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Prediction of forming limit diagrams using machine learning

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Abstract. Measuring forming limit diagrams (FLDs) is a time consuming and expensive process. Data-driven and artificial intelligence approaches have been used to facilitate finding relationships between alloy composition, and manufacturing processing conditions with mechanical properties of materials. Machine learning (ML) methods are a promising route to predict FLD of aluminium alloys that are increasingly used in automotive structural applications. In the present work, we developed a machine learning (ML) based tool to establish the relationships between alloy composition / thermomechanical processing route to the material's FLD, which is a measure of formability. Measured FLDs of various 5XXX and 6XXX aluminium alloys along with their chemical composition and thermomechanical processing parameters like homogenization, hot and cold rolling parameters etc. and the respective mechanical properties like n and r values were manually curated and stored in a database. A two-stage ML model was trained on this database. In the first stage, the minimum and maximum points of the minor strain were predicted using a feature set incorporating chemical composition, thermomechanical processing parameters, and n and r values using support vector regression (SVR). In the second stage, the predicted minor strain in the first stage was used as input in addition to the same feature set to predict the major strain using gradient boost regression (GBR). The trained ML model successfully predicted FLDs with R^2 value above 0.93. To study the impact of the difference between a predicted and a measured FLD on stamping simulation results, finite element simulations of a cross die were performed. The difference in draw depth of the cross-die using the predicted FLD and the measured FLD was between 5 to 10%. The current results show that ML can be a viable way for predicting FLDs.

1. Introduction

The automotive industry is gradually replacing structural components with lightweight aluminum alloys to produce energy efficient and / or high performance vehicles with a smaller carbon footprint [1-4]. Aluminum is also infinitely recyclable as such it poses as an environmentally sustainable materials solution. In the production of vehicle components, aluminum sheet is shaped with stamping, hemming, drawing and various other forming operations. In any forming operation, understanding the formability of the sheet material is crucial. The forming limit diagram (FLD) is one of the conventional ways of estimating formability of sheet materials [5,6]. The FLD is a graphical representation of critical major and minor strains, above which localized necking occurs, and is used as a measure of sheet formability.



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FLDs play an important role at the component design stage especially, when simulating the actual forming process in finite element models. Laboratory measurement of FLDs are very labor-intensive and time consuming [7,8]. Computational approaches have been developed to predict FLDs to overcome these challenges. Visco-plastic self-consistent (VPSC) [9] crystal plasticity models, which also implement the Marciniak–Kuczynski (M–K) [10] approach were shown to accurately predict FLD of metals [11–13]. Wu et. al [11] combined VPSC methods and finite element simulations with tensile experiments at different directions, bulge tests and texture measurements and accurately predicted the FLD of AA5182 alloy in a significantly shorter time than conventional FLD measurements.

There is currently no viable theoretical approach that can predict FLD of the sheet metal before it is manufactured. The biggest challenges in predicting a FLD for a material lies in the complex nature of the microstructural features. The microstructure of a sheet metal depends on the alloy's chemical composition and processing conditions. As such, developing a theoretical approach that can relate all the microstructural features to the formability is very difficult. An alternative approach can be application of artificial intelligence methods to construct relationships between alloy composition and processing conditions, and formability. With the increase in high performance computing resources and recent advances in artificial intelligence methods, machine learning (ML) has been demonstrated to be successful in predicting materials properties for various applications [14–17]. This paper investigates whether ML is a promising route to predict FLD of an aluminum alloy sheet.

Here, we employ ML techniques to predict FLD of aluminum alloys as a function of alloy composition and thermomechanical processing parameters, which determine the microstructure of an aluminum alloy sheet during production, and hence the formability of sheets [18]. We show that ML models can predict FLDs of aluminum alloys for the alloys that we included in our dataset. We validate the ML predicted FLD in a finite element (FE) simulation of a cross-die stamping process. Material failure predicted using ML predicted FLDs are comparable to failure predicted using experimentally measured FLDs. With further development, we believe that FLDs predicted by ML models can be used in forming operations, and can also be utilized to design new alloys and processing conditions to optimize formability of aluminum alloys.

