Prediction of forming limit diagrams from tensile tests of automotive grade steels by a machine learning approach

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Abstract. Steels’ formability is extremely important to the automotive industry. This property is usually assessed through the Forming Limit Diagrams (FLDs), which comprise the regions of maximum strains, where neither necking nor fracture of the material is observed. In this work, the use of Machine Learning algorithms was evaluated for the FLDs’ construction, based on the tensile properties of a group of steels. A set of historical data, consisting of tensile tests values and measured FLDs, based on Nakajima method of various AHSS, HSLA and IF steels, was used to build the model. In order to evaluate the predictive capacity of the model, experimental and Keeler-Brazier FLDs were compared. The proposed method was able to predict with great correlation and low mean error the FLDs of those materials. The results show a viable route for predicting FLDs based on tensile properties.

1. Introduction
Forming Limit Diagrams (FLDs) are widely used in the automotive industry to assess the strain limits in processes involving the mechanical forming of sheets metals [1].

Even though the use of FLDs is associated with cost reduction, evaluation of stamping dies and materials selection, the experimental process to acquire its information requires time, laboratory resources and it is limited to the availability of relatively large samples [2,3].

The study of the correlation between FLDs and mechanical properties in tensile tests is a field of constant development and improvement [1]. The ongoing studies are based on classic theoretical models, such as Keeler-Brazier (KB) and Marciniak-Kuczynski (MK) [4], crystal plasticity [4,5], as well as accumulated damage models, which are consolidated methods for assessing the formability of materials [5]. However, since the application of these models depends on an exhaustive number of tests and calibrations, artificial intelligence techniques have been surging as a feasible alternative to reverse these problems. For instance, with the improvement of the processing capacity of new computer systems, Machine Learning (ML) algorithms have been applied for materials properties prediction, considering their distinct applications [4].

In this context, the present work investigated the formability prediction, evaluated through the FLDs of different types of steels applied in the automotive sector, through the use of ML algorithms. The predicted results were compared with the experimental data in order to assess the robustness of the models. To do this, it was used the FLDs based on Nakajima method, in accordance with ISO 12004-2 standard [6], and Keeler-Brazier theoretical FLDo, which comprises the value of the true major strain ($e_1$) when the true minor strain ($e_2$) is equal to zero.
2. Materials and methods

2.1 Historical database
A database consisting of a set of historical tensile properties and FLDs at necking of different automotive steels grades was used. The specification limits used in this work are shown in table 1. It is worth mentioning that the referred steels are used in a range of applications, such as A and B pillars, roofs, doors, among others.

| Automotive Steels Grades | Ultimate Tensile Strength Range (MPa) | Thickness Range (mm) |
|--------------------------|--------------------------------------|----------------------|
| DP and CP                | 490 to 980                           | 0.60 to 2.00         |
| TRIP                     | ≥ 780                                | 1.20 to 1.60         |
| HSLA                     | 350 to 460                           | 0.65 to 2.90         |
| IF and BH                | 140 to 240                           | 0.50 to 2.00         |

The database, consisting of 62 different samples of cold-rolled and hot-rolled steels, industrially produced by Usiminas SA, was manually built. Each sample had its respective values of thickness (t), Ultimate Tensile Strength (UTS) and Yield Strength (YS), as well as the anisotropy coefficient (R), strain hardening (n) and uniform (EU) and total (EL) elongations. The listed mechanical properties values were obtained from tensile tests, carried out according to the ASTM E8 standard [7]. The FLDs were empirical obtained in accordance with the ISO 12004-2 standard, using the AM3 method [6] and a Nakajima hemispherical punch with a diameter of 100 mm. For each sample, the corresponding major and minor true strains at the onset of necking were used to construct the FLDs dataset. In this work, only the geometries of uniaxial tension, plane strain and equibiaxial stretching strain paths were used to train, validate and test the machine learning models.

Furthermore, the estimated measurement uncertainty associated with the FLDs test procedure was calculated in accordance with the ISO/IEC Guide 98 [8] and based on the works of Refs. [9,10].

2.2 Pre-Processing
The data of tensile properties presented different measurement scales, ranging from 0.05 (strain hardening values) up to 1000 (UTS values), which could cause certain inefficiency in the learning steps of the machine learning algorithms [11,12]. To overcome this problem, it was used a scale function, as reported in equation (1), to transform the database into numbers between 0 and 1, in order to minimize any interference.

\[ Scale(x) = \frac{x - \min(x)}{\max(x) - \min(x)} \] (1)

Where \( x \) is the value to be scaled as a function of the maximum and minimum points of each property attribute.

2.3 Modelling of Machine Learning Algorithms
To build the FLDs prediction models, supervised machine learning methods conditioned to the caret (Classification and Regression Training) library [13], belonging to the free statistical software R [10], were used. For the purpose of the study, it was evaluated the performances of widely used ML algorithms, described as follows: K-Nearest Neighbor (KNN) [15], General Linear Regression Models (GLM) [1], Support Vector Machine (SVM) [16], Cubist (CUB) [15], Random Forest (RF) [17], and Lasso and Elastic-Net Regularized Generalized Linear Models (GLMNET) [18].

