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Optimizing the Validation Process of Resistance Spot Welds in the Automotive Industry Using TOPSIS and K-fold Cross-Validation

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***Abstract*—In a complex and constantly evolving environment, decision-making has become a major challenge for organizations, governments, and individuals. Faced with this complexity, Multi-Criteria Decision Making (MCDM) methods have proven to be valuable tools. Among them, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) technique stands out for its ability to provide informed and justified decisions. This issue is particularly relevant in the automotive industry, where resistance spot welding plays a critical role in the assembly of car bodies. However, the choice of optimal welding parameters requires taking into account many conflicting criteria. In this conference paper, we will present the results of training an artificial neural network, with the objective of classifying and validating weld spots according to their dimensions, indentations, and sheet thicknesses. This innovative approach aims to optimize the resistance spot welding process in the automotive industry, leveraging the advancements in artificial intelligence.**

Keywords— ANN, MCDM, TOPSIS, AI, K-fold, Quality, RSW

I. INTRODUCTION

The automotive industry, whether in Morocco or internationally, is constantly evolving [1 - 6]. The quality of resistance spot welding (RSW) is of crucial importance in the manufacturing of safe and reliable vehicles. RSW is widely used in automotive production to assemble metal components such as car bodies and chassis, due to its efficiency, speed, and low cost. Each vehicle can contain between 6,000 and 7,000 welding points, and the total number per day can reach 7 million welding points on a production line [7 - 11]. However, ensuring the quality of RSW remains a major challenge due to the complexity of welding parameters and variations in materials and manufacturing conditions. In this context, multi-criteria decision-making (MCDM) methods offer a promising approach to evaluate and optimize welding parameters to improve the quality of RSW. These methods allow for the consideration of various criteria to select the optimal welding parameters. The technique for order preference by similarity to an ideal solution (TOPSIS) is one of the most commonly used MCDM techniques to evaluate alternatives and identify the best solution. In this approach, TOPSIS compares each alternative to an ideal and anti-ideal criterion, and then calculates the Euclidean distance between each alternative and these two references to rank them in order of preference [12 - 20]. In the field of automotive manufacturing, the integration of artificial neural networks (ANNs) into multi-criteria decision-making (MCDM) methods offers new perspectives for the optimization of resistance spot welding (RSW). ANNs are capable of learning from complex data and modeling nonlinear relationships between the studied parameters and the performance of RSW. In 2014, a study examined the use of an artificial neural network (ANN) to optimize the resistance welding (RSW) parameters of the 6061-T6 aluminum alloy [21]. In 2021, another study focused on predicting the contact resistance of spot-welded joints on three-sheet zirconium assemblies using ultrasonic simulations and an artificial neural network (ANN). This study concluded that the combination of numerical simulation and ANNs proved effective for the prediction and optimization of resistance welding of multi-materials [22]. In this study, we propose to combine Artificial Neural Networks (ANNs) with the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method to develop a more accurate prediction model aimed at classifying and validating the quality of welding points. This synergy capitalizes on the learning capabilities of ANNs to apprehend complex structures, while integrating the robustness and efficiency of the TOPSIS method in multi-criteria decision-making. Thus, welding processes can be optimized in a more targeted and efficient manner, resulting in significant improvements in terms of quality and productivity.

Input data, such as diameter and indentation, are collected using the ultrasonic technique with a Resistance Spot Weld Analyzer (RSWA) device (2D Matrix Array Technology) [23]. Sheet metal thickness is automatically deduced by subtracting the indentation from the total sheet metal thickness.

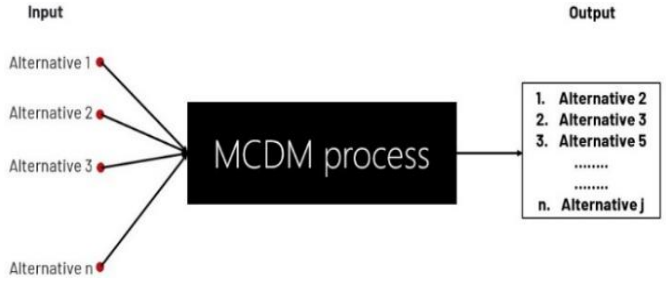
Regarding the weighting of each criterion, we first defined the relative importance of each criterion compared to the others.