2. Methodology

2.1. Dataset

Aluminum sheets are used in aerospace, automotive, packaging or construction applications. In each application, an aluminum alloy is selected based on its specific properties that are intrinsic to the alloy family. The composition of each sheet is set in the casting step in Figure 1. Following that, the cast ingot is subjected to a homogenization heat treatment to eliminate inhomogeneity in the microstructure before being fed into a breakdown mill, where it is rolled back and forth until the thickness reduces to a few inches as shown in Figure 1. Subsequently, the slab is rolled in a hot tandem mill and later cold rolled to the desired thickness. At the last step, sheets are heat treated, in continuous annealing and solutionizing heat treatment (CASH) processes. During the production flow in Figure 1, important processing parameters are automatically measured for each sheet. The composition of each alloy is measured using optical emission spectroscopy (OES) at the casting step. Homogenization time and temperature, hot rolling entry and exit temperatures, thickness reduction during hot and cold rolling, CASH time and temperature, and natural aging time are selected quantities that are recorded. The properties of produced sheets are finally measured using various mechanical, physical and chemical methods for quality control. For automotive applications, tensile properties are measured according to ASTM E8 standard, and FLDs are measured for each aluminum alloy to verify their desired formability. The details of the FLD measurement methodology is given in Ref. [11]. Briefly, the FLD of a sheet is measured using Nakajima hemispherical punch within the bounds of ISO-12004-2 standard. Thirteen geometries with a minimum of three samples per geometry are used to obtain sufficient data for an accurate FLD fit. The average of the three points are used to construct FLD for each alloy.

From the above data collection route, we manually curated our dataset that includes FLDs, and work hardening exponent (n) and plastic strain ratio (r) values from tensile tests for 18 different proprietary aluminum alloys belonging to 5XXX and 6XXX alloy family at T4 temper along with the detailed information of their chemical composition, and thermomechanical process history. Attributes were carefully selected from the process history of the sheet, which can affect its microstructure during the production to consider as a possible feature. Consequently, 27 features were collected for each target FLD.

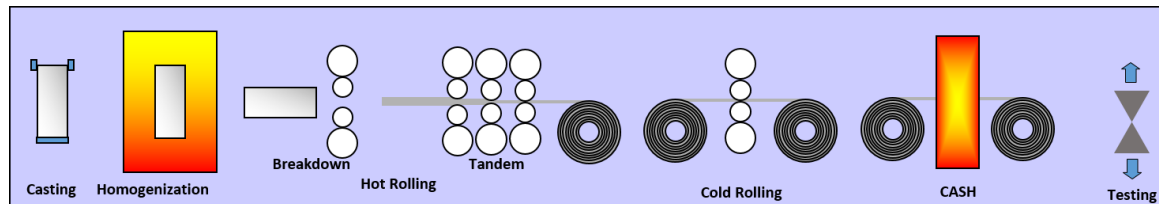


Figure 1. Processing route for rolled aluminum sheet production.

2.2 Machine learning workflow

The workflow using ML methods to predict FLD using the collected data is shown in Figure 2. As we have a feature-rich dataset with respect to limited number of FLDs, a feature selection and engineering procedure was essential to overcome the high dimensionality constraint of our existing dataset. The number of features were reduced based on their statistical importance. In feature reduction process, first, the ML model is trained on the initial set of features, and the importance of each feature is obtained. Then, the least important features were removed from the current set of features. That procedure was repeated on the remaining feature set, recursively until the desired number of features to select is reached. In the chemical composition data, as the variation and quantity of Ti, Zr, Zn, V and other trace elements were very small (<0.001), these elements showed less or no correlation with FLD data. Therefore, only chemical composition of six elements (Cu, Si, Mn, Mg, Fe and Cr) were included as features. Subsequently, we carried out recursive feature elimination, in which the features are ranked based on their contribution to the overall accuracy of the model. As a result, the number of features were reduced to 12, which included 6 elemental composition, 4 process parameters, along with the, n and r values from tensile tests (Figure 2).

Once the features were finalized, we used them to develop a ML model that can estimate uncertainty in the predictions as well. Details of the ML model are given in the Section 2.3 We kept two alloys' FLD data outside of our training set as a test dataset to assess the predictive capability of the trained ML model. In Figure 2 at the final step, to study the impact of the difference between a ML predicted and a measured FLD on stamping simulation results, finite element simulations of a cross die were performed. The maximum draw depths obtained in a FE stamping model of a cross die using the measured and predicted FLD were compared.

