Accelerating Sheet Metal Forming with AI

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Abstract

Designing sheet metal parts is a challenging and specialized task that demands a deep understanding of engineering principles and extensive industrial experience. This process relies heavily on heuristic knowledge and practical expertise acquired over many years. While this approach has been practical, it is inherently time-consuming requiring expert involvement and prone to human error, limiting the efficiency and accuracy of the design process.

With the development of artificial intelligence (AI), a significant transformation is underway in the design and optimization of sheet metals, with notable examples such as W. L. Chan et al. [2], A. Derogar et al. [3] and F. Han et al. [10], among many others. AI methods are now being integrated into the design process to streamline operations and to efficiently reduce the time required for the design forming process. These methods aim to simplify the inherently complex design tasks, reduce reliance on manual expertise, and significantly shorten the time required to develop and refine designs. This shift enhances the overall efficiency of the design process, but this needs to be further investigated.

Simulations are a commonly used approach in the design of sheet metals but further extends the design workflow and limits efficiency. To address these challenges, we specifically explored Multi-Layer Perceptrons (MLPs) among suitable AI methods. MLPs are especially in addressing engineering design challenges and minimizing errors in experimental data. They are well-suited for optimizing design parameters and making predictions based on datasets, which would be too time-consuming with traditional simulation methods, as noted in S. Kashid et al. [1] and W. L. Chan et al. [2]. An MLP-based approach can significantly reduce the time spent on simulations by learning from existing data and providing faster and more accurate predictions.

This paper aims to develop a methodology that integrates a MLP into the design of sheet metal forming to accelerate the processes. Our approach approximates the feasibility and formability parameters and evaluate the performance of these parameters predicted based on material properties, geometry of the sheet metal part, lubrication and process parameters enabling the identification of optimal designs at a faster rate. In this paper, sheet metal forming simulations using OpenForm are employed to generate the training data for our MLP model. The trained MLP is then used to predict the optimal configurations of different metal parts. Our methodology does not only accelerate the design process but also provides reliable means of exploring design alternatives and assessing their robustness.

To ensure the reliability of the developed MLP, its performance is compared with other AI models. The results show that our proposed method predicts design configurations with least error compared to other AI models. Furthermore, it performs well not only on the targeted metal part designs used for model training but also on other types of designs, saving time in the forming process and reducing the time taken to explore the design space from 5 hours to less than 1 second. What distinguishes our approach is that it aims to be generalized allowing for broad applications across various metal part designs. This integrated approach offers a robust and efficient solution for optimizing sheet metal part design, setting a benchmark for future advancements in the field.

1. Introduction

The design of sheet metal parts is an important task in engineering because it directly impacts the quality of final products, playing an important structural role in numerous industrial applications. The sheet metal forming refers to the stretching of a flat sheet metal blank between a punch and a die, and the process includes drawing, bending and to some extent, blanking and stretch forming. Experimental and FE-based simulation works yield favourable outcomes in analysing the process using a simulation software like OpenForm, LS-Dyna or AutoForm. However, the sheet metal forming process is still complex, expensive and highly dependent on heuristic knowledge and practical expertise acquired over many years, as noted in W. L. Chan et al. [2]. Although various computer-aided systems, including Computer-Aided Design (CAD) and Computer-Aided Engineering (CAE), have been utilized to simplify the complex processes and save time, domain experts are still essential for making decisions at various stages of design process. Despite the high costs the required expert experience, this process is still widely adopted in industry to design sheet metal parts due to its repeatability and productivity.

Thanks to the development of AI solutions, many data-driven approaches have been proposed to solve complicated problems in almost all areas of engineering. Instead of the conventional process using experimental and simulation techniques, many researchers have used data-driven solutions for various applications, including manufacturability analysis, process planning and finite element simulation in the sheet metal forming process. The development of sheet metal parts typically involves multiple design parameters. Even a minor change in any targeted design parameter results in a new design configuration, requiring additional simulations to evaluate the structural behaviour of sheet metals. Identifying the optimal result is very time-consuming, as it requires running various simulations, each with a different set of parameters, until the optimal and feasible configuration is achieved. To overcome this challenge, neuronal networks can be employed to identify complex non-linear relationships among the design parameters.