To use those models, the dataset was divided into three categories: training, validation, and test. The training data was used to adjust the models, while the validation one, to select the model based on its
best predictive performance. The test data, in its turn, was used to evaluate the generalization (prediction) error of the selected ML algorithm. In this work, 95% of the data (59 samples) were selected as the training-validation set, and the remained 5% (3 samples), employed as the test set.

As the database was small and as an attempt to avoid overfitting, the resampling or cross-validation k-fold technique was applied in the training step [11]. Details of k-fold cross-validation methods are described in Ref. [19]. In this work, we used a repeated k-fold cross-validation, with 10 folds (k=10) and 5 repetitions per fold.

Then, the ML models were first trained, considering the original training dataset. The prediction results were evaluated based on the errors found for each model when considering the original data. The performance of the models was calculated based on the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the Coefficient of Determination (R²) values [11]. The hyperparameters of each model were adjusted to minimize the RMSE values and approximate the R² values to the unit, as an attempt to maximize the correlation between the values predicted by the model and the empirical data.

2.4. Prediction of Forming Limit Diagrams
To evaluate the prediction errors of the proposed method, the FLDs predicted by the ML algorithms were compared to the experimental FLDs values. Moreover, the predicted FLDs were compared to the theoretical values obtained through the Keeler-Brazier model. This evaluation was done for CP800, DP800 and TRIP800 steels (test set), which did not participate in the learning and validation steps of the algorithms.

3. Results and discussion

3.1 FLDs construction
Figure 1 shows the FLD of the DP800 steel not used in the training nor test dataset. In this case, the curve of a DP800 with 1.6 mm thickness is represented, considering the measurement uncertainty (uncertainty band) and the safety margin (dashed line). It is worth pointing out that the safety margin was calculated considering the relative distance as 20% of the mean FLD in terms of major true strain [20]. Moreover, the major source of uncertainty estimated for all 62 samples was associated with the test repeatability and the measurement system accuracy, contributing with 75% and 20% of the overall uncertainty, respectively.

![Forming Limit Diagram (FLD)](image.png)

**Figure 1.** Forming Limit Diagram (FLD) at the onset of necking for a DP800 steel with 1.6 mm thickness, considering the safety margin and the measurement uncertainty.
Additionally, it can be observed in figure 1 that the equibiaxial stretching strain path presented the higher scattering of the experimental data. This behavior was noted for all samples in the dataset. The values of the uncertainty band (expanded measurement uncertainty) presented a good agreement with those obtained by Janssens et al. [10] and stands within the region of safety margin. Nevertheless, further investigations are needed in order to understand the relations between the procedure to detect the onset of necking and the scattering of data, considering different strain paths.

3.2 ML training performance
The average results of the training steps, using the k-fold cross-validation method, are reported in tables 2 and 3 in terms of MAE, RMSE and $R^2$ parameters values for major and minor true strains, respectively.

| Table 2. Average MAE, RMSE and $R^2$ values of the ML models for the major true strain ($e_1$). |
|---------------------------------|---------------------------------|---------------------------------|
| Uniaxial Tension               | Plain Strain                    | Equibiaxial Stretching          |
| MAE    | RMSE     | $R^2$   | MAE    | RMSE     | $R^2$   | MAE    | RMSE     | $R^2$   |
| CUBIST | 0.031    | 0.037   | 0.999  | 0.017   | 0.021   | 0.940  | 0.044   | 0.050   | 0.606  |
| GLM    | 0.036    | 0.043   | 0.980  | 0.024   | 0.030   | 0.855  | 0.054   | 0.063   | 0.498  |
| GLMNET | 0.031    | 0.037   | 0.990  | 0.018   | 0.022   | 0.875  | 0.044   | 0.049   | 0.551  |
| KNN    | 0.040    | 0.046   | 0.977  | 0.027   | 0.032   | 0.834  | 0.048   | 0.056   | 0.505  |
| LM     | 0.037    | 0.043   | 0.982  | 0.024   | 0.030   | 0.827  | 0.055   | 0.063   | 0.497  |
| RF     | 0.033    | 0.041   | 0.981  | 0.023   | 0.027   | 0.833  | 0.046   | 0.051   | 0.555  |
| SVM    | 0.043    | 0.056   | 0.968  | 0.024   | 0.030   | 0.818  | 0.053   | 0.059   | 0.534  |

| Table 3. Average MAE, RMSE and $R^2$ values of the ML models for the minor true strain ($e_2$). |
|---------------------------------|---------------------------------|---------------------------------|
| Uniaxial Tension               | Plain Strain                    | Equibiaxial Stretching          |
| MAE    | RMSE     | $R^2$   | MAE    | RMSE     | $R^2$   | MAE    | RMSE     | $R^2$   |
| CUBIST | 0.029    | 0.034   | 0.800  | 0.010   | 0.011   | 0.427  | 0.064   | 0.075   | 0.345  |
| GLM    | 0.378    | 0.043   | 0.772  | 0.013   | 0.015   | 0.421  | 0.071   | 0.083   | 0.460  |
| GLMNET | 0.026    | 0.032   | 0.790  | 0.009   | 0.011   | 0.506  | 0.059   | 0.069   | 0.431  |
| KNN    | 0.031    | 0.037   | 0.785  | 0.010   | 0.012   | 0.392  | 0.064   | 0.073   | 0.473  |
| LM     | 0.038    | 0.044   | 0.713  | 0.013   | 0.015   | 0.448  | 0.071   | 0.088   | 0.395  |
| RF     | 0.028    | 0.035   | 0.885  | 0.009   | 0.011   | 0.573  | 0.061   | 0.072   | 0.279  |
| SVM    | 0.032    | 0.041   | 0.738  | 0.008   | 0.011   | 0.486  | 0.063   | 0.073   | 0.395  |

