Surrogate Model and Multi-objective Evolutionary Algorithm Applied to Automotive Stamping

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***Abstract*—Automotive parts stamping is a process of forming metallic parts that are used in the manufacture of automobiles, such as the Internal Tailgate. The problem is characterized as a multi-objective optimization problem, as it involves the optimization of multiple antagonistic objectives simultaneously. In this study, we used the Extra Trees multivariate regression algorithm to characterize the problem and use it as a surrogate model for the Non-dominated Sorting Genetic Algorithm II. Our goal is to explore the possibilities of simultaneously minimizing Fracture, Insufficient Elongation, and Wrinkling. In addition, we apply data correlation analysis and machine learning model sensitivity analysis tools to assess the quality of the surrogate model and allow preliminary decision-making. The tools of data correlation analysis and sensitivity analysis of the Machine Learning model are applied to assess the quality of the surrogate model and allow prior decision-making. The results achieved when using the proposed approach with these auxiliary tools help to establish an efficient model, identify suitable stamping parameters, and reduce the costs associated with conducting empirical research conducted by experts in the field.**

***Index Terms*—Surrogate model, Sensitivity analysis, Correlation analysis, Multi-objective evolutionary algorithms, Stamping.**

I. Introduction

Automotive stamping is an industrial process that involves creating metal parts used in various automotive components manufacturing. Although essential for vehicle production, automotive stamping can present challenges that affect both the quality of parts and the efficiency of the process. Among these challenges, proper material selection, part design, and manufacturing processes are highlighted.

There are several motivations for improving the automotive stamping process, such as improving product quality through minimizing errors, reducing costs by decreasing scrap rates, increasing customer satisfaction through product quality improvements, and enhancing safety [6].

Although the motivations are clear, developing process improvements can be complex for several reasons, one of which is that the problem itself is considered multi-objective, as it involves optimizing multiple conflicting objectives simultaneously. During the stamping process for the production of an automotive part, it is necessary to find a balance between the minimization objectives and their real-world functionality. In certain scenarios, the choice of objectives to be achieved during the stamping process may vary according to the function of the part produced. When the part has a structural purpose, the fracture rate (FRA) is a priority, while in exposed and aesthetic parts, wrinkling (WRI) and insufficient stretching (IS) become essential [5]. In this sense, the minimization of the areas resulting from FRA, IS, and WRI are the objectives to be achieved during the stamping process.

The approach of using Multi-objective Evolutionary Algorithms (MOEA) to explore stamping parameters has been applied in some works in recent years [1] [10] [15]. The application of such algorithms aims to explore various scenarios previously impossible using numerical simulation methodology. The goal of applying MOEA is to find a set of solutions that represents the ideal compromise between the different objectives, forming the so-called “Pareto front”, which is a collection of non-dominated solutions.

The use of surrogate models can be a viable option to assist decision-making in the stamping process, especially in process optimization. Multivariate regression algorithms are attractive options for predicting process behavior, since the target variables are in the continuous domain, in addition to being able to reduce processing time by serving as surrogate models in the minimization process using MOEA [13].

The objective of this article is to present a surrogate model analysis in a multi-objective optimization problem of stamping automotive parts. In this regard, the article presents the use of two tools: data visualization with variable correlation analysis and sensitivity analysis in a Machine Learning (ML) model used as a surrogate model, both applied in two case studies.

The tool used to collect numerical simulation data is the AutoForm[1], where each data sample is formed by the variables of an experiment and its results. The collected dataset is used to create a multiple output regression model using the Extra Tree (ET) [4] algorithm. The aim of using regression models instead of using the AutoForm simulation software is to reduce the time and cost needed to perform physical experiments. Finally, the constructed regression model is used by the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [2] algorithm to search the variable space. As the output of the system, a set of non-dominated solutions is given to a specialist as possible stamping solutions of an automotive part. The architecture is applied in two case studies, one laboratory, named "Cup", and a real part of an automobile, named "Internal Tailgate".

This work is organized as follows. Section II details the concepts involved in the development of the proposed approach. In Section III, there is a description of some related works. The proposed model for approaching the problem is detailed in Section IV. Then, Section V presents the case studies and the technologies used. Finally, in Section VI, the conclusions obtained and the possibilities for future work are presented.