This paper proposes a methodology that integrates MLPs to explore design space to determine the best fitting design solution and the desired parameter configuration in the sheet metal forming process. Particularly, this paper contributes by:

- Providing an approach that utilizes MLPs to accelerate the design process of sheet metals
- Experiments and result comparisons between the proposed approach, prior research, and recently introduced AI models
- Evaluating the proposed solution using real-world data
- Assessing the suitability of addressing two key issues that should be considered when implementing data-driven solutions

This paper is structured as following. Section 2 covers the related works to sheet metal forming and recent trends in machine learning that can leverage the data from sheet metal forming process. Section 3 describes our approach in detail. Section 4 follows with our experimental setup, including datasets, AI models used for performance comparison, and evaluation methods in detail. Section 5 discusses and examines the experimental results. Section 6 provides an in-depth exploration of potential challenges and scenarios encountered when integrating data-driven solutions in real-world applications. Our intuitive and user-friendly application, seamlessly integrating our proposed model, is highlighted in Section 7. Section 8 concludes our research by summarizing the key contributions and covering the findings from the research and experiment. Finally, suggestions for potential improvements are provided. In the appendix, we offer a comprehensive description of the architecture of the proposed model, including the number of layers and neurons that define the model's structure.

2. Related Work

H. Liu et al. [18] highlighted that AI methods are widely utilized in sheet metal forming. However, most of the collected metal forming data would lack critical information of the formed products and metal forming process itself. This leads to unstable and inaccurate predictions while applying the AI methods on a different metal forming process since the available training data is insufficient. In A. Derogar et al. [3], an AI model was designed to predict forming limit diagrams for titanium and aluminium alloy sheets. W. Muhammad et al. [4] proposed an AI model to predict microstructural features such as the size, shape, and volume fraction. In I. Czinege et al. [21], an AI model was proposed to predict minor and major strains based on forming limit curves. A. Marques et al. [22] and T. Trzepieciński et al. [23] also proposed AI models for predicting fracture strain and friction, which are key outputs in sheet metal forming. To the best of our knowledge, there has been limited research on predicting various design parameters using AI methods in the context of sheet metal forming process, and no comprehensive methodology has been deployed. Papers we have reviewed have focused on applying AI methods in predicting a limited number of targeted design parameters, which are trained on a small amount of metal part and material type data. When applying an AI method trained on a small amount of metal part and material type data to real-world scenarios, it may not perform well when new metal parts or materials are introduced. This is because the trained AI model has not learned about these new metal parts and materials, making it an exclusive model rather than an inclusive one. The model we proposed aims to be inclusive and trained on data from 10 different metal parts as illustrated in Figure 3. We have confirmed that it performs well when new metal parts are introduced. Additionally, since the model was trained to predict 10 feasibility and formability parameters simultaneously, it has learned to capture the relationships across these parameters and make accurate predictions.