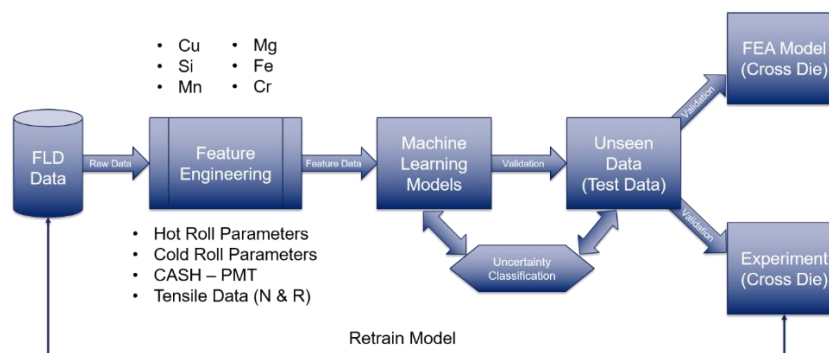


Figure 2. Machine learning workflow for predicting forming limit diagrams and validation.

2.3 Machine learning model

An FLD consists of major strain on the Y-axis and minor strain on the X-axis. As discussed above, the trained ML model predicts major strain as a complex function of the minor strains with the given chemical composition and processing parameters in the feature set. As minor strains are not in the feature set, first the range limits of minor strains for each alloy needed to be predicted. Accordingly, the ML model consisted of two stages that are sequentially coupled:

- i) Stage 1 – Prediction of minor strain range limits: Multi-output support vector regression (SVR) [19] is used to predict the range limits (max. and min.) of the minor strain with respect to chemical composition (Cu, Si, Mn, Mg, Fe and Cr), thermomechanical processing parameters (%Hot roll, Hot rolling exit temperature, %Cold roll, CASH temperature) and n and r values.
- ii) Stage 2 – Prediction of major strain as a function of minor strain values interpolated from the predicted range: The predicted minor strain in Stage 1 along with the engineered feature set (chemical composition, thermomechanical processing parameters and n and r) are used as an input to the second model, which used gradient boost regression (GBR) [20]. The variation in the major strain predictions within the ensemble of trees are used to estimate the uncertainty associated with each prediction [21].

The accuracy of the models were calculated as a ratio of the root mean squared error (RMSE) to R^2 . The SVR and GBR models' hyper-parameters, which are intrinsic parameters that are adjusted for each model were optimized to minimize this objective function (RMSE/ R^2), and achieve the highest training accuracy possible. The hyper-parameter tuning is performed using a global genetic algorithm optimization scheme. We use leave-one-out cross validation score to estimate the accuracy and evaluate the models. This method is commonly used for small datasets, such as in this work. In leave-one-out-cross-validation, one randomly selected data point is excluded during training, and is used to validate the predictive accuracy of the model after training. This allowed us to minimize overfitting our model to the training data and gave the ability to create a generalized model. All ML model developments were carried out using Scikit-LEARN package in Python [22].

2.4 Finite element simulations

Finite element simulations of stamping of a cross-die geometry (see Figure 6) was carried out using commercial stamping simulation package, AUTOFORM. The tolerance between the dies was set at 2.5 mm and the mesh was auto selected using the AUTOFORM default settings. The material file was constructed using the hardening curves generated from tensile test data and the measured and predicted FLDs were used as an input. The friction coefficient was arbitrarily chosen as 0.1 and the clamping load in simulation was chosen to be 150 kN so that neither wrinkling, nor localized thinning occurred. The simulation was run in displacement control to a draw depth of 60 mm.

In the FE model, a FLD is used to predict the areas with risk of splits as a post-processing step. The max. draw depth was computed when any material point reached the limit strain. We compared the maximum drawing depths obtained with predicted and measured FLD to test the usability of predicted FLDs in forming simulations.

