# MACHINE LEARNING-BASED ANALYSIS ENGINE TO IDENTIFY CRITICAL VARIABLES IN MULTI-STAGE PROCESSES: APPLICATION TO THE INSTALLATION OF BLIND FASTENERS

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**ABSTRACT:**

Quality control in manufacturing is a recurrent topic as the ultimate goals are to produce high quality products with less cost. Mostly, the problems related to manufacturing processes are addressed focusing on the process itself putting aside other operations that belong to the part's history. This research work presents a Machine Learning-based analysis engine for non-expert users which identifies relationships among variables throughout the manufacturing line. The developed tool was used to analyze the installation of blind fasteners in aeronautical structures, with the aim of identifying critical variables for the quality of the installed fastener, throughout the fastening and drilling stages.  The results provide evidence that drilling stage affects to the fastening, especially to the formed head's diameter. Also, the most critical phase in fastening, which is when the plastic deformation occurs, was identified. The results also revealed that the chosen process parameters, thickness of the plate and the faster type influence on the quality of the installed fastener. **Keywords: Analysis Engine, Multi-Stage Processes, Critical Variables, Machine Learning, Blind Fasteners.**

## 1.- INTRODUCTION

Recent advances in the manufacturing industry have triggered out the capacity of acquiring, storage and processing of the data. Furthermore, thanks to the sophisticated analysis techniques, the machines can perform in a more efficient, collaborative and communicative way [1]. There are innumerable investigations [2,3,4] that make use of Artificial Intelligence methods to model and optimize manufacturing processes. Thus, there is a vast amount of research work regarding to machining operations that uses Machine Learning (ML) models to generate knowledge of the process and extract information about the performance of the process based on the collected data. It is possible to find relatively simple models, from Polynomial or Multiple Regression [5,6] to more sophisticated ones, such as Neural Networks [3,4], Bayesian Networks [7], Decision Trees [8] or Support Vector Machines [9].

One of the manufacturing processes where ML techniques are applied is machining. The optimization of machining parameters was the subject of diverse [10,11] research as proper optimization of the process has become a challenging task, mainly because machining plays an important role in the economic aspects of metal cutting operations. For instance, in a turning process the cutting parameters of cutting speed, feed force and depth of cut should be optimized for achieving minimum cost of machining and minimum production time [12] Nonetheless, for efficient optimization, it is necessary to understand how the cutting parameters influence the process, thus this can be posed as a prediction problem.

Some authors carried out a survey about the application of soft computing techniques in machining to make predictions [13].  Soft computing techniques were applied to machining processes as they are preferable compared to physics-based, models, due to the complexity and uncertainty of the machining process. Among the reviewed techniques there were Fuzzy Logic [14] and Neural Networks [15] to make predictions in the machining processes of turning, milling, grinding and drilling. The prediction was focused to surface roughness, tool wear and tool life, wheel wear, cutting force, grinding force and drilling force. The optimization techniques of Genetic Algorithm [16], Simulated Annealing [17], Ant Colony Optimization [18] and Particle Swarm Optimization [19] were used to optimizing the neural network parameters.

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Moreover, there are other research works that make use of statistical techniques, such as statistical testing [10], correlation analysis or variance analysis (ANOVA) [20] to detect the most influencing variables in manufacturing processes. Although these statistics methods offer the opportunity to interpret the results easier than the methods based on ML, there is an increase in the number of investigations [21,22] that draw on ML techniques. Decision Trees for instance, offer the chance to know how each input variable affects to the output, by interpreting the rules of the generated tree or knowing the weights of the input variables in the generated tree.

Most of the investigations that make use of ML techniques to analyze data are focused on a single stage of the manufacturing process and are less abundant those that take into account the overall effect of the whole line production [23,24]. These research works mostly focus on developing models for the generation and propagation in time of the errors for specific cases, but do not offer a generalist approach to the line analysis. In addition, these models should offer an understanding about the relationship between variables, to interpret what is happening in the process.

In this investigation, an analysis engine based on ML techniques for non-experts in data analysis was developed to detect the critical process variables in a production line. The analysis can be focused in a particular process or consider previous processes of the line. For that purpose, Random Forests are used, that are based on Decision Trees, to interpret the relationship generated between input variables and the output variable.

The fastening process is a complex task that involves multiple fields of knowledge such as metallic materials, composite materials, classical mechanics, machining and manufacturing among others. It should be noted that it is not easy to develop a predictive model for fastener's quality prediction, including the effect of process parameters and installation diagram, due to non-linear behavior of the fastening mechanism. For this reason, this problem is suitable to be deal with ML techniques and was chosen as a case study. Though blind fasteners are an interesting joining solution for the aerospace industry due to their advantages for automation the in-line inspection of their installation is not yet feasible [25]. Up to date, fastener installation and immediately previous drilling have analyzed and attempted to be controlled separately [26, 27]. By analyzing the two consecutive stages together drilling variables affecting to the installation could be identified and taken into consideration. This represents a meaningful and simple case for the tool developed.

## 2.- METHODS

The analysis engine aims to detect dependence relationships between process variables and variables related to the quality of the part done to identify critical variables. For that purpose, an analysis engine, was created for non-expert users in data analysis field. The main advantage that offers the tool is that it is not necessary for non-expert users to have programming skills. The tool is intuitive due to the user-friendly interface, where the user configures the input and output variables, and some other parameters related to the validation of the model by typing them or joining the arrows of the boxes.

