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A PROPOSAL FOR REAL-TIME FAILURE PREVENTION IN SHEET METAL FORMING USING MACHINE LEARNING

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Abstract. *This study proposes a methodology for real-time failure prevention in sheet metal forming using machine learning techniques. The increasing use of Advanced High-Strength Steels (AHSS) in the automotive industry, while beneficial for weight reduction and safety, introduces challenges due to their low ductility and high strength, which increase the risk of fractures during forming. To address this, the methodology integrates Industry 4.0 technologies and digital transformation principles to monitor critical process variables—temperature, electric current, vibration, force, and displacement—during Nakazima tests. An Arduino-based data acquisition system was developed to collect real-time sensor data. The data were analyzed using unsupervised machine learning models: Local Outlier Factor (LOF), K-Means, and Isolation Forest. Among these, LOF achieved the highest accuracy, exceeding 80% in predicting failure events. Statistical analysis revealed that temperature had the strongest correlation with deformation, making it the most effective variable for failure prediction. The methodology was validated through laboratory experiments using three steel types (DP780, HSLA340, and IF) and followed a structured nine-step framework to ensure replicability. An adherence indicator was also developed to evaluate sensor feasibility based on cost, accuracy, integration, and scalability. Results confirmed the methodology's effectiveness in enhancing process reliability and reducing material waste. The approach offers a practical and scalable solution for predictive quality control in industrial forming processes, contributing to smarter and more sustainable manufacturing systems.*

Keywords: *Sheet Metal Forming, Machine Learning, Failure Prediction, Advanced High-Strength Steels (AHSS) Real-Time Monitoring*

1. INTRODUCTION

The manufacturing industry currently faces the challenge of the digitalization trend, which is accelerating the adoption and use of digital technologies in manufacturing. According to Boffa and Maffei (2020), digital transformation (DT) triggers a fundamental technological shift in the industry, enabling the creation of smart and connected factories. The implementation of digital transformation can vary from company to company depending on the level of digital maturity within the organization.

This work aims to propose the use of sensing in the sheet metal forming process and identify the correlation of measurements with failure/fracture in the process and, through the use of machine learning, propose a methodology that can identify the failure in advance and prevent the process from continuing until the material fractures.

1.1 BACKGROUND

This technological advancement within factories is being driven by industrial digital transformation, resulting in a new fundamental paradigm shift in industrial production toward smart and connected factories, known as the “Fourth Industrial Revolution” or Industry 4.0.

Wu et al. (2024) mention that the advent of Industry 4.0 results in smarter factories and more efficient manufacturing processes. However, regardless of the benefits, the implementation of Industry 4.0 may not be suitable for all sizes of industries.

According to Rahmani et al. (2024), due to growing demands, manufacturing industries that use metals as raw materials will need to adopt DT innovations such as the use of IoT (Internet of Things) devices, artificial intelligence, big data, sensors, and robotics due to increasing market demand.

As reported by Treatstock (2024), manufacturing that uses steel involves several transformation processes, such as stamping, welding, forging, machining, bending, and cutting. Stamping, also known as sheet metal forming, is a technology used for producing finished products. This technique is employed across a wide range of production industry sectors.

According to Trzepieciński (2020), sectors such as aerospace, automotive, and home appliance industries make extensive use of sheet metal forming. The prevalence of this technique can be attributed to its efficiency, versatility, and ability to produce high-quality parts with precision and consistency.

This transformation process, although crucial, can suffer complications during execution, known as failures. Among these complications, fractures in the stamping process are frequently observed. Such failures can arise due to a variety of factors, including material quality, operational conditions, and the precision of the machines used.

In this context, Baluch et al. (2014) indicate that Advanced High Strength Steels (AHSS) are increasingly used in the automotive industry due to fuel economy, lower weight, and greater safety in collisions.

Fekete (2006) reports that materials made from AHSS with tensile strength above 800 MPa may exhibit ductile shear fracture in bending radii under tensile loads—an uncommon failure mechanism in sheet metals.