3. Results and discussion

As stated earlier, ML model consisted of two stages. Figure 3a shows the fitting result of the Stage 1 for predicting the minor strain range limits compared to measured minor strain range limits. Accordingly, accuracy of SVR model in Stage 1 achieved an R^2 of 0.93 and the RMSE of 0.01. The predictions in Stage 1 for minor strains were later used as an input in Stage 2 in addition to the features. Figure 3b shows the predicted major strain values compared to measured major strain values as estimated using GBR. The R^2 score for the Stage 2 model is 0.98 and the RMSE value is 0.006. In both models R^2 and RMSE values imply achievement of high accuracy in predicting major and minor strains that form the FLD. The high accuracy of FLD prediction can also be seen in Figure 4 that compares original (measured) and predicted FLD for a proprietary 6XXX aluminum alloy, which was included

in the training dataset. In Figure 4, shaded areas around the FLD curves show the uncertainty in the predictions calculated from the ensemble of models in GBR. The low uncertainty associated with our predictions further confirms the high confidence of ML model in predicting FLD of this alloy.

To further test the predictive power of the above trained ML model, FLD of two additional AA6XXX proprietary alloys were estimated, which was not included in the training set. FLD prediction results, and the uncertainty estimated in GBR models for these alloys are shown in Figure 5. The graphs are an overlay of the predicted FLD over the measured FLD. For unseen data, ML model resulted in R^2 of 0.96 and RMSE of 0.009. Figure 5 shows that for Alloy A, the difference in the minimum point in FLD (FLD_0) of ML predicted and measured FLD was 0.02. For Alloy A, there is also little difference (<0.02) in FLD at the biaxial and uniaxial regions. In general, ML model under-predicted the formability of Alloy A, but within only a 5-10% from the measured results. In Figure 5, for Alloy B the predicted results are even better; the difference between the FLD_0 for the predicted and measured FLD is less than 0.01. Overall for alloy B, the difference between measured and predicted FLD is less than 5% error. Consequently, our trained ML model is successful in predicting FLD of aluminum alloys that were not in the training set.

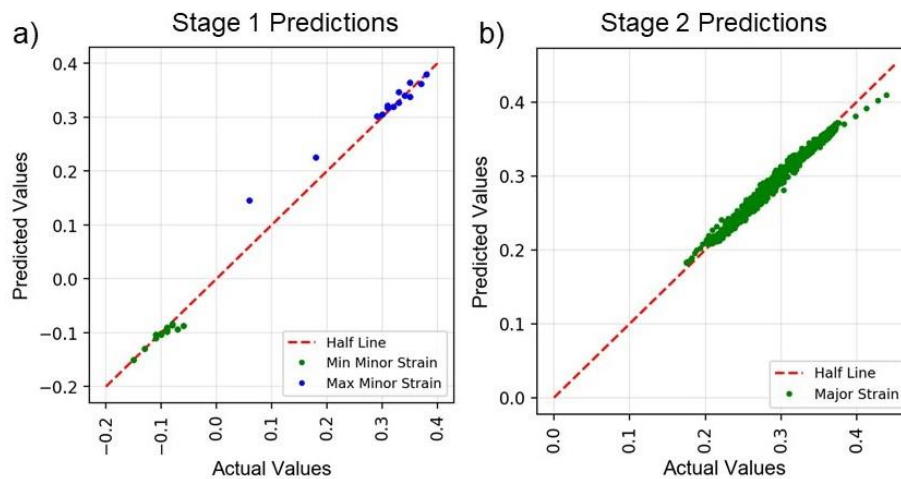


Figure 3. Fitting results for a) step 1 and b) step 2 predictions for minor and major strain, respectively.

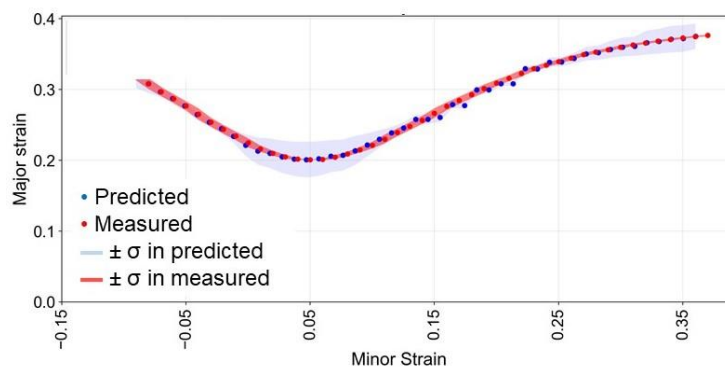


Figure 4. Predicted FLD of an alloy overlayed on an original measured FLD. Blue shaded areas show the uncertainty in the gradient boost regression and red shaded area show the standard deviation in the measurements.