Data can be appeared in various formats, such as tabular, time series, images, text, audio, and video. In S. Kashid et al. [1], a review paper, the existing literature on the application of AI methods to sheet metal forming process summarizes data in tabular format. Additionally, it was also confirmed that the data from W. L. Chan et al. [2], A. Derogar et al. [3], F. Han et al. [10], A. Alsamhan et al. [19], I. Czinege et al. [21], A. Marques et al. [22], and T. Trzepieciński et al. [23] all followed the tabular data format. The data acquired for training our proposed model is also in tabular format. Since the data is in tabular format, many researchers have conducted experiments using AI models specifically designed for tabular data format. Among these, MLPs have been a popular choice due to its effectiveness in handling structured data. In the field of AI, regardless of the industry, selecting an MLP-based model for tabular format has long been considered the obvious and default choice. However, the AI field is advancing rapidly, and new models capable of handling tabular data are continually being developed. These emerging models provide alternative approaches to the traditional MLP, offering opportunities to improve performance and adapt to the evolving demands of AI applications. To the best of our knowledge, we have not come across a recent study that compares AI models specifically designed for tabular data. In this paper, we aim to explore the potential of new AI models for this purpose. Notable among these AI models except MLP are TabTransformer by X. Huang et al. [7] and TabNet by S. Ö. Arik et al. [8]. TabTransformer, introduced in 2020, is a deep learning architecture for tabular data modeling, inspired by the attention mechanism from Transformer by A. Vaswani et al. [9], enabling models to dynamically focus on relevant parts of the training data, similar to how humans pay attention to certain aspects of a visual scene or conversation. On the other hand, TabNet, introduced in 2021, utilizes a sequential attention mechanism to focus on the most relevant features at each decision step, providing both interpretability and efficiency.

Based on the research we have reviewed, there has been no inclusive model proposed specifically for sheet metal forming, while our model is trained to work well with new metal parts and capture the relationships between multiple targeted parameters. Furthermore, none of the papers we found, including X. Huang et al. [7] and S. Ö. Arik et al. [8], addressed the latest trends in AI, such as transformer-based approaches. What distinguishes our study is that our proposed methodology allows for broad application across various metal parts, materials and design parameters. By examining the latest modeling and evaluation techniques in AI, we aim at providing a compressive approach with high-performance and predictive power, as out detailed evaluation proves.

3. Methodology

Optimizing design parameters by simulating various design combinations can be inefficient and time-consuming when trying to identify feasible and desired parameter configurations, as it requires multiple cycles to achieve this goal. Our approach predicts design parameters trained on the limited design space to identify the most optimal design parameters within the design space defined by users.

According to V. L. Hattalli et al. [15], the quality of metal parts formed by the sheet metal forming process depends on multiple parameters such as material properties, including Young's modulus and yield strength, geometry of the workpiece, lubrication, process parameters (applied forces etc.) and more. In principle, it is possible to acquire good quality parts by optimizing the process parameters. Figure 1 shows the design parameters that decide the quality of parts. Parameters with inward arrows represent design parameters fixed depending on materials and their properties, as well as geometry, lubrication, and process parameters. Parameters with outward arrows are feasibility and formability parameters, which are the targeted design parameters we aim to predict.