Baluch et al. (2014) also mention that due to high strength and low formability, early fractures are observed in various forming operations, requiring fracture investigation. To avoid these failures, methodologies such as using higher-capacity presses are necessary for forming or cutting, and tools wear out quickly. Lubricants, tool materials, and coatings require careful selection, while greater springback (leading to dimensional inaccuracy) is an important issue that requires further development and consideration.

Due to the characteristics of low ductility and high hardness, which cause fractures during the forming process, Aksen et al. (2020) propose the use of predictive models to avoid fracture. However, this approach works with failure prediction and not real-time evaluation, making the process dependent on prior simulations and parameterizations.

Similarly, Coelho et al. (2022) report that intensive industrial digitalization is driving massive data collection at all stages of production, enhancing predictive maintenance and anomaly detection to optimize the manufacturing of products.

Thus, there is an opportunity where integrating industrial process digitalization with the use of predictive models can enable a solution for real-time prevention of forming failures, ensuring quality and reducing operational costs.

The literature also shows that there are real-time analysis methods, machine learning, and based on existing predictive models for sheet metal forming, it is possible that the combined application of these technologies can predict fractures in real time during sheet forming and thus take immediate action to avoid losing parts during the production process.

Since the sheet metal forming process is widely used and contains elements common to other manufacturing processes, it is understood that, with the validation of a real-time data acquisition process, it can be replicated in other industrial processes.

1.2 LITERATURE REVIEW

Industrial digitalization has driven changes in production processes, especially with the consolidation of Industry 4.0, a concept described by Lasi et al. (2014) as the integration between physical and digital systems through sensors, connectivity, and intelligent automation. According to Zangiacomi et al. (2019), this transformation has accelerated the adoption of digital technologies in factories, making processes more efficient and connected. Within this scenario, sheet metal forming remains an important process in the manufacturing of industrial components, although, as noted by Trzepieciński (2020) and Heibel et al. (2017), it is subject to failures such as fractures and deformations that compromise the quality of the final product.

The introduction of advanced high-strength steels (AHSS), according to Baluch et al. (2014), has brought benefits in terms of lightness and structural safety, but also increased the complexity of the process due to the lower ductility of these materials, as already pointed out by Fekete (2006). To address these limitations, monitoring techniques such as infrared thermography have been successfully explored. Ibarra-Castaneda (2006) highlights the effectiveness of thermography in non-destructive testing, while Lejon et al. (2018) demonstrate its usefulness in identifying thermal variations associated with critical stresses during forming.

SHEET METAL FORMING

As reported by Treatstock (2024), manufacturing processes involving steel consist of various transformation techniques such as stamping, welding, forging, machining, bending, and cutting. Stamping, also known as sheet metal

forming, is a technology used for the production of finished products. This technique is employed across a wide range of sectors in the manufacturing industry.

Although this transformation process is crucial, it is susceptible to complications during execution, commonly referred to as failures. Among these complications, fractures in the stamping process are frequently observed. Such failures may arise due to a variety of factors, including material quality, operational conditions, and the precision of the machines used (Treatstock, 2024).

Figure 1 shows a typical configuration tool of a metal forming process and its parts.

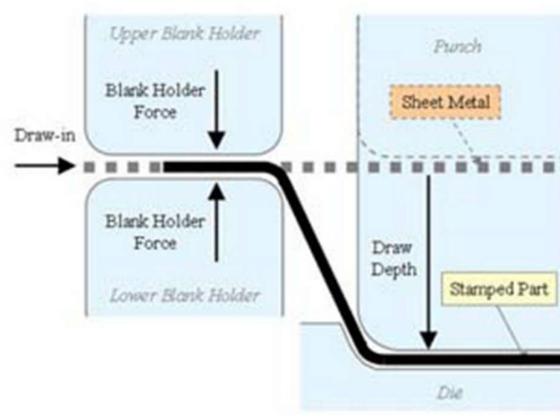


Figure 1. Metal Forming tool configuration and parts, from Lim et al (2008)

FAILURES IN SHEET METAL FORMING

Fracture by stretching refers to failure in the bending region under tensile stress. This type of fracture may not be predicted by the conventional Forming Limit Curve (FLC), as the material can fail before the strains reach the expected forming limit (Billur et al., 2010). Figure 2 shows the most common metal sheet failures that happen during the forming process