II. Theoretical Background

A. Automotive Stamping

The forming of automotive parts is considered one of the most critical processes in production, as the quality of the final result strongly depends on the properties of the material used and the operating conditions employed.

With regard to material properties, it is essential to know the mechanical characteristics, such as yield strength, tensile strength, and elongation, to determine the material's ability to deform without breaking during metal stamping [7] [9].

Automotive mechanical forming is fundamental for the production of metallic parts and can be carried out in several ways, such as stamping, forging, and lamination. The manufacture of automotive parts, in turn, involves a process composed of several steps, including design, cutting, stamping, modeling, and others [5].

In the case of deep stamping, this conformation is used when the depth of the stamped part exceeds the diameter [5]. This method is indicated to create components that need different diameters and complex shapes, where the raw material is placed in the blank holder and molded by applying a compression force that presses the material over two molds, forming the desired part. It is possible to carry out this process cold or hot, depending on the characteristics of the metal used and the complexity of the part.

Finally, it is important to highlight that optimizing the metal stamping process is complex, as it involves the careful choice of several parameters and the search for a balance between antagonistic characteristics, such as the lightness and the resistance of the part. Also, the main objective is to minimize the area of failure in the resulting part, which can include areas of wrinkling (WRI), under-stretch (IS), and fracture index (FRA).

B. Surrogate Models

A surrogate model refers to a technique used in data analysis and process optimization to build models capable of representing complex systems or processes. This model can be used to predict the behavior of the system in question under different conditions or to optimize the process without having to resort to the real system every time [8].

Building a surrogate model involves using statistical or ML techniques to create a behavioral approximation of a system that often cannot be easily measured or calculated.

Surrogate models can also be used in multiobjective problems, in which optimization involves searching for a set of solutions that meet the requirements of all goals in a balanced way. There are several approaches to building surrogate models for multiobjective problems, such as using models based on regression trees [8]. There are some benefits of using a surrogate model, such as reduction of time and costs required to perform experiments, ease of modeling, ease of experimentation under different conditions, and the ability to perform analyses and optimizations without affecting the original system.

The evaluation of surrogate models is a fundamental step in the process of creating these models. The choice of methods should be based on the characteristics of the problem in question. These methods can be used alone or combined to assess the quality of the surrogate model in different aspects.

Quality is directly related to its ability to predict the behavior of the original system. For this, there are several evaluation methods, some of the most common methods include residual analysis, cross-validation (CV), bootstrap, comparison with the original system, and finally, sensitivity analysis [11].

C. Multi-objective Evolutionary Algorithm

An evolutionary algorithm is based on Darwinian Evolution's survival of the fittest and uses concepts such as reproduction, mutation, recombination, and selection. A given environment is filled with a population of individuals striving to survive and reproduce. The fitness of these individuals is determined by the environment and is related to how successful they are in achieving their goals [2]. When it is

[1]AutoForm: www.autoform.com

possible to find a combination of variables that impact different production criteria, we call this a multi-objective optimization problem.

In an optimization problem, the model is known, along with the desired outcome, and the task is to find the inputs that lead to that outcome. The NSGA-II is an evolutionary algorithm for solving multi-objective optimization problems, which has non-dominated sorting of the solutions every generation, whose goal is to divide the solutions found into hierarchical boundaries, and also select its best individuals through sorting and then clustering distance. The NSGA-II clustering distance ordering is responsible for creating selection criteria for individuals when it is not possible to select an entire hierarchical level and is based on the distance of the individual from all the others and priority is given to the individuals that are farther apart, promoting greater diversification [3].

III. Related Work

In [12] is presented a multivariate regression model with the Random Forest algorithm, and with the NSGA-II, to minimize failures in the stamping process. It uses as a case study a part without many details, the roof of a vehicle. Finally, even with manually collected data, it obtained interesting results in the optimization of FRA, WRI, and IS objectives.

The work done in [1] simulates and optimizes the partitioning of cooling in hot stamping. It uses an automotive B-pillar as a case study, analyzing by minimizing the maximum thickening rate and the maximum thinning rate located in the fast and slow cooling parts of the part. It applies the Optimal Latin hypercube design, the response surface methodology (RSM), and the NSGA-II, to relate and study the influence and parameters of hot stamping, the friction coefficient, sheet austenitizing temperature, holding time, heating zone temperature, the upper binder force, and the lower binder force.