Then, we calculated the geometric mean of these relative importances for each criterion. It is from these geometric means that we determined the final weighting of each criterion [24].

II. METHODOLOGY

A. *Multi-Criteria Decision Making (MCDM)*

MCDM is a powerful tool that allows complex decisions to be made in a more structured and transparent manner. Although it requires specific skills, its many advantages make it an increasingly used method in various fields. To implement the MCDM approach, we need to clearly define the problem, identify the possible alternatives, determine the relevant evaluation criteria and their importance, evaluate the performance of each alternative, and then aggregate these evaluations to obtain a ranking or selection, as illustrated in the overall approach shown in Fig. 1.



MCDM presents a multitude of advantages, namely the consideration of the complexity of real problems, the structuring and formalization of the decision-making process, the promotion of stakeholder participation, the identification of the best compromises, and the improvement of the quality and justification of decisions. However, it also has disadvantages and limitations, such as the subjectivity in the weighting of criteria, the complexity of data collection and aggregation, the risk of being perceived as a "black box", and the sensitivity of the results to assumptions and input data[13], [23 - 29].

B. *TOPSIS method*

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method is a multi-criteria analysis tool (MCDM) that aims to identify the best alternative among a set of options. Its principle is to select the alternative closest to the positive ideal solution and farthest from the negative ideal solution [30 - 38], as illustrated in Fig. 1:

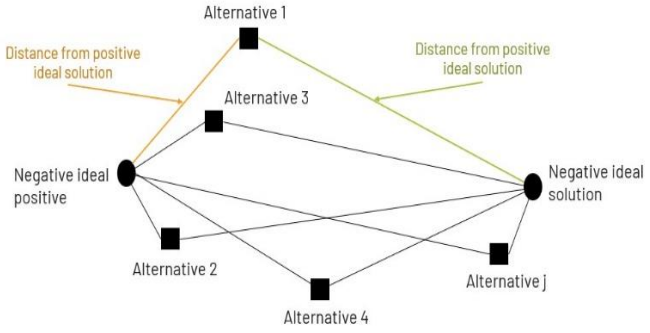


Fig. 1. TOPSIS Diagram

The application of the TOPSIS method begins by constructing the decision matrix $X = [x_{ij}]$ where x_{ij}represents the performance of alternative i with respect to criterion j. Then, the normalization of this matrix to obtain comparable values, where $R = [r_{ij}]$, the normalized matrix with $r_{ij} = \frac{x_{ij}}{\sqrt[2]{\sum_1^m {x_{ij}}^2}}$ (1)

Then it proceeds to determine the weighted matrix $V = [v_{ij}]$; $V = (v_{ij}) = \omega_j \times r_{ij}$ (2)

Where ω_j is the weight of criterion j.

We then determine the positive ideal solutions $A^+ = \{a_1^+, a_2^+, a_3^+ \dots, a_n^+\}$ and We then determine the negative ideal solutions $A^- = \{a_1^-, a_2^-, a_3^- \dots, a_n^-\}$.

Then, for each alternative, we calculate the Euclidean distances to these two solutions D+ et D- :

$$D_i^+ = \sqrt{\sum_j (r_j^+ - p_{ij})^2} \quad (3) \; ; \; D_i^- = \sqrt{\sum_j (r_j^- - p_{ij})^2} \quad (4)$$

Finally, we calculate the relative proximity coefficient P_f :

$$P_f = \frac{D_i^-}{D_i^- + D_i^+} \quad (5)$$

The final ranking of the alternatives is then done in descending order of this Pf coefficient, with the best alternative being the one whose value is closest to 1.