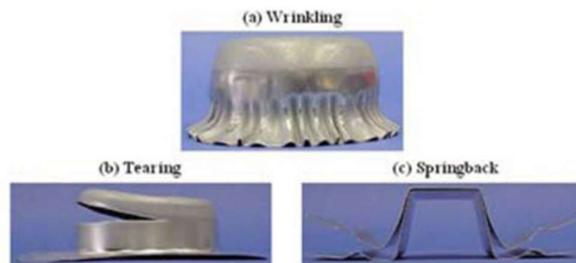


Figure 2. Metal Sheet failures a) Wrinkling, b) Tearing, c) Springback from Lim et al (2008)

Due to the characteristics of low ductility and high hardness, which cause fractures during the forming process, Aksent et al. (2020) propose the use of predictive models to prevent fracture. However, this approach focuses on failure prediction rather than real-time evaluation, making the process dependent on prior simulations and parameterizations.

In the same vein, Coelho et al. (2022) reports that intensive industrial digitalization is driving the massive collection of data at all stages of production, enhancing predictive maintenance and anomaly detection to optimize the manufacturing of industrial products.

ARTIFICIAL INTELLIGENCE

Artificial Intelligence (AI) broadly refers to computer programs that automate tasks associated with human thinking, such as perception, problem-solving, and planning (Cao et al., 2024). Cao et al. (2024) mention that since the first application of AI in 1952, in the form of a checkers program, AI has transformed various industries, especially in the fields of natural language processing, computer vision, and recommendation systems.

These advances are mainly due to progress in machine learning, a subfield of AI in which computer programs learn directly from data, unlike traditional programs with explicitly coded rules and instructions (Cao et al., 2024).

According to Jan et al. (2023), Artificial Intelligence and machine learning technologies, is a combination of a large volumes of data obtained through digital data acquisition technologies, have emerged as key enablers of the cyber-physical systems that underpin Industry 4.0. Jan et al. (2023) also note that although AI is often used synonymously with machine learning, AI is a comprehensive discipline that includes various dimensions of intelligence such as perception, sensing, reasoning, and knowledge representation, in addition to machine learning.

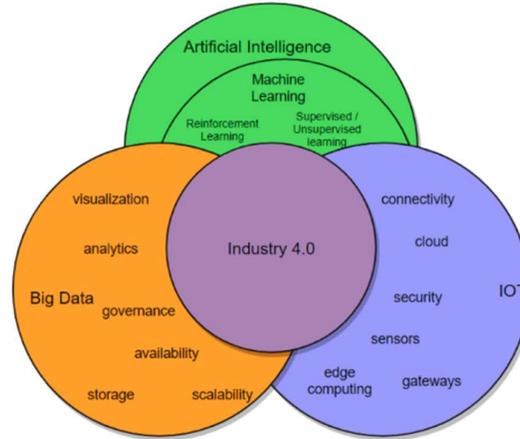


Figure 3. Artificial Intelligence and Industry 4.0 from Jan et al (2023)

MACHINE LEARNING

According to Lejon et al. (2018), machine learning (ML) methods proven algorithms for detecting anomalies in the press hardening process of automotive components. Machine learning is commonly used for classification problems where numerous data examples are available for each studied category. In contrast, problems involving anomaly detection often lack a large number of anomaly examples (Lejon et al., 2018).

According to Tancredi et al. (2022), machine learning techniques have been successfully applied across various sectors, such as predictive maintenance, quality management, and zero-defect manufacturing.

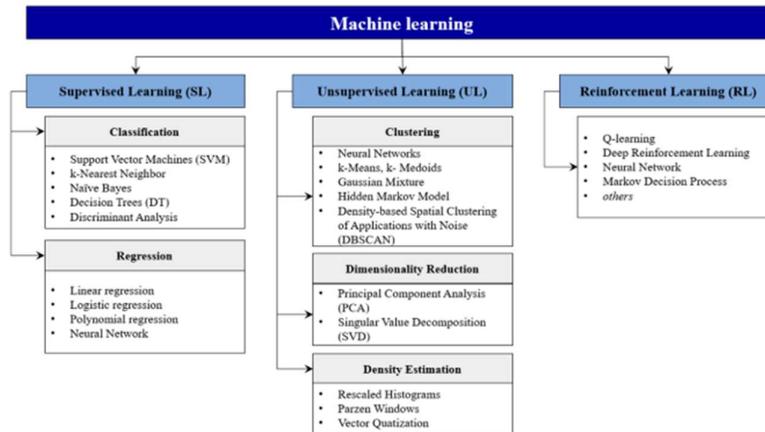


Figure 4. Classification of Machine Learning Algorithms from Párizs et al (2022)