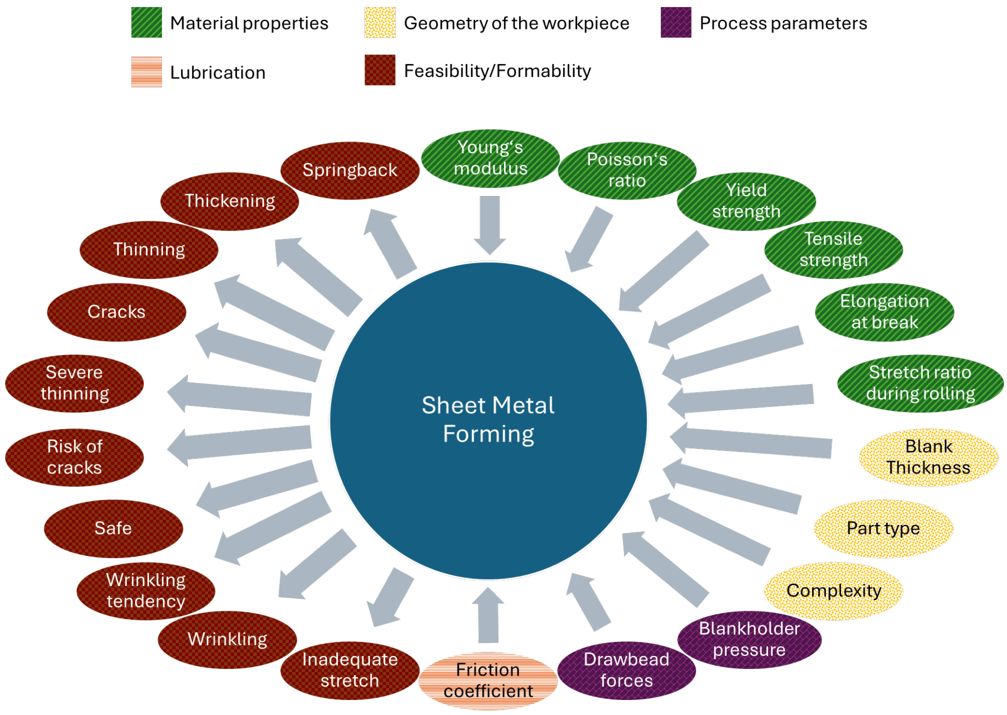

Figure 1: Design parameters in sheet metal forming

As mentioned previously, the research papers such as W. L. Chan et al. [2], A. Derogar et al. [3] and F. Han et al. [10] have focused on integrating MLP to predict a few design parameters. Consequently, if there are multiple parameters to predict, a less efficient approach is adopted, requiring training a separate AI model for each target parameter. The potential problem in previous research is that the independently trained AI models fail to capture the interdependencies among the parameters being predicted. Our proposed MLP model addresses and resolves this issue effectively. As illustrated in Figure 2, multiple design parameters, including material properties and more, are used to train our MLP model to learn the complex interrelationships among the parameters. Detailed explanations of the architecture are provided in Appendix A. As a result, our model predicts multiple design parameters simultaneously, and its accuracy comes from the model's ability to understand and learn the relationships across these parameters.

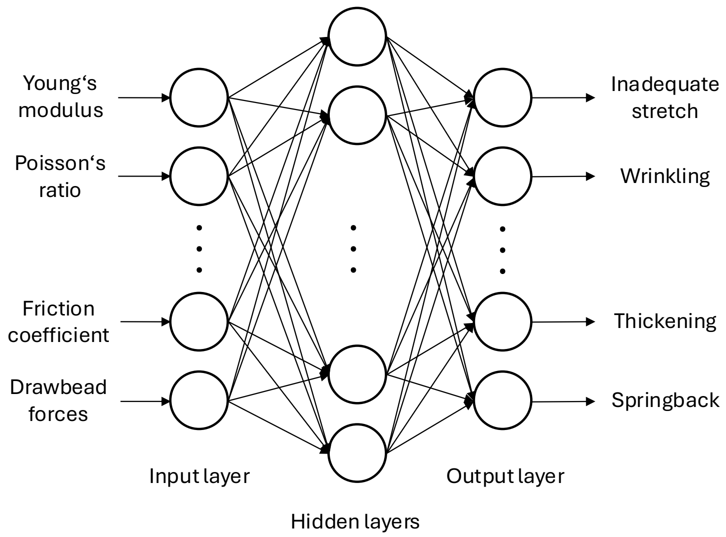

Figure 2: Architecture of our proposed MLP model

4. Experimental setup

Bellow, we describe the experimental setup used in this paper. We start with describing the dataset in Section 4.1, followed by the AI models used for comparison in Section 4.2. The evaluation metrics are described in Section 4.3.

4.1. Dataset

To obtain the dataset for training our MLP model, we executed multiple simulations on 10 metal parts as illustrated in Figure 3, including A-Pillar, B-Pillar, Tail gate, Cross member, and so on, with various configurations, resulting in a total of 857 variants. The dataset was split into training, validation and test sets with a ratio of 80/10/10.