C. *Artificial Neural Networks (ANN)*

They are machine learning models inspired by the functioning of the human brain. They are composed of multiple layers of interconnected neurons that learn to perform specific tasks from training data, where each neuron receives inputs, performs simple mathematical operations (such as a weighted sum followed by an activation function), and produces an output that is transmitted to the neurons of the next layer. The weights of the connections between the neurons are adjusted iteratively during the learning phase to minimize the error between the model's predictions and the target values, as seen in equation (6) and Fig. 2 [39 - 49].

$$y = f(\sum_1^n \omega_{ni} \times x_i + b) \quad (6)$$

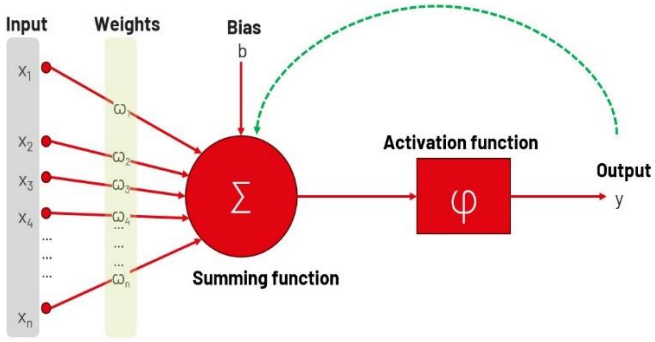


Fig. 2. Process ANN

The learning of a neural network consists of adjusting its parameters (weights and biases) in order to minimize the cost function that reflects the difference between the model's outputs and the target values. This adjustment of the parameters is generally done by an iterative optimization method, such as gradient descent, as shown in equations (7) and (8).

$$\omega_{ni} \leftarrow (\omega_{ni} - \vartheta \frac{\partial L}{\partial \omega_{ni}}) \quad (7) \; ; \; b \leftarrow (b - \vartheta \frac{\partial L}{\partial b}) \quad (8)$$

D. *K-Fold Cross-Validation.*

Since its introduction by M. Stone in 1974 [52], the K-fold cross-validation method has seen the emergence of several distinct variants. These include the stratified K-fold cross-validation variant, which ensures a balanced distribution of classes within the datasets [53]. There is also nested K-fold cross-validation, an approach known for its usefulness in hyperparameter optimization and selecting the most performing models [54]. In addition, repeated K-fold cross-validation is distinguished by its ability to provide a more stable and reliable estimate of the performance of the evaluated models [55]. Moreover, group-

based cross-validation is particularly suitable for the accurate evaluation of data with a grouped structure [56]. Finally, block-based cross-validation is particularly useful for the fine evaluation of time-series data [57]. Thus, these different variants of K-fold cross-validation offer specific advantages depending on the characteristics and structure of the data to be analyzed. Applications of the K-fold method include modeling a photovoltaic-thermal (PV/T) air system using machine learning techniques [58], optimizing the parameters of the friction stir welding process for AA2050-T8 aluminum alloy [59], automatic detection of porosity in welds made by the pulsed gas tungsten arc welding (P-GTAW) process, used in particular in the nuclear industry [60], and automatic classification of Hindi poems into 3 categories (romance, courage, sadness) using machine learning techniques [61]. The principle of applying K-fold cross-validation is to provide a reliable and robust estimate of the performance of a model, taking into account the variability of the results. It is widely used to evaluate and compare the performance of different models on the same dataset. Its principle consists of dividing the provided data into K subsets of equal (or approximately equal) size, of which the model is trained K times, using K-1 subsets for training and the remaining subset for testing [62], see Fig. 3:

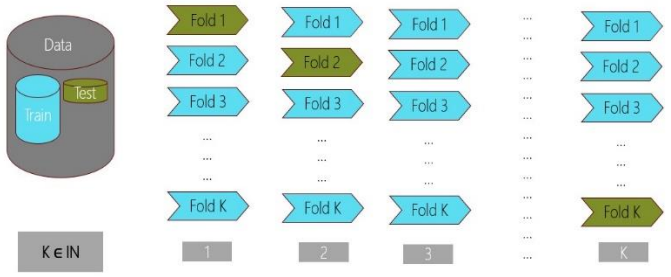


Fig. 3. K-Fold cross validation

E. Evaluation of the chosen model

To evaluate a regression model, we could use a wide variety of metrics. In our study, we have chosen to work with a number of indicators such as the MSE (Mean Squared Error) which represents the squared difference between the predicted value and the real value that we would expect to see on average. It is expressed in the same unit as the target value squared, as shown in equation (9). While the MAE (Mean Absolute Error) defines the average of all the absolute prediction errors, where the prediction error is the difference between the real value and the predicted value. Using the absolute value of the prediction errors prevents the mutual cancellation of errors. The MAE value is expressed in the same unit as the target value, as shown in equation (11). However, the RMSE (Root Mean Squared Error) is the square root of the mean squared error and can be interpreted as the average +/- expected difference between a predicted value and the real value. It is the standard deviation of the residuals (the difference between the observed value and the predicted value of a feature). The RMSE value is expressed in the same unit as the target value, as shown in equation (10). Finally, we have the R2 (Coefficient of Determination) The coefficient of determination R-squared (R2) is a unitless measure of the correlation of the features with respect to the target, as shown in equation (12).

$$MSE = \sum_{1}^{n} \frac{\left(y_{i,obs} - y_{i,predict}\right)^2}{n} \quad (9)$$

$$RMSE = \sqrt{\sum_{1}^{n} \frac{\left(y_{i,obs} - y_{i,predict}\right)^2}{n}} \quad (10)$$

$$MAE = \frac{1}{n} \times \sum_{1}^{n} \left|y_{i,obs} - y_{i,predict}\right| \quad (11)$$

$$R^2 = 1 - \sum_{1}^{n} \frac{(y_{i,obs} - y_{i,predict})^2}{(y_{i,predict} - y_{mean})^2} \quad (12)$$

III. MODELING THE SOLUTION

After collecting the results of the non-destructive test using the ultrasound technique, our work will aim to design a deep learning algorithm in order to automate the process of sorting and validating the spot welds. The general scheme of our study will unfold as shown in Fig. 4. The first step is to gather and prepare the data that will be used to train the deep learning model. This may include collecting, cleaning and formatting the data to make it compatible with the model. Secondly, before proceeding with the training, it is important to validate the data to ensure its quality and representativeness. This may involve consistency tests, the identification and management of missing values or anomalies, which is why we will use K-fold cross-validation. Once the data is prepared, the deep learning model is trained using this data. This generally involves optimizing the model parameters to minimize a cost or error function. After training, it is necessary to evaluate the model's performance on an independent validation dataset. This allows measuring the model's ability to generalize to new data and identifying any potential overfitting or underfitting issues.

Fig. 4. Learning Process

The input elements of our model will be the electrode indentation, the sheet thickness and diameter, the model will calculate the true values of the proximity factor which will be used to train our model, while using the K-fold cross-validation whose objective is to determine the best K that gives the best values of MSE, MAE, RMSE, and R2, and the optimal number of iterations in order to have a better cost function, such that K={2,3,4,...,15} as shown in Fig. 5.

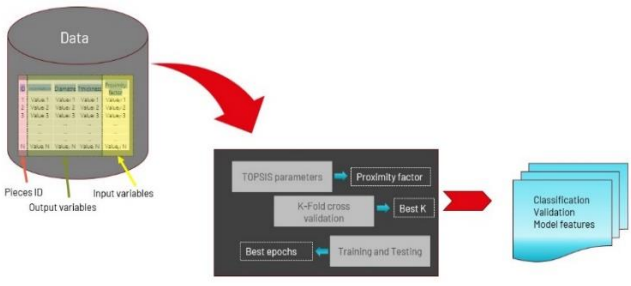


Fig. 5. Application diagram

<u>The parameters of the studied model are:</u>

- Model used: MLPRegressor (Multi-Layer Perceptron Regressor)
- Model configurations:
- Hidden_layer_sizes=(1000, 1000): two hidden layers of 1000 neurons each

- Max_iteration=1000: maximum number of training iterations
- Random_state=42: random initialization of parameters with a fixed seed
- Early_stopping=True: activation of early stopping to avoid overfitting
- Validation_fraction=0.2: proportion of validation data used for early stoppingModèle utilisé : MLPRegressor (Regressor à Réseau de Neurones Multicouche)

IV. RESULTS AND DISCUSSION

In Fig. 6, we have the predicted values for each K in comparison with the actual values, while calculating the values of the test evaluation indicators shown in the table.

