and blue indicates low ones. Features on the right positively impact prediction, whereas those on the left have a negative impact. Positive and negative pertain to the impact on the model's output, not its performance.

a)

b)

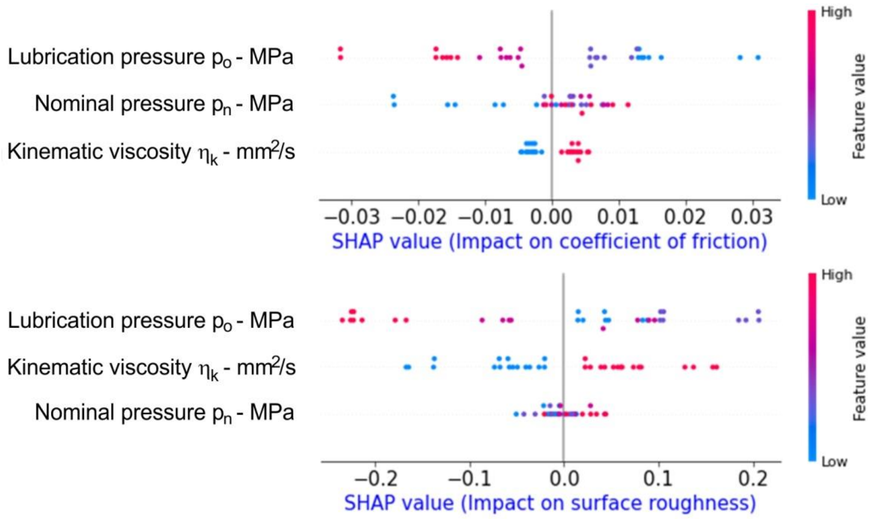

Fig. 8. Summary plot of SHAP value impact on a) coefficient of friction b) average roughness Sa.

A high lubricant pressure (depicted in red on the far left) decreases the estimated COF by about −0.03. If this attribute had not been included, the prediction would have been 0.03 or higher. The red point on the far right indicates a nominal pressure value of 0.01, implying that it lack results in a COF forecast below −0.01. The farther the distance a point is from the centre, the more significant the characteristic becomes.

Figure 9 shows the variation in SHAP values while predicting COF. Each line on the plot represents a unique model prediction. In Figure 10, the total positive feature values are presented. The representation is detailed in a SHAP decision plot (Fig. 10a), a SHAP bar plot (Fig. 10b), and SHAP force plots (Fig. 10c). The SHAP force plot offers extensive insights into the factors that have the most significant impact on the model's predictions for specific observations and displays the real values of the features.

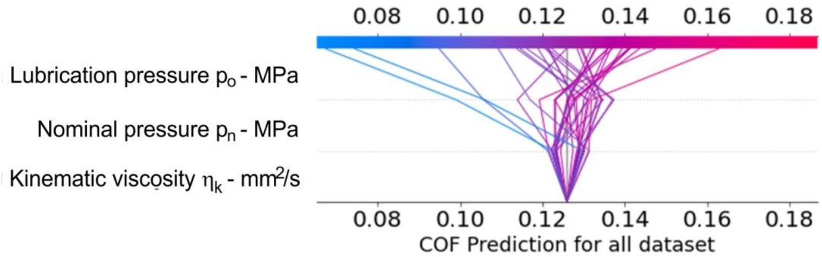

Fig. 9. All prediction values of COF using SHAP decision plot.

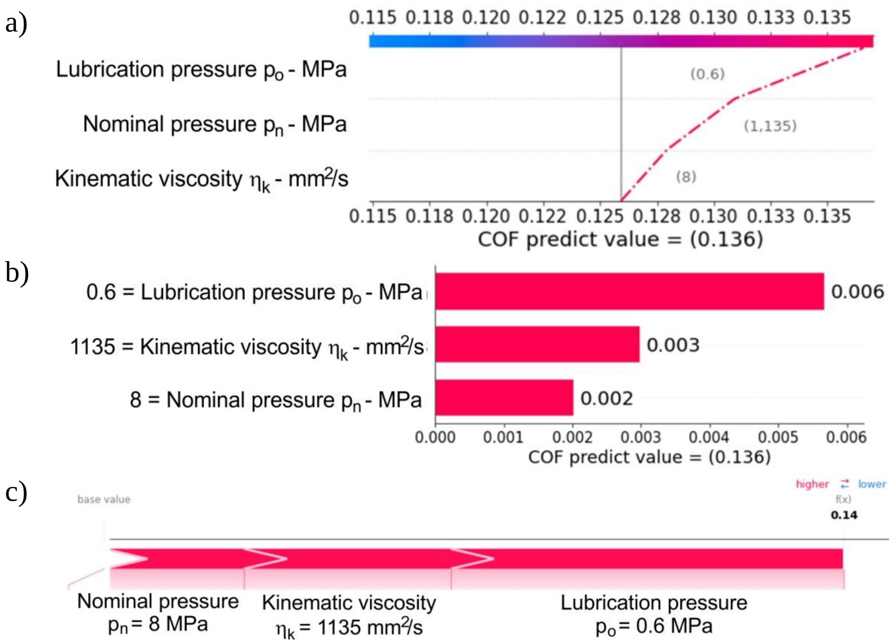

Fig. 10. Positive SHAP values using a) SHAP decision plot, b) SHAP bar plot, and c) SHAP force plot.