To try to reduce unsatisfactory defects conducted by the stamping process, such as WRI and cracking, [14] performs optimization on its parameters based on an improved Particle Swarm Optimization–Genetic Algorithm and Sparse Autoencoder–back-propagation Neural Network model. A double-C piece is used for the study, and its thickness variation is used as the assessment standard. Lastly, the implementation demonstrates that the wrinkling of the optimized double-C part is significantly reduced and the forming quality is improved.

IV. Proposed Model

In this section, the model to approach the automotive stamping problem is presented. The surrogate models are created based on stamping numerical simulation data considering a number of automotive part-dependent input variables and three outputs: WRI, IS, and FRA. These outputs are the objectives for the NSGA-II algorithm, which will explore the space of variable values. To collect experimental data, the AutoForm simulation software was used. Figure 1 presents a visual representation of the proposed model. The details of the proposed model are explained below:

In step 1, the parameters and domain selection process define the design of AutoForm software experiments. This process is conducted by a metallurgy specialist, who uses his skills to determine the critical stamping variables for the desired part. A proper definition of these variables has a direct impact on the evaluation of the regression model. Ideally, the specialist creates a plan with a range of experiments that uniformly cover the variable search space. Step 2 performs all the simulations defined in the previous step, using numerical simulations from the AutoForm software and following the expert's instructions. Later, the database is created with the data acquired.

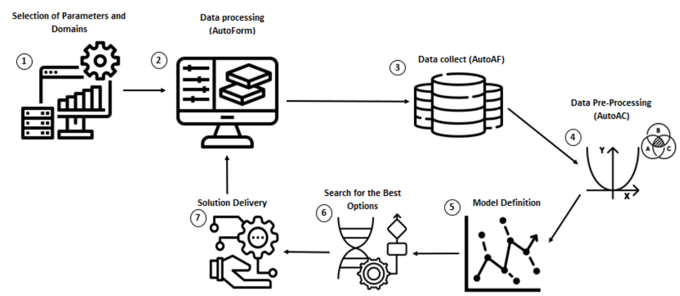

Fig. 1. Proposed model.

In step 3, the AutoAF software was developed to get data more efficiently. The AutoAF features image recognition and auto-click functions, allowing it to use visual cues from the AutoForm software to detect the simulation completion time and specific placements to perform simulation opening, data extraction, and saving steps automatically. This solution was developed due to the lack of tools to integrate AutoForm simulation software with external software, which previously required manual data extraction, which was very time-consuming.

Step 4 consists of pre-processing the database generated by the AutoForm simulation software using the software developed by the team, called AutoAC. The AutoAC has the ability to calculate the thresholds for each objective (WRI, IS, and FRA) and the area of each simulation. Subsequently, an exploratory analysis of the data is carried out, using visualizations and correlation analysis of variables using Spearman's statistical method. If any of the parameters show a low correlation with the objectives, the selection of parameters and domains must be reassessed, as such a variable has little impact on the model's results, and may even significantly impair the quality of the creation of the surrogate model.

To evaluate the visualization of the correlation analysis (i.e. heat-map plot), the intensity of the colors or values in the cells corresponding to the combinations of variables being analyzed must be observed, the higher the value, the greater the correlation. Also, the sign preceding the correlation value indicates the direction of the correlation. A direct or positive correlation is indicated by a positive value or lighter color, while a reverse or negative correlation is indicated by a negative value or darker color. It is important to notice that the direction of correlation indicates whether variables move in the same direction (positive correlation) or in opposite directions (negative correlation) as their values change.

In step 5, the surrogate model is created using the Extra Tree (ET) multivariate regression algorithm. The Leave-one-out (LOO) CV method was employed. After creating the model, a sensitivity analysis is performed to assess its quality. The aim of this analysis is to observe signs of overfitting, underfitting, and poor characterization of the problem. If any of these signs are observed, the parameters, simulation domains, and settings of the created ML model are reevaluated.

The search for the best configuration of variable values is performed in step 6 using the NSGA-II, in which the previously created surrogate model is used as the fitness function. The objective is to find the Pareto front, which represents the set of optimal or non-dominated solutions for multiple objectives. Therefore, the objective is to find input parameters that result in stamped parts with the smallest possible failure area, without sacrificing other objectives.