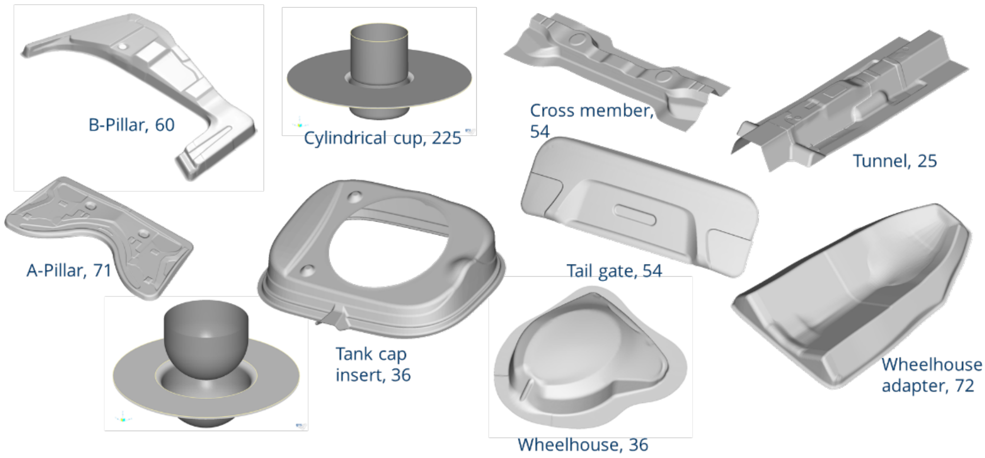

Figure 3: Training dataset of 857 variants with 10 metal parts

4.2. AI models for comparison

To demonstrate the superior performance of our proposed MLP model, we trained AI models commonly used in previous on the dataset we obtained. Next, we compared their performance in terms of prediction accuracy to determine which model operates most effectively. The list of AI models used in this paper for performance comparison are shown in Table 1.

Table 1: List of AI models used in this paper

Model	Details	Remark
Multiple MLPs [14]	Used in previous research to predict a single target parameter	A separate model is required for each target parameter. Citation: 21326
Decision Tree [13]	Predicts output by splitting data into a tree-like structure	Citation: 32577
Random Forest [12]	Combined multiple decision trees from an ensemble perspective	Citation: 10782
XGBoost [11]	Combined multiple decision trees improved by correcting mistakes from previous trees	Citation: 50762
TabTransformer [7]	Transformer based model to capture relationships between categorical and numerical data	Citation: 451
TabNet [8]	A deep learning model designed for tabular data	Citation: 1525
Ours	A single MLP model predicts multiple target parameters.	-

4.3. Evaluation metrics

In regression tasks that aimed at minimizing errors between predicted and actual values, the most commonly used evaluation metrics are Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). MAE measures the average magnitude of errors between predicted and actual values. MSE calculates the average of the squared errors between predicted and actual values, giving more weight to larger errors whereas RMSE is the square root of MSE, providing error magnitude in the same unit as the target values, making it more interpretable. In this paper, we use the following metrics that widely used to compare the performance of our MLP model to other AI models:

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)

5. Result

We compared our approach with six AI models to evaluate their performance in predicting targeted design parameters. The evaluation results for the models are listed in Table 2. The results show that our model significantly outperforms the previous research such as Multiple MLPs by Rosenblatt, F. [14] with MAE values of 7.08 (training split), 6.87 (validation split), and 6.61 (test split), compared to 73.11, 76.72, and 76.67, respectively, indicating better accuracy and generalization. Decision Tree and Random Forest, which are typically used for tabular data formats, also exhibited weaker performance compared to ours. Furthermore, TabTransformer and TabNet showed lower performance compared to than ours as well. XGBoost showed better performance in the training split with MAE of 0.71, MSE of 6.82, and RMSE of 2.61, but its performance worsened in the validation and test splits, with higher MSE and RMSE values, indicating ultimately less promising due to overfitting issues. When a model has higher MSE and RMSE in the validation and test splits compared to the training split, it means that the model is not generalizing well to new design configurations. In other words, it would not perform well on data with a slightly different configuration or a new metal part, while it would make accurate predictions on data like the data we used to train the model.