APPLICATION OF ARTIFICIAL INTELLIGENCE IN INDUSTRY

As highlighted by Mazzei (2022), Industry 4.0, or the Fourth Industrial Revolution, represents rapid changes in the industrial world due to the combined improvements of technologies that merge the physical and digital worlds. These technologies refer to the interconnectivity of the Internet of Things (IoT), robotics, and peripheral devices, as well as the intelligent automation enabled by artificial intelligence (Mazzei, 2022).

Given the complexity and scale of industrial challenges, the proven success in the scalability and automation of the predictive power of machine learning holds great potential to thrive in this context (Mazzei, 2022). In recent years, researchers and companies have increasingly explored machine learning for Industry 4.0, seeking these benefits.

However, industrial applications of machine learning are complex due to the number of interconnected knowledge areas (Mazzei, 2022). In his study on the use of artificial intelligence in industry, Mazzei (2022) emphasizes that having the right information is a critical point, as it allows for the identification of key aspects of how the technology will be used—such as which research directions may contribute effectively or which solutions may be practical and implementable.

1.3 EVALUATION METRICS IN MACHINE LEARNING MODELS

Performance evaluation metrics are widely used to assess the effectiveness of machine learning models in both regression and classification problems. Some of the most frequent used are Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Accuracy, and Precision, each serving specific evaluation purposes.

According to Emmert-Streib et al. (2019), RMSE is a metric employed in regression problems. It calculates the square root of the average of the squared differences between the predicted and actual values. This metric penalizes larger errors more heavily, making it particularly useful when significant deviations are undesirable.

MAE (Mean Absolute Error), on the other hand, measures the average magnitude of the errors in a set of predictions, without considering their direction. This metric provides a clear interpretation of the average error magnitude.

For classification problems, Accuracy is one of the most commonly used metrics. It represents the proportion of correct predictions among the total number of cases evaluated. However, in cases of imbalanced datasets, Accuracy alone may not be sufficient.

2. PROPOSED METHODOLOGY

The proposed methodology for preventing failures in the mechanical forming process of metal sheets involves nine main steps, each step was made to lead the solution to the best results.

2.1 PROPOSED MODEL DESCRIPTION:

Step 1: Process Knowledge

Mapping the production process flow to identify critical points that may influence the occurrence of failures and where relevant data can be collected. This includes a study of each stage of the process, from the receipt of raw materials to the final product, identifying the expected transformations at each phase. The deliverable for this step is a process roadmap, detailing each transformation the material undergoes, the operating parameters of each piece of equipment, and the points where the most critical variables should be monitored.

Step 2: Identification and Classification of Variables

Listing and classifying processes, material, and equipment variables. The variables are divided into three main categories: material variables (measurable changes during transformation), equipment variables (data collected from equipment), and process variables (related to material transformations). Variables are also classified in terms of approach and training method for machine learning algorithms, being either supervised or unsupervised.

Step 3: Preliminary Testing

Conducting initial tests to verify the feasibility of reading and measuring the identified variables. The goal is to assess whether the available measurement technologies can capture relevant and consistent data. During testing, variables with inconsistent or insufficient readings will be discarded or adjusted. Integration between data acquisition systems should also be tested to ensure they can correctly record values in real time.

Step 4: Specification Definition

Establishing minimum specifications and technical requirements for data collection of the variables during process execution. This includes defining the ideal sampling frequency, the required accuracy for each sensor, and the appropriate measurement range. This step also specifies the criteria for selecting sensors and measurement systems, considering robustness, reliability, and compatibility with the operating environment.

Step 5: Experiment Validation

Executing preliminary tests under real or similar operating conditions to validate the data collection methodology. Any necessary adjustments to the setup or measurements should be made at this stage. The deliverable for this phase is a functional version of the experimental procedure.