Step 7 delivers the selected best results including machine parameters and the percentage of predicted area for each objective. To verify the accuracy of the model, it is necessary to select one of the solution vectors generated as output and parameterize a new experiment in the AutoForm software with the characteristics of this solution vector. If the validation is not satisfactory, the NSGA-II parameterization is reassessed.

V. Experiments, Results, and Analysis

In this section, the experiments carried out and the results obtained in two case studies are presented. Both studies aim to minimize WRI, IS, and FRA objectives. The substitute model used is the ET from the Sklearn[2] library, in which the LOO CV strategy was employed due to the low quantity of data available. To define the parameters of the ET algorithm, a factorial experiment search approach was adopted.

To assess the quality of the regression model, the root mean square error (RMSE) metric was used. All source code was developed using Python language and the pymoo library [2] was used to apply the NSGA-II algorithm. The implementation of objective functions and parameterization were the necessary steps to start the evolutionary process. A total of 1000 generations were applied with a population of 100 individuals (candidate solutions) with real coding. Each individual consists of a solution vector with a number of input variables, and the objective functions are WRI, IS, and FRA.

A. Case Study 1 - Cup

This case study is known as "cup" and is a laboratory solid with a shape illustrated in Figure 2. Its distinctive geometry offers a wide variety of applications in the field of mechanical engineering and is frequently used in various everyday situations. The "Cup" is an essential component for testing and validating new developments, and is constantly used in laboratories. This solid is generally used in material resistance tests, such as mechanical tests to evaluate physical properties, such as traction, compression, and flexion, in samples of different materials.

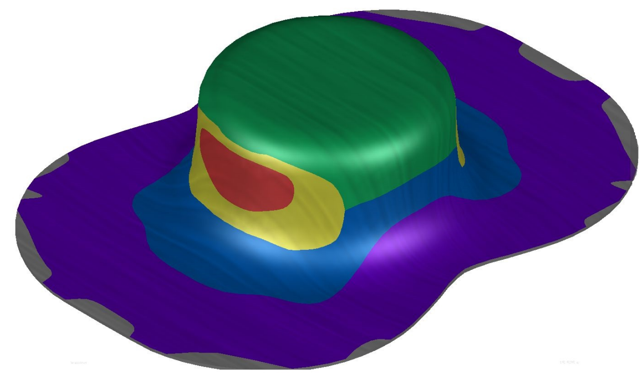

Fig. 2. Case Study 1 - Cup. Areas of wrinkling (WRI - highlighted in purple), under stretch (STR - highlighted in grey), and fracture index (FRA - highlighted in red).

1) Selection of Parameters and Domains: In this case study, the Coefficient of Friction (FRI), Swift Hockett Sherby Combination Factor (SWI), Yield Stress (YIE), Constant Force (CON), and NValue (NVA) variables were initially considered by the specialist. Table I presents the domains and parameters used to generate the database by the AutoForm software. Based on these parameters, it was possible to generate a database with 747 AutoForm simulations, with 5 inputs (FRI, SWI, YIE, CON, and NVA) and 3 outputs (WRI, IS, and FRA).

TABLE I
Parameters and domains of case study 1 (cup).

Parameters	***Minimum***	***Medium***	***Maximum***
FRI	0.13	0.15	0.19
SWI	0.5	0.75	1
YIE	145.867	171.608	240.251
CON	38000	47500	57000
NVA	0.159	0.199	0.239

2) Data Pre-Processing: In order to evaluate the significance of the parameters defined, after the database generation stage, the correlation analysis is employed as shown in detail a) of Figure 3. This tool allows a previous data investigation, in order to better understand the relationships between the variables before the creation of the surrogate model.