Table 2: Evaluation results

Model	Training			Validation			Test		
	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE
Multiple MLPs [14]	73.11	1632.97	40.41	76.72	1534.02	39.17	76.67	1641.50	40.52
Decision Tree [13]	4.56	462.93	21.52	5.62	895.58	29.93	6.06	951.98	30.86
Random Forest [12]	2.3	115.05	10.73	5.82	658.89	25.67	5.67	593.38	24.36
XGBoost [11]	0.71	6.82	2.61	4.88	587.83	24.25	4.17	392.31	19.81
TabTransformer [7]	6.29	668.55	25.86	6.96	1060.36	32.56	6.01	611.27	24.72
TabNet [8]	32.21	7424.67	86.17	27.21	4099.81	64.03	25.62	4782.77	69.16
Ours	**7.08**	**153.84**	**12.40**	**6.87**	**155.17**	**13.46**	**6.61**	**131.41**	**11.46**

When compared to other AI models, our approach outperforms others in predicting the targeted design parameters with smaller errors. Although our model recorded higher MAE values across all data splits compared to Decision Tree, Random Forest and XGBoost, this could be due to a few larger errors that have less impact on MSE and RMSE because of their squaring nature. While MSE and RMSE are more sensitive to larger deviations, they are balanced by smaller errors, whereas MAE directly averages the errors without amplification according to V. Plevris et al. [16]. Additionally, our model shows minimal performance differences across each data split. For instance, our model achieves RMSE of 12.40 (training), 13.46 (validation), and 11.46 (test), while XGBoost shows MAE of 2.61 (training), 24.25 (validation), and 19.81 (test). This highlights that our model not only generalizes better but also maintains consistent performance across all splits. Furthermore, rather than training multiple MLP models for each target parameter, as often adopted in previous research, our model effectively captures the correlations and hidden relationships among the targeted design parameters, showing superior accuracy and reliability compared to Multiple MLPs.

6. Case study

When adopting data-driven solutions in various industries, the main concern is whether the training data can represent the entire range of data, as in our case, various metal part designs. Additionally, there is always the question of whether a trained MLP model can effectively predict new input data with different patterns than the training data, such as new configurations and new metal part designs in our case. Since the model is trained on 10 different metal parts with several configurations, two fundamental questions arise:

- Can it accurately predict designs with new configurations parameters that are not used for model training?
- Can it effectively predict design parameters of entirely new and different metal parts?

The subsequent sections address each of these questions.

6.1. Metal parts with new configuration

To demonstrate that our approach performs well on configurations beyond those used for model training, we created 1039 different variants using the same metal part designs used for model training, but with configuration parameters that were not included in the original training dataset. With the different metal parts designs that we used for model training as shown in Table 3, our proposed model performs with similar accuracy on the new dataset as it did during training. With 1039 different variants, the MAE did only improve slightly, showing that our model can handle new configurations as well.

Table 3: Evaluation with new configurations and metal part designs (The table shows only the scores used for testing)

Dataset	Size (Num. variants)	MAE	MSE	RMSE
10 metal parts for model training	857	6.61	131.41	11.46
10 metal parts with new configurations	1039	6.29	136.78	11.70
New metal parts	315	6.90	133.80	11.57

6.2. New metal part designs

To evaluate our MLP model on three new metal part designs as illustrated in Figure 4, we created 315 variants with entirely new metal part designs – Front fender, reinforced A-Pillar and Floor panel - that were not used in model training. As illustrated in Table 3, our model demonstrated consistent performance on the new metal part designs, with only a slight increase in evaluation metrics. The MAE rose from 6.61 to 6.9, MSE from 131.41 to 133.80, and RMSE from 11.46 to 11.57, indicating only a minor decline in performance. These results suggest that our model generalizes well to previously unseen metal part designs while preserving accuracy.