Step 6: Data Collection

Beginning broader data collection with enough experiments to generate a sufficiently large dataset for AI training. The data acquisition system must be configured to record variable values in real time or as close to it as possible. Sampling must be representative of different operational scenarios, capturing both normal operation and anomalies.

Step 7: Artificial Intelligence Training

Using the acquired data to train artificial intelligence models. Supervised variables are used to train supervised models, while unsupervised variables are explored to identify patterns correlated with process failures. Classification models such as neural networks or decision trees should be applied to associate variables with failure or non-failure states.

Step 8: Data Analysis and Indicator Creation

Generating indicators of adherence to the proposed methodology. These indicators are categorized and weighted according to their representativeness in the methodology: implementation cost, phenomenon prediction, data accuracy, ease of integration, and scalability. Implementation cost should be calculated based on the implementation cost compared to the unit production cost of each part under study. Phenomenon prediction should consolidate the results of individual variables, considering their representativeness in the prediction model chosen in previous steps.

Step 9: Generation of the Overall Adherence Indicator

Summing individual indicators considering the weighting of each. The overall adherence indicator will serve as the basis for determining the feasibility of using the monitoring system for the analyzed process. For sensors with an overall adherence indicator below 5, it is concluded that the sensor does not provide sufficient contributions to be productively used in the process. For sensors with an indicator between 5 and 8, it indicates potential but limited added value. For sensors with an indicator above 8, real-time monitoring implementation will add value to the process and consistently prevent failures.

2.2 METHODOLOGY VALIDATION

The proposed methodology was applied in a laboratory environment to validate its effectiveness in real-time failure prediction in the sheet metal forming process. The validation was carried out at the Plasticity Laboratory of the Federal University of Paraná (UFPR), using a hydraulic press equipped with additional sensors to monitor critical variables.

Figure 5 shows the experimental setup and the sensors used to acquire data during the tests.



Figure 5 Experimental setup with sensors mounted on a physical structure and monitoring interface screens, a) Arduino®, b) Temperature Sensor, c) and d) temperature sensor setup, e) Current Sensor, f) Current sensor setup, g) Vibration Sensor, h) Vibration Sensor setup, i) Ladder configuration to setup the experiment, j) Deformation and pressure acquisition, k) Temperature, vibration and Current acquisition, from Authors (2025)

Initially, preliminary tests were conducted to verify the feasibility of reading and measuring the identified variables. During these tests, the sensors and data acquisition systems were adjusted to ensure accurate and appropriately frequent measurements. The sensors used included an infrared temperature sensor, an electric current sensor, and a piezoelectric vibration sensor.

After the initial adjustments, the data collection methodology was validated under real operating conditions. Nakazima tests were carried out, in which the metal sheets were subjected to deformation until failure occurred. During

the tests, real-time data were collected for variables such as temperature, electric current, vibration, punch force, and displacement.

The Table 1 shows the summary of the collected data and the statistics of the information. This analysis is important to understanding the behavior of the experiment and check if the results are consistent.

Table 1 – Analysis of Test 1 of DP780 Steel

	Current	Temperature	Vibration	Deformation	Strength
Total Samples	134	134	134	103	103
Mean	18.5953	25.14821	169.1269	194.3301	546.6408
Minimum	12.21	24.33	0	12	0
25%	18.97	24.48	0	106	215,5
50%	19.01	24.99	0	200	492
75%	19.41	25.745	212.25	282	879
Maximum	21.35	26.47	864	360	1276
Standard Deviation	2.082448	0.687681	289.9291	102.3834	386.7637

Figure 6 shows the values from Test 1 of the DP780 steel across the collected samples. The data were normalized so that all variables could be displayed on a single graph without scale distortion.