Based on the analysis of the correlations between the parameters and the objectives, we can conclude that the SWI variable does not present a significant correlation with any of the objectives. This indicates that the SWI variable can be considered inappropriate to be included in the analysis model, as it is not related to the objectives in question and can introduce unnecessary noise in the analysis. With that, the optimization process goes back to the first step "Selection of parameters and domains", removing the SWI variable. For research purposes, the flow of the project was followed and the

[2]Sklearn website: https://scikit-learn.org/

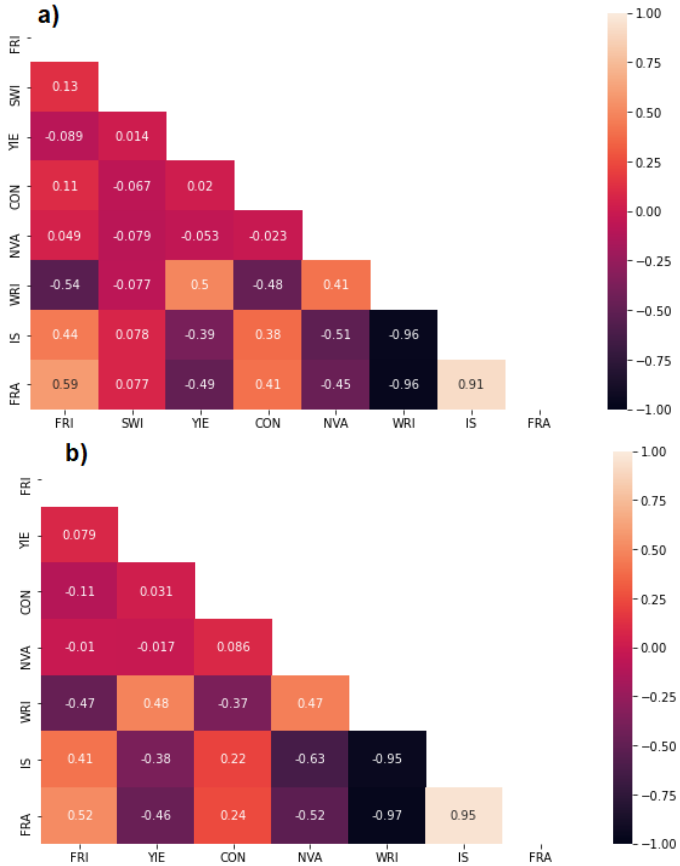

Fig. 3. Correlation between variables - (a) 5 variables, (b) 4 variables

other steps were carried out with the objective of evaluating the impacts on the creation of the surrogate model.

3) Model Definition: The adjusted parameters for ET in this study consist of a number of 80 estimators and a maximum depth of 17. These parameters were defined using a factorial experiment for parameter definition.

In order to evaluate the model, a sensitivity analysis was performed, the results of which are shown in Figure 4. This analysis involves predicting 100 fractional values for each input variable within the ranges determined during parameter selection (represented on the X-axis). The predicted values are then plotted on the graph (Y-axis).

The SWI variable, represented by item e) in Figure 4, presents possible difficulties during prediction. Some significant points can be observed, such as a small result interval on the Y axis, indicating a limited correlation between the variable and the objective, resulting in a reduced influence in the construction of the model. Furthermore, abrupt results are observed, suggesting that the model is having difficulties in learning the most important relationships or is suffering from underfitting.

4) Search for the Best Options: To verify the impact of parameter redefinition on the optimization of the automotive stamping process, a surrogate model was used (with a database of 5 and 4 variables, respectively). This model was submitted

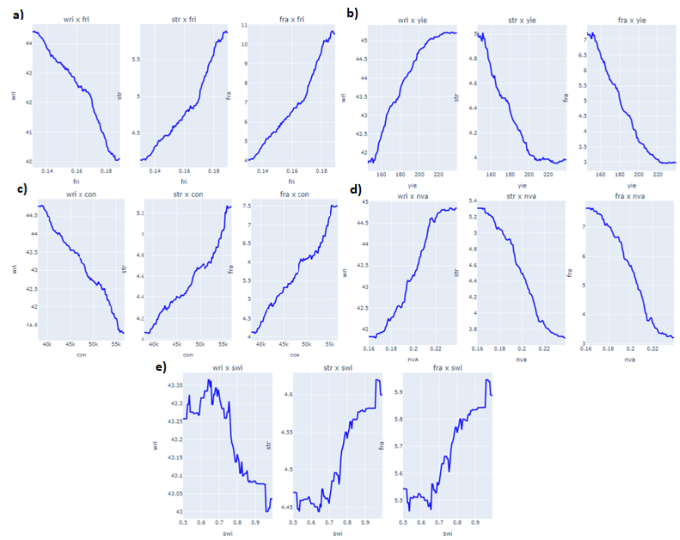

Fig. 4. Sensitivity Analysis - (a) FRI, (b) YIE, (c) CON, (d) NVA, and (e) SWI.

to the NSGA-II optimizer and the results are presented in the form of Pareto fronts in Figure 5.