Figures 11 and 12 emphasise the significant factors that impact the COF and average roughness Sa, providing insights into their relative importance and how each feature influences the model's outcomes This approach evaluates the impact of each characteristic on each row of the dataset. Upon investigation, it is clear that changes in lubricant pressure significantly affect both COF and surface roughness, showing slight fluctuation. Kinematic viscosity has the most negligible impact on COF, whereas nominal pressure is the least significant factor in determining surface roughness.

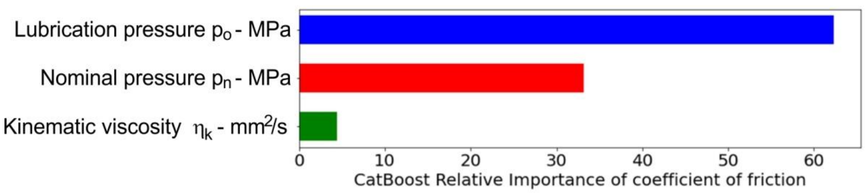

Fig. 11. Relevance importance of various input factors on the coefficient of friction.

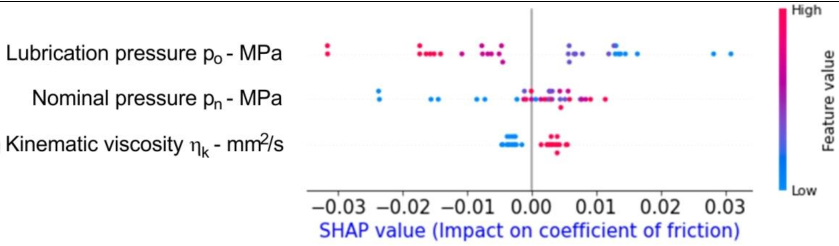

Fig. 12. Relevance importance of various input factors on the average roughness Sa.

4. Conclusions

The study used the CatBoost machine learning algorithm, created by Yandex researchers and engineers, to analyse and determine the factors affecting the coefficient of friction for three types of deep-drawing quality steel sheets. The researchers visualised the COF prediction models using Shapley's decision plot, which incorporates cumulative SHAP. The study results in the following conclusions:

- CatBoost demonstrated good prediction accuracy for the coefficient of friction and average roughness, with R^2 values between 0.995 and 0.992 for the training dataset and between 0.894 and 0.895 for the testing dataset.
- This approach emphasises the uniqueness of each process condition and showcases the intricate interaction of many components, each producing varying impacts on individual results.
- The research highlights the substantial influence of variations in lubricant pressure on both COF and surface roughness, with only minor fluctuations seen. Kinematic viscosity of lubricant has the least effect on COF, whereas nominal pressure is the least important component affecting surface roughness.

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Zastosowanie Wzbudzenia Kategorycznego do Modelowania Zachowania Tarciowego Blach Stalowych DC05 w Teście Ciągnienia Pasa Blachy

Streszczenie

Modelowanie współczynnika tarcia, chropowatości powierzchni i powiązanych procesów tribologicznych podczas kontaktu powierzchni blachy i narzędzi jest trudnym wyzwaniem ze względu na spłaszczanie, bruzdowanie i sczepianie nierówności powierzchni. Podczas tworzenia modeli analitycznych ważne jest, aby ostrożnie wybierać odpowiednie parametry procesu. Zapewni to produkcję elementów formowanych z blachy spełniających wymagane standardy jakościowe i pozbawione wad. W pracy analizowano wpływ ciśnienia nominalnego, lepkości kinematycznej smaru i ciśnienia smaru na współczynnik tarcia i średnią chropowatość powierzchni blach stalowych głębokotłocznych DC05. Do wyznaczenia współczynnika tarcia wykorzystano test przeciągania pasa blachy. W pracy tej wykorzystano algorytm uczenia maszynowego CatBoost, stworzony przez firmę Yandex, w celu oszacowania wartości współczynnika tarcia i chropowatości powierzchni. Przeprowadzono kompleksowe badania parametrów procesu tarcia. Modele przewidywania współczynnika tarcia na podstawie funkcji SHapley Additive exPlanations (SHAP) przedstawiono za pomocą wykresu decyzyjnego Shapleya. CatBoost charakteryzuje się wyjątkową dokładnością przewidywania potwierdzoną wartością R^2 w zakresie od 0.955 do 0.894 zarówno w przypadku zbiorów danych uczących, jak i testowych dla współczynnika tarcia, a także od 0.992 do 0.885 w przypadku średniej chropowatości powierzchni.

Słowa kluczowe: współczynnik tarcia, tarcie, kształtowanie blach, blacha stalowa, chropowatość powierzchni