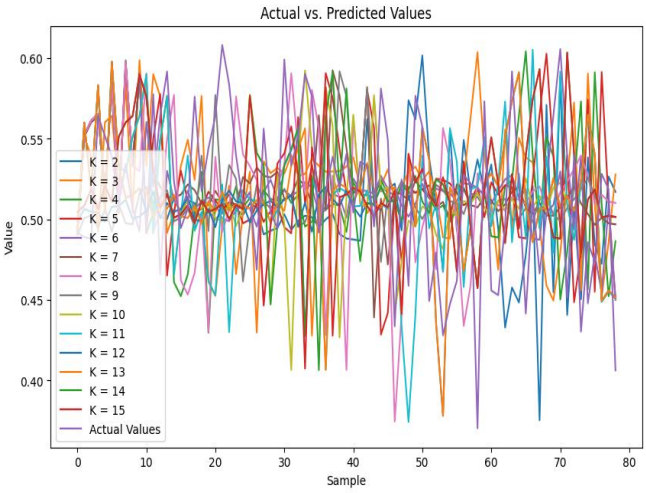


Fig. 6. Actual vs predicted values

TABLE 1. RESULTS OF MODEL EVALUATION PARAMETERS

K	MSE	MAE	RMSE	R^2
2	0.0032	0.0449	0.0567	0.9984
3	0.0035	0.0469	0.0596	0.9998
4	0.0033	0.0459	0.0576	0.9997
5	0.0037	0.0504	0.0610	0.9995
6	0.0028	0.0433	0.0533	0.9997
7	0.0026	0.0418	0.0510	0.2398
8	0.0039	0.0507	0.0624	0.3197
9	0.0027	0.0423	0.0519	0.2770
10	0.0030	0.0451	0.0547	0.9995
11	0.0040	0.0501	0.0629	0.9995
12	0.0026	0.0430	0.0510	0.9998
13	0.0030	0.0444	0.0544	0.9998
14	0.0033	0.0463	0.0576	0.2733
15	0.0037	0.0481	0.0605	0.2734

The best model according to these results presents the best balance between an excellent explanatory power R2 close to 1 and very low prediction errors, namely, MSE, MAE and RMSE. According to the TABLE 1, the best model corresponds to the value of K = 12, because the coefficient of determination R2 is the highest for K = 12, at 0.9998. This means that the model with 3 explanatory variables explains 99.98% of the variance of the target variable, which is excellent. Moreover, the other error measures are also the best for K = 12, namely, MSE = 0.0026, which is very low, MAE = 0.0430 and RMSE = 0.0510 with an optimal number of iterations equal to 126 iterations. Fig. 7 illustrates the graph of the predicted values and actual values for the parameter K=12, which is the most suitable for our data.

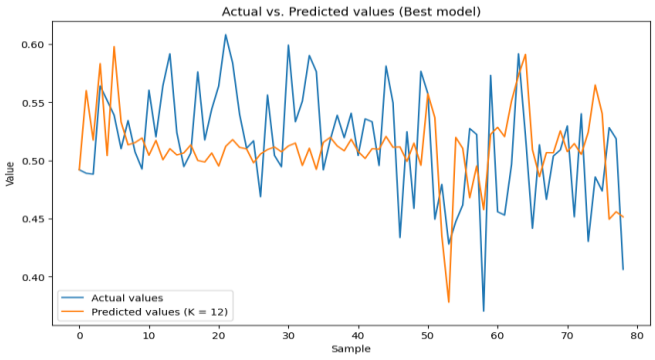


Fig. 7. Actual vs predicted values for K=12

This graph shows a comparison between the actual values (in blue) and the predicted values (in orange) for a model with K=12. Here are the main elements to note:

- Dynamics of the values: The actual and predicted values follow similar trends, with peaks and troughs at the same locations. This indicates that the model captures the overall dynamics of the phenomenon well.
- Punctual deviations: Although the dynamics are well reproduced, we observe punctual deviations between the actual and predicted values. Some samples show more significant differences than others.
- Overall performance: Overall, the model seems quite effective at predicting the values, with an ability to follow the major trends. However, improvements could be made to reduce the punctual deviations.
- Optimization potential: Analyzing these punctual deviations could help identify avenues for improving the model, for example by adjusting certain parameters or exploring other architectures.