An advantage of NSGA-II is its ability to provide consistent Pareto fronts, which allows the selection of individuals from a single run for analysis of results. These individuals were validated in AutoForm, and a direct relationship was observed between the results found and the output of the stamping process, showing a significant impact.

The results obtained are presented in Table II, where the deviation between the predicted measurements and the simulation results are compared using the RMSE metric.

TABLE II
RESULTS OF CASE STUDY 1 (RMSE METRIC).

Objective	***5 variables***	***4 variables***
WRI	1.048	0.836
IS	0.654	0.469
FRA	2.269	1.119

It is possible to observe that the error is reduced for all objectives when using only the correlated variables (a database with 4 variables). In general, both exploratory analysis tools indicated possible problems in the SWI variable, and its removal proved that its presence was harming the predictability of the model. Therefore, the specialist's intervention could have been anticipated and the parameters could have been properly defined even before the creation of the surrogate model.

B. Case Study 2 - Internal Tailgate

Case study 2 is focused on the analysis of the part Internal tailgate, which is a real component found in automobiles. This part is located at the rear of the vehicle, more precisely in the trunk area.

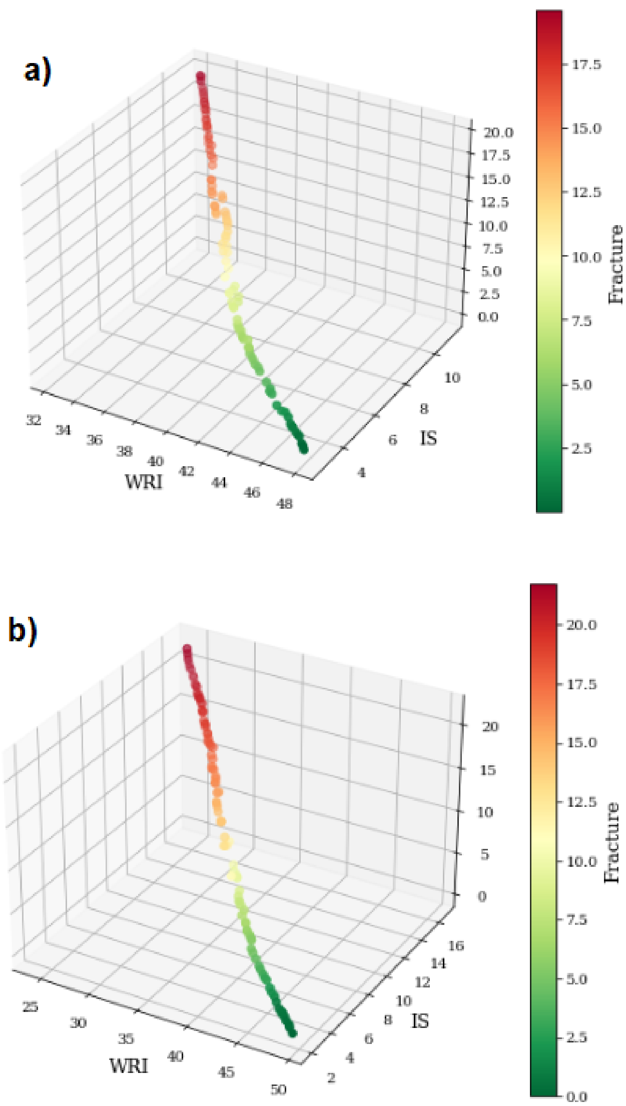

Fig. 5. Pareto Front - a) 4 variables, b) 5 variables

Figure 6 presents construction details of the Internal tailgate part, revealing important information about its structure and characteristics.