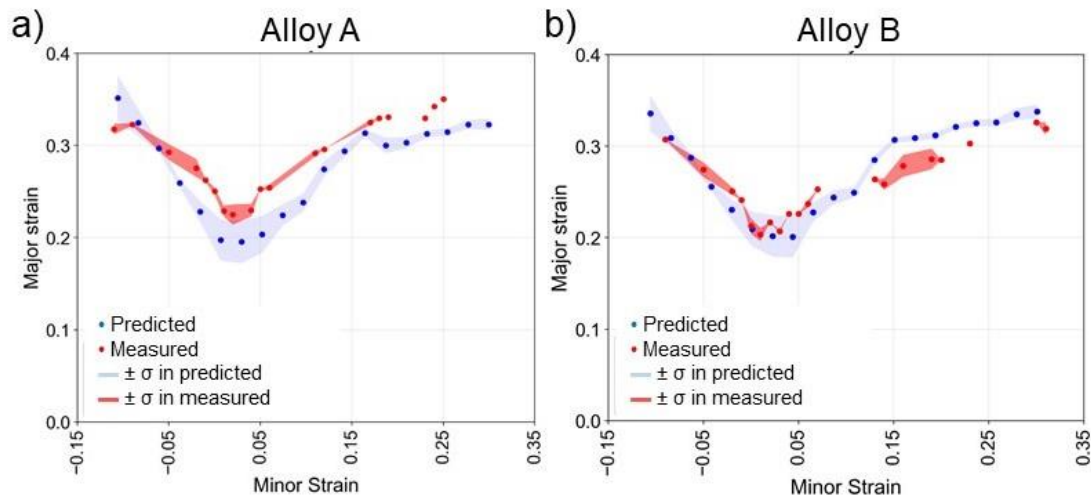


Figure 5. Predicted FLDs for 6xxx aluminum alloys, namely a) Alloy A and, b) Alloy B, which were not included in the ML model training data.

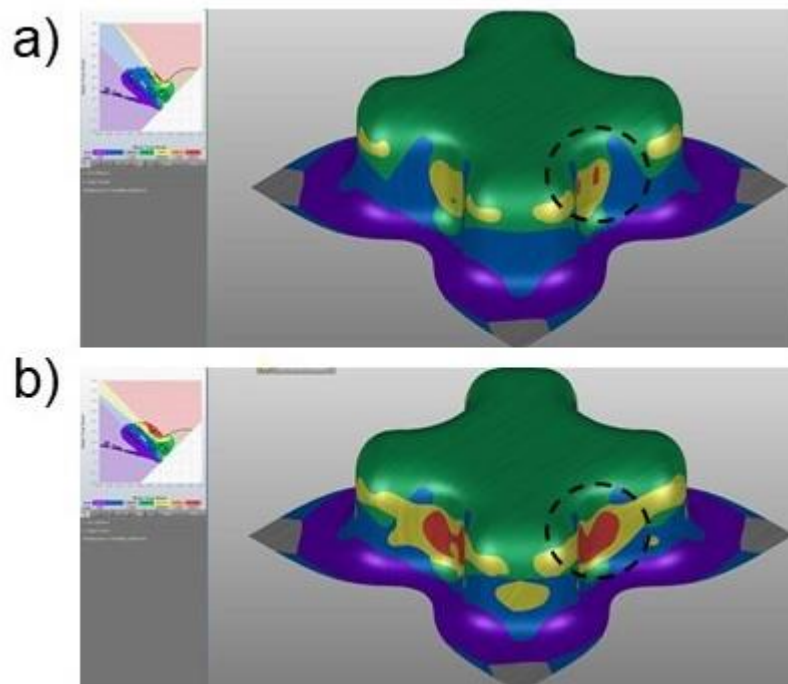


Figure 6. Stamping simulation results of a cross-die geometry using a) measured, b) predicted FLD for 6XXX alloy A.