It can be observed that the adjustment failures (greater values of MAE/RMSE and lower values of $R^2$) are in the true strain pairs ($e_2, e_1$) associated with the equibiaxial stretching strain path, which means that greater prediction errors are expected in this case, especially for the data of minor true strain ($e_2$).

3.3 Selection of best fit algorithms
As can be noted from the above results, the best performance models, based on MAE/RMSE/$R^2$ parameters are related to the CUBIST, RF and GLMNET algorithms. Although, the final model was based on the selection of the best fit algorithms, which comprise the lowest mean prediction error, considering the major true strain ($e_1$), as compared to the experimental data for the CP800, DP800 (with 1.2 mm thickness, in this case) and TRIP800 steels. The relative errors between the experimental data
and those obtained by ML, as well as the relative errors for the FLD₀ (plane strain) predicted by the Keeler-Brazier equation [1], are illustrated in figure 2.

![Relative Mean Error (%)](image)

**Algorithm Model**

**Figure 2.** Relative mean errors of the ML evaluated models considering the predicted values and the real data of the true major strain (e₁).

It is observed that the biggest errors occurred for the equibiaxial stretching strain path. As stated earlier, these results are most associated with the lowest values of the R² parameter and the higher values of MAE and RMSE. Furthermore, the results showed that the ML models presented a lower mean error when compared to the Keeler-Brazier equation.

However, considering the usual scattering of the experimental data and the measurement uncertainties related to the tests and the relative safety margin usually employed in practical application of the FLDs, it is possible do consider that the KNN, SVM, RF, GLMNET and CUBIST algorithms have a good prediction agreement with the experimental data, despite their relative errors range (3 up to 18%). Similar results were found by Chheda and co-workers [3] during the prediction of FLDs in aluminum alloys. It is noteworthy, though, that the authors worked with an industrial processing data and chemical composition of aluminum alloys, which were not evaluated in this work.

As a result, and as well illustrated by figure 2, it can be stated that, in this case, the results of the predicting models showed a better fit to the experimental data than the one obtained by the Keeler-Brazier equation [1].

3.4 Prediction of FLD

Figure 3 shows that the mean difference between the predicted and the measured FLD₀s (plane strain) was -0.01 for CP800 and TRIP800 steels. For the DP800 steel with 1.2 mm thickness, this difference was 0.009. When considering the uniaxial tension and the equibiaxial stretching strain paths, the mean differences values were -0.003 and +0.003, respectively, for all the three steels evaluated. It is possible to be noted, however, that the larger deviations are in the TRIP800 FLD, especially for the equibiaxial stretching strain path.

In general, the final model underpredicted the FLD₀ and the uniaxial tension strain paths and overpredicted the equibiaxial stretching strain path. The mean absolute relative errors were within 1-6% for uniaxial tension, 6-11% for FLD₀ and 2-13% for equibiaxial stretching strain path.
The results obtained from the final model showed a good adhesion to the experimental data, which suggests the possibility of using it to predict the FLDs as a function of tensile properties only. Thus, it is possible to assess the formability of the steels even before their application, reducing the risks and costs arising from failure due to wrinkling, thinning and fracture during stamping. Moreover, the model can be used to generate a material database to sheet metal forming simulations when the experimental data is not available yet. Future works should consider the prediction of FLDs at fracture and integrate different strain paths.

**Figure 3.** Predicted and real (original measurement) FLDs for: a) CP800, b) DP800 and c) TRIP800.

4. Conclusions

Machine Learning algorithms were used to predict the FLDs at necking of automotive steels based only on tensile properties. The average relative error between the experimental results and those obtained by the final prediction model was 7%. In general, the proposed ML model underpredicted the FLDs and the uniaxial tension strain paths and overpredicted the equibiaxial stretching strain path, when compared with the experimental FLDs of CP800, DP800 and TRIP800 steels. This value can be accepted for practical applications given the scattering of experimental data, the measurement uncertainties, and the use of safety margins in FLDs construction.

The results achieved with the final model also suggest that this approach can be implemented in the development of new steels, reduction of costs of try-outs operations, and in the formability evaluation of steels even before their application into die press with reasonable accuracy. Future works and developments should consider the prediction of FLDs at fracture and integrate different strain paths. Furthermore, it can be considered the use of industrial features, such as chemical composition and
processing parameters, as input data in the prediction models. In this way, the effect of the industrial features in the materials’ behavior will be better understood, allowing changes during the industrial production that should improve the steels’ formability.

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