1) Selection of Parameters and Domains: In this case study, the variables Constant Force (CON), Coefficient of Friction (FRI), Tensile Strength (TEN), and Yield Stress (YIE) were initially considered by the expert. Table III presents the domains and parameters used to generate the database by the AutoForm software. Based on these parameters, it was possible to generate a database with 200 AutoForm simulations, with 4 inputs (CON, FRI, TEN, and YIE) and 3 outputs (WRI, IS, and FRA).

2) Data Pre-Processing: In order to evaluate the significance of the parameters defined after the database generation step, the correlation analysis is employed as shown in Figure 7.

After analyzing the correlations between the parameters and the objectives, we obtained results that allow us to conclude that all defined input variables have a substantial correlation with the established objectives. This finding reinforces the validity and effectiveness of the proposed experimental design.

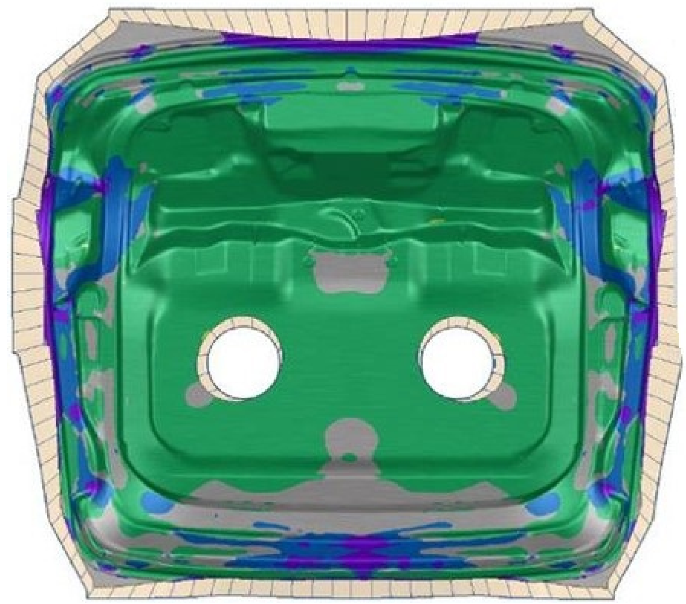

Fig. 6. Case Study 2 - Internal Tailgate. Areas of wrinkling (WRI - highlighted in purple) and under stretch (IS - highlighted in grey).

TABLE III
PARAMETERS AND DOMAINS OF CASE STUDY 2 (INTERNAL TAILGATE).

Parameters	***Minimum***	***Medium***	***Maximum***
CON	400000	900000	$1.4e^6$
FRI	0.13	0.15	0.17
TEN	300	356.435	400
YIE	205.692	244.385	274.385

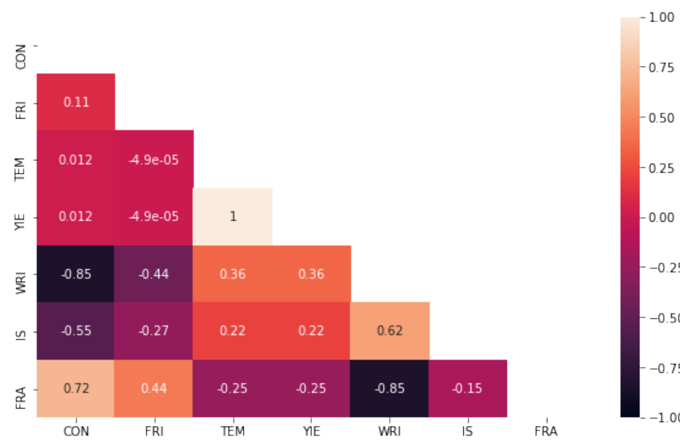

Fig. 7. Case study 2: Correlation between variables.

It is noteworthy to highlight the presence of a significantly strong correlation between the CON input variable and the WRI and FRA objectives. This indicates that the CON variable exerts a relevant influence on the desired results.

3) Model Definition: The adjusted parameters for ET in this study consist of a specific number of 170 estimators and a maximum depth of 30.

To evaluate the model, a sensitivity analysis was performed and it was possible to observe that the TEN and YIE variables have less significance. Although their range may be restricted, they contribute in a complementary way to the data set and can provide insights that help to better understand the scenario under study. Thus, it is essential to consider all available variables, in order to obtain a comprehensive and accurate understanding of the context under study.