Figure 4: 315 variants with new metal parts

This is likely because the model has successfully learned the structural behaviours and relationships among parameters across various metal part designs that used for model training.

7. Graphical user interface

We developed a user-friendly graphical interface leveraging our MLP model to enable users to explore the entire design space that users defined and directly determine design configurations, making the process more intuitive and accessible. In our application, when users select a design and material, the parameters related to material properties are automatically set based on the chosen material. The remaining parameters, for example, blank thickness and friction coefficient, are directly defined by the user to explore the desired design space.

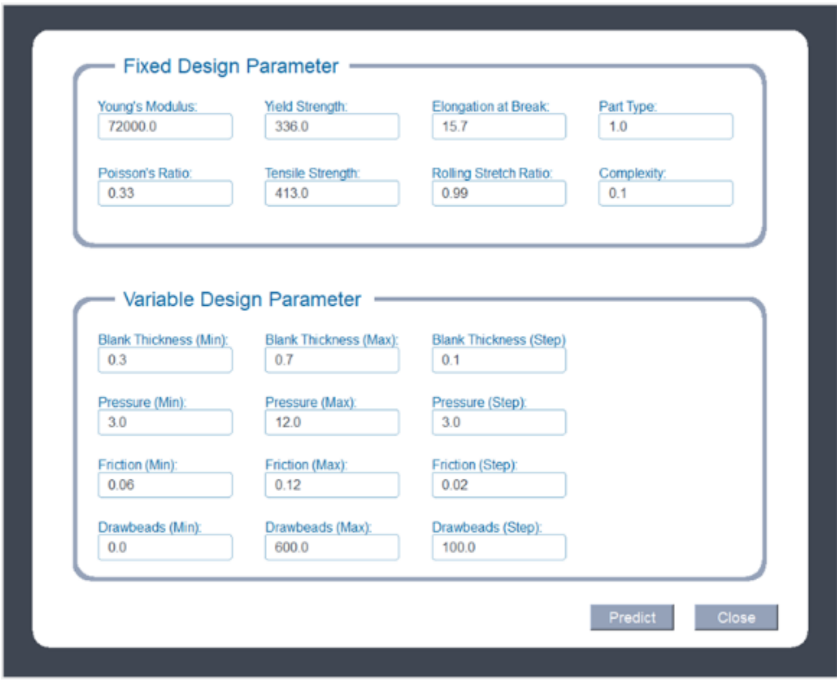

Figure 5: Design space setup interface – Users define the space they want to explore for blank thickness, blank holder pressure, friction coefficient, and drawbead forces