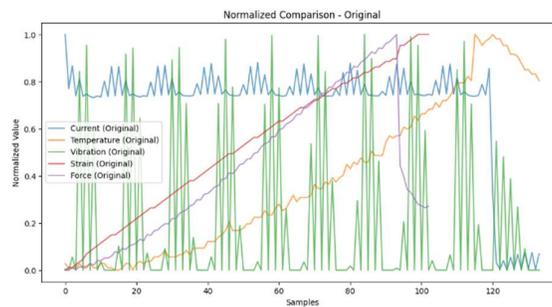


Figure 6. Graphic of normalized data of Steel DP780

The collected data were analyzed using machine learning models, including Local Outlier Factor, K-Means, and Isolation Forest. The data analysis indicated that the temperature variable was the most effective in predicting failures, showing a high correlation with sheet deformation. The Local Outlier Factor model delivered the best results in anomaly detection, with accuracy exceeding 80% in most of the cases. The Figure 7 show the result of the Machine Learning prediction using LoF and the point of failure predictions.

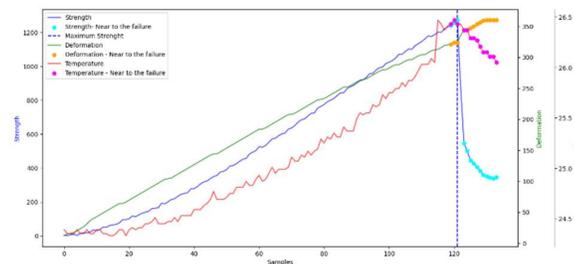


Figure 7. Local Outlier Factor Graphic of Strength, in Newtons (N), Deformation, in Millimeters (mm), and Temperature in Degrees Celsius (°C), from Authors (2025)

The qualitative results of the validation demonstrated that the proposed methodology is effective in real-time failure prediction, contributing to waste reduction and increased efficiency in the sheet metal forming process. The integration of the sensors into the existing monitoring system was carried out simply and quickly, confirming the practical feasibility of the methodology.

3. ANALYSIS OF RESULTS

Data Collection

The sheet metal forming tests were performed using a hydraulic press equipped with sensors to measure electrical current, temperature, vibration, Strength and deformation. Data were collected during the Nakazima tests and analyzed to validate the proposed methodology. Statistical analysis and Pearson correlation were used to assess the accuracy and representativeness of the data.

Test Results

The results indicated that temperature is the most effective variable for predicting failures, with high accuracy and correlation with deformation. In all tests, the Pearson correlation established between temperature and deformation was greater than 0.9, indicating a strong correlation. Strength also showed a high correlation with deformation, but not as significant as temperature. The electrical current and vibration variables did not show a significant correlation with deformation, indicating that they are not useful for predicting failures in this context.

Machine Learning Models

Machine learning models, especially the Local Outlier Factor, showed good results in detecting anomalies before failures occur, with accuracy above 80% in some cases. The Isolation Forest model also showed good results, especially for DP780 steel, with accuracy above 80%. The K-Means model, on the other hand, had an average accuracy below 50%, indicating that it was not effective for this type of analysis.

Adherence Indicators

Adherence indicators were generated considering the criteria of implementation cost, prediction of phenomena, data accuracy, ease of integration and scalability. The results indicated that the current and vibration variables do not have sufficient contribution to be used in the process. The Strength and deformation variables have potential for accuracy, while the temperature variable has the greatest potential to add value in detecting process failures.

4. CONCLUSION

The proposed methodology for failure prevention in the sheet metal forming process using machine learning proved to be effective and promising. The test results confirmed that the temperature variable is the most effective for predicting failures, showing high accuracy and strong correlation with strain. The Local Outlier Factor model delivered the best results in anomaly detection, with accuracy exceeding 80% in some cases. Strength also showed a high correlation with strain, though not as significant as temperature.

The variables of electric current and vibration did not show significant correlation with strain, indicating they are not useful for failure prediction in this context. The machine learning models, especially Local Outlier Factor and Isolation Forest, performed well in detecting anomalies before failures occurred. On the other hand, the K-Means model had an average accuracy below 50%, indicating it was not effective for this type of analysis.

Adherence indicators showed that the current and vibration variables do not contribute sufficiently to be used in the process. The Strength and strain variables have potential for accuracy, while the temperature variable has the greatest potential to add value in failure detection within the process.

Implementing this methodology in real production environments can contribute to waste reduction and increased efficiency in the sheet metal forming process. The analysis of the results positively validated the initial research question and provided support for the proposed methodology to be adopted in real-world production settings.

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