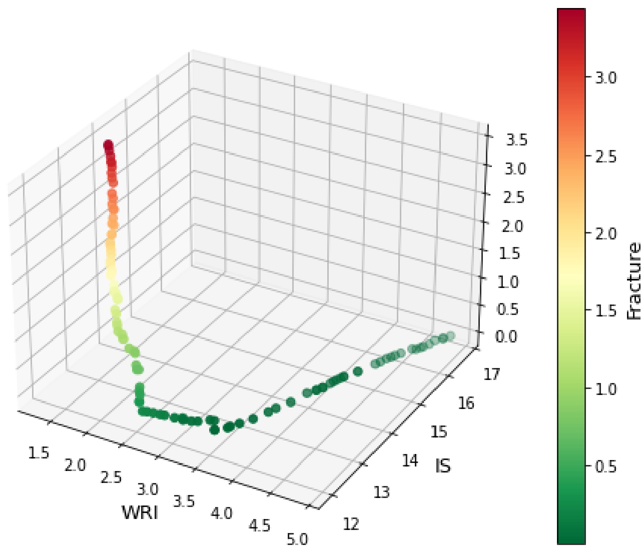

Fig. 8. Pareto Front Study 2.

4) Search for the Best Options: The surrogate model was submitted to the NSGA-II optimizer, and the results obtained were represented in the form of Pareto fronts in Figure 8. This approach allows the specialist to have access to a pool of options, which facilitates a more agile and precise definition of the best set of parameters and most suitable domains to achieve the desired results.

The table IV presents the configuration of the variables and results of the objectives obtained by the original stamping of the part and compares with the configuration obtained by the proposed approach. The result obtained by the proposed model provides a piece free of fractures and reduces the initial wrinkling by 15,7%, also reducing the stretching region by 7,8%. That is, the result obtained by the model brings a significant improvement not only in the conformation of the part but also in the cost of its development.

TABLE IV
DIFFERENCE IN PROPORTION OF AFFECTED AREA, IN PERCENTAGE, BY OBJECTIVE

	CON	***FRI***	***TEN***	***YIE***	***WRI***	***IS***	***FRA***
Empirical	390000	0.15	350	245	4.63	14.76	0
Optimized	473229, 89	0.15	324, 92	218, 59	3.93	13.6	0

VI. Conclusion and Future Work

The forming of a steel sheet by stamping is a complex mechanical process, widely used in the automotive industry, where it has demanding criteria in several aspects [9]. The challenge is to obtain parts with minimal defect rates, especially in terms of FRA, WRI, and IS. Currently, professionals who work in the development of parts and stamping tools use their knowledge to configure a set of parameters, whose ideal combination to minimize failures is very much based on experience and on trial and error steps. However, this empirical approach can slow down the development process and increase the risk of problems throughout production.

In this study, we propose the use of visualization tools to assist in decision-making before and after the creation of a surrogate model. Furthermore, we present a hybrid model that combines multivariate regression with the Extra Tree algorithm and multiobjective evolutionary optimization using the NSGA-II algorithm. The objective is to provide support to specialists in the field, identifying the optimized values of the stamping process variables that deal with the problems of FRA, WRI, and IS. To achieve this goal, we use complementary tools that offer consistency and robustness in the intermediate stages of the process.

The correlation and sensitivity analysis tools of the variables, as well as the proposed hybrid model, were applied in two case studies: a laboratory one, called “Cup”, and another involving a real part of an automobile, called “Internal Tailgate”. The results obtained were positive both in the application of the hybrid system and in the use of visual analysis tools.

When choosing to use ML algorithms as a surrogate model, it is essential to ensure its ability to adequately characterize the problem. In this context, the use of intermediate tools for correlation and sensitivity analysis proved to be effective, providing support to specialists in the field and anticipating decision-making, mainly in the definition of parameters and simulation domains.

The application of analysis tools by the proposed hybrid system resulted in good results. In the “Cup” case study, we observed a significant improvement in the predictive capacity. In the case study “Internal Tailgate”, a notable improvement in the conformation of the part was proven, in addition to a reduction in the costs associated with its development.

In future work, it is intended to verify how the system behaves in case there are fewer or more variables for optimization, aiming to further reduce the areas of FRA, WRI, and IS. It is also valid to study other MOEA to determine the resulting pool of options for experts.

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