We further studied the impact of differences between predicted and measured FLD by using them in a stamping simulation. Figure 6a shows the areas at risk of failure in the stamping of a cross-die, when experimentally measured FLD was used to estimate areas of risk of splits. Figure 6a shows that the failure occurs on the sidewall of the cross-die and %Area of risk of splits is estimated as 7.8%. Similarly, when the ML predicted FLD was used, failure occurred on the sidewall of the cross-die as shown in Figure 6b, but with a higher 16.2% Area of risk of splits. When an experimental FLD was used cross-die could be drawn up to a depth of 36 mm without indication of failure, whereas when predicted FLD was used, maximum draw depth was predicted to be 34.5 mm. As a result, ML predicted

FLD estimated a draw depth within 8% when compared to that with the measured FLD. This under estimation of the draw depth should be expected, since ML model also under predicted the FLD.

It is well known that the FLD is affected by the sheet thickness [11] and sheets with higher thickness have better formability. To test whether our model captures this effect, we changed the % reduction of hot and cold rolling parameters, as thickness of the sheet was not one of the feature in the original dataset. The predictions of our model are presented in Figure 7, which shows that formability improves with increasing sheet thickness similar to the conventional wisdom.

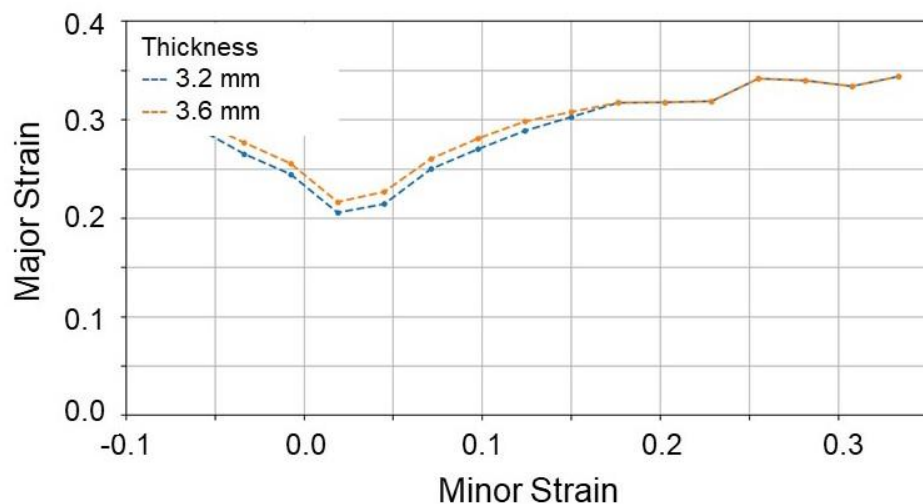


Figure 7 Effect of thickness on the FLD for Alloy A

In summary, a ML method developed in this study successfully predicted the FLD for alloys based on their relation to chemical composition, processing conditions and mechanical properties like n and r values. These features were selected from the parameters that were employed in aluminum sheet production, which are related to the microstructure of aluminum alloys, but not necessarily the most complete attributes that define formability of aluminum sheets. In addition, the model assumes all features are independent of each other, which is generally not the case in real conditions. The predictions obtained from the ML model are within 10% error compared to measurements, which is reasonable considering that such a prediction would otherwise not be possible without measuring the FLD. The current model is trained using 5XXX and 6XXX alloy data, so that, this model is not expected to predict FLD for wide composition ranges of aluminum alloys. Additional data needs be included from a variety of aluminum alloys with wide range of composition and thermomechanical process parameters to increase the capability of models in predicting FLDs. Within these guardrails, the present ML model can be used to evaluate FLD of 5XXX and 6XXX alloys.

In a future work, additional features from processing parameters, elemental properties and possibly micrographs will be considered. Furthermore, if an accurate model that would not use n and r values can be developed, it would also eliminate use of tensile test data to predict FLDs. Such a model would allow prediction of FLDs before the sheet material is produced.

4. Conclusions

A machine learning (ML) workflow was developed to predict forming limit diagrams (FLDs) of 5XXX and 6XXX aluminum alloys based on features that included alloy composition, processing parameters and n and r values from tensile tests. The ML model had an overall accuracy of R^2 greater than 0.93 for the training dataset. For 6XXX alloys that were not included in the dataset, ML model slightly under-predicted the FLD₀ of the FLD. The use of predicted FLD in finite element simulations resulted in 5-10% lower achievable draw depth in stamping of a cross-die. The ML model, with further developments, may be, used to gain insights into the relationships between alloy composition and

thermomechanical treatments for designing new alloys to optimize formability of 5XXX and 6XXX aluminum alloys.

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