Evolution of the cost function: At the beginning of the training, the loss function is quite high, around 0.18. This indicates that the model has not yet learned the characteristics of the training data well. However, we observe a rapid decrease in the loss function over the first few iterations, dropping below 0.05 after only 20 iterations. This shows that the model is able to effectively learn the patterns present in the training data. Subsequently, the loss function continues to decrease more slowly and stabilizes around a value close to 0, around 60-80 iterations. This suggests that the model has reached an optimal performance level on the training data. Overall, we observe a rapid convergence of the loss function towards a minimum value, which indicates that the model training process is progressing satisfactorily (Fig. 8). As a result, this graph shows the model's good ability to capture the overall dynamics, while highlighting possibilities for optimization to reduce the punctual deviations between actual and predicted values. A more in-depth analysis of the residuals could help identify potential sources of error and advance the model's performance.

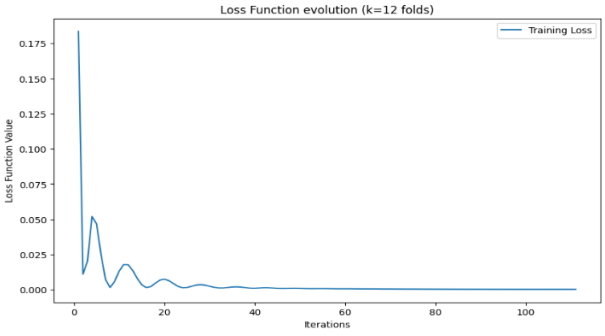


Fig. 8. Loss Function K=12

V. CONCLUSION

In conclusion, this study highlights the crucial importance of the quality of resistance spot welding (RSW) in the automotive industry. Faced with the challenges related to the complexity of welding parameters and variations in materials, multi-criteria decision-making (MCDM) methods, such as TOPSIS, offer a promising approach for the evaluation and optimization of welding processes. The integration of artificial neural networks (ANNs) in these methods opens up new perspectives, enabling more accurate modeling of the relationships between welding parameters and RSW performance. By combining ANNs with the TOPSIS method, it is possible to develop more robust and efficient predictive models, leading to significant improvements in terms of quality and productivity in automotive manufacturing. The results of this study demonstrate that the proposed model, particularly with a K parameter equal to 12, presents an optimal balance between a high explanatory power (R2 close to 1) and minimal prediction errors (low MSE, MAE, and RMSE). The analysis of the predicted values compared to the actual values highlights the model's ability to capture the overall dynamics of the phenomenon, while identifying avenues for improvement to reduce the punctual deviations. Finally, the evolution of the cost function during the model training confirms the rapid convergence towards optimal performance, thus illustrating the efficiency of the optimization process. Overall, this study offers a valuable contribution to the optimization of welding processes in the automotive industry, paving the way for significant advancements in quality and efficiency.

This research emphasizes the critical role of high-quality resistance spot welding (RSW) in car manufacturing. Since RSW involves complex settings and material variations, the study proposes a new approach for optimizing the welding process. This approach combines two methods:

TOPSIS (multi-criteria decision-making): This method helps evaluate and improve the welding process by considering multiple factors.

Artificial Neural Networks (ANNs): These networks can learn complex relationships between welding settings and the resulting weld quality.

By combining TOPSIS with ANNs, the researchers created a more accurate model to predict the best welding settings for a desired outcome. This model achieved a high success rate (close to 100% accuracy) with minimal errors. The analysis showed the model can capture the overall welding process behavior and pinpoint areas for improvement. Additionally, the training process converged quickly, indicating efficient optimization. In conclusion, this research offers a valuable tool for optimizing RSW in car manufacturing, ultimately leading to better quality and production efficiency.

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