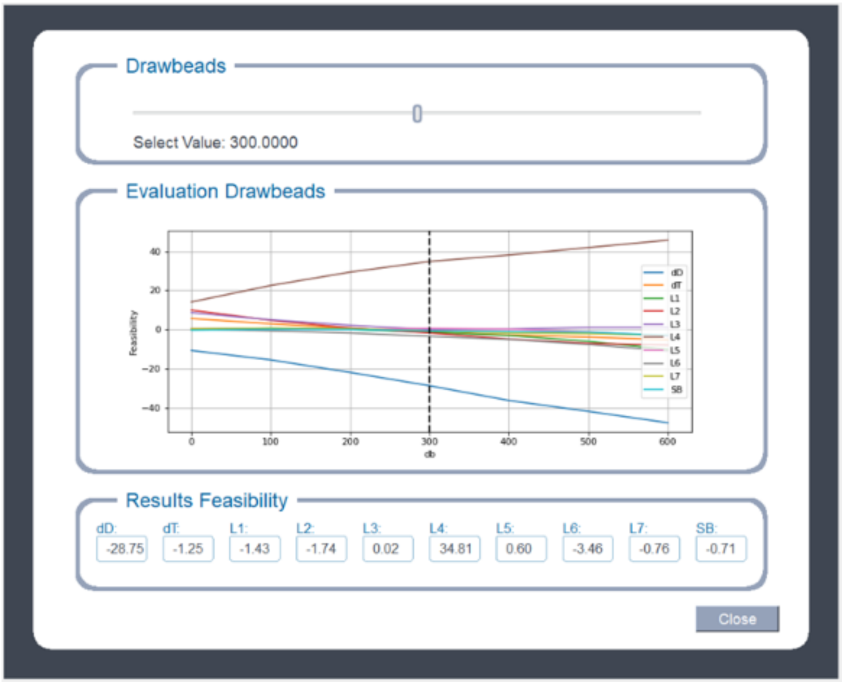

Figure 6: User-friendly design space explorer – Users can easily compare the predicted feasibility and formability parameters in real time.

Afterwards, our MLP model predicts the targeted design parameters such as feasibility and formability parameters based on material properties and the defined design space. Users can explore the design space interactively and observe how the targeted parameters respond to selected inputs through graphical visualizations. Once users finalize the parameters for simulation, our application is designed to seamlessly integrate these values into a forming tool called OpenForm. After the FE-model is prepared (pre-processing stage), the model will be simulated using the parameters predicted by our MLP model. Afterwards the simulation result has to be analysed (post-processing stage).

8. Conclusions and potential improvements

Designing sheet metal parts is a complex task requiring deep engineering knowledge and years of experience. To shorten this time-consuming process, many researchers have started adopting AI methods in their works. In this paper, a new MLP model was designed for predicting multiple targeted parameters for sheet metal forming. The results show that our MLP model outperforms existing models, and it is superior to the state-of-the-art models emerging in the AI field. Additionally, we were able to show the predictive capability of our model for new metal parts and configurations. It demonstrates that our model works inclusively and robust across a wide range of scenarios often encounter in the industrial forming processes.

Integrating our proposed approach into the conventional forming simulation process could be achieved as follows:

- MLP model prediction: our model predicts optimal design parameters within the design space defined by users.
- Simulation execution: a simulation is executed with the predicted parameters.
- Result analysis: the simulation result is analysed to validate our MLP model's predictions.
- Iterative improvement: based on the analysis, our MLP model can be further improved, and the cycle of prediction, simulation, and analysis leads to continuous improvement of the MLP model.

This automated process not only improve simulation efficiency but also enhance the accuracy of predictions. By extending this approach, we can further increase the accuracy and efficiency of forming simulations, leading to faster and more reliable decision-making in future metal part designs.

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Appendix A: Architecture details

In this appendix, we provide a comprehensive description of the architecture used for the proposed model. This section includes details on the number of layers, neurons in each layer, activation functions and other essential parameters that define the structure of the proposed model.

1. Overview

The proposed model consists of 6 hidden layers and an output layer. The input layer takes the material properties, geometry of the workpiece, lubrication, and process parameters as features, while the hidden layers capture relationships between features. The output layer predicts feasibility and formability parameters.

2. Layers configuration

- Input layer: The input layer contains 12 neurons, where 12 represents the number of features in the data.
- Hidden Layers:
    - Layer 1: 256 neurons
    - Layer 2: 20 neurons
    - Layer 3: 420 neurons
    - Layer 4: 100 neurons
    - Layer 5: 184 neurons
    - Layer 6: 300 neurons

  All hidden layers use the ReLU (Rectified Linear Unit) activation function.
- Output Layer: The output layer consists of 10 neurons with a linear activation function, which predicts the feasibility and formability parameters.

3. Optimizer and Hyperparameters

- Optimizer: The model uses Adam optimizer with a learning rate of 0.001.
- Batch size: A batch size of 32 was selected.
- Epochs: The model was trained for 100 epochs with early stopping based on the validation loss to prevent overfitting. If the validation loss did not improve for 30 consecutive epochs, training was stopped.