## 2.1. DEVELOPED TOOL

The developed tool offers two different functionalities, the generation of the model and the verification of the model. The first aims learning a function *f* and validating the quality of it. Also offers the opportunity to interpret most significant variables in the model to identify the critical variables in the process. The second functionality is to use a previously learnt model with new data. Depending on the current quality of the model, the user can decide whether the model still fits well, or it is necessary to train it again.

There are some stages, such as exploratory data analysis, pre-processing or data cleaning, that are considered previous stages to ML, that are not included in the tool. There are specific tools for that purposes such as Machine Learning Studio module from Azure or libraries of R and Python programming languages.

For training the data in the corresponding regression and classification tasks, the Random Forest [28,29] algorithm is used. It belongs to the family of the ensemble learning [30] algorithms that combines Decision Trees with majority voting (classification) or computing the average (regression). The following measurements are used to perform the validation of the generated model: $R^2$ for both regression and classification, accuracy for classification and RMSE for regression.

$R^2$: Measures how well are replicated the observed values, based on the total proportion of variance of the values explained by the model [31].

Accuracy: Proportion of correct classified instances by the model, against all instances.

Root Mean Squared Error (RMSE): Is the standard deviation of the residuals, prediction errors, defined in Equation (1).

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$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}{n}} \quad (1)$$

Where $n$ is the number of instances, $y_t$ the real observed value and $\hat{y}_t$ the predicted value by the model.

### 2.1.1. Integration of the analysis engine

The analysis engine was integrated in an on-line platform developed in collaboration with other partners of the European project ForZDM [32]. The platform offers algorithms integrated in services of web REST, allowing the use from other tools, such as the access to the data from different sources, other REST services or data uploaded directly to the platform. This architecture offers as a novelty, the integration of the process data in real time with the off-line quality measurements of the final part.

The generated models in the learning stage are saved in the server. Thus, it is possible to verify the model with new data whenever the user wants. The platform has a user interface where each developed algorithm is presented as a stage that includes some entries and exits. These stages can be connected among them in a cascade, where finally appears a visualization component that allows to access to a table with results or to a figure. The functionalities of the tool were programmed using scikit-learn [33] module of Python programming language.

## 3.- INSTALLATION OF BLIND FASTENERS: A CASE STUDY

Blind fastening is a particular type of mechanical fastening where the fastener is introduced from the front face of the assembly. The scientific community has made a big effort in understanding and modelling [30] the fastening process, as well as developing methods to evaluate the unions joined by fasteners.

## 3.1. DESCRIPTION OF THE DATABASE

The database used for the study is compound of 463 fastener installation cases and 112 variables, obtained from real experimental procedure. Table I shows the main test conditions where the "Test N" is the number of tests, "Thickness" indicates the thickness of the plate, the "Theoretical Grip" is a range of thicknesses in which a grip can be installed, the "Installed Grip" indicates the thickness in which the fastener was installed, and the "Batch" is the batch used, A or B.

Table I also shows the outcome of the tests. Regarding to the "Grip-code selection", AIR is a fastener installed without the presence of a plate, LARGE is a fastener whose grip (related to fastener length) is much longer than is desirable for the thickness of the plate, NOK is an incorrectly selected fastener with a slightly inappropriate grip for the plate thickness, OK is a correctly selected fastener, and SMALL is a fastener whose grip is much smaller than desirable for the plate thickness. The "Inst. outcome" indicates if the fastener was not installed (NO INSTALLED), if the fastener was installed correctly (OK) or the fastener was installed but not correctly (NOK). The "Group" classifies the installation outcomes based on the fastener made selection and the resulting quality of the installation and "Inst. N." refers the quantity of fasteners belonging to each of the groups.

| Experimental procedure's conditions | | | | | Outcome of the tests | | | |
|---|---|---|---|---|---|---|---|---|
| Test N | Thickness | Theoretical Grip | Installed Grip | Batch | Grip-code selection | Inst. outcome | Group | Inst. N. |
| 0-59 | 0 | G0 | G300/G350/G400 | A/B | AIR | NO INSTALLED | 1 | 60 |
| 60-119 | 2,3 | G100 | G300/G350/G400 | A/B | LARGE | OK | 2 | 0 |
| 120-179 | 3,2 | G150 | G300/G350/G400 | A/B | LARGE | NOK | 3 | 120 |
| 180-219 | 8,89 | G350 | G350/G400 | A/B | NOK | OK | 4 | 53 |
| 220-279 | 8,26 | G350 | G300/G350/G400 | A/B | NOK | NOK | 5 | 47 |
| 280-319 | 7,62 | G350 | G300/G350 | A/B | OK | OK | 6 | 96 |
| 320-359 | 10,16 | G400 | G350/G400 | A/B | OK | NOK | 7 | 4 |
| 360-399 | 11,43 | G450 | G350/G400 | A/B | SMALL | OK | 8 | 0 |
| | | | | | SMALL | NOK | 9 | 20 |

*Table I. Summary of the main test conditions and outcome of the tests.*

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The variables used in the analysis are classified in different groups as shown in Table II. The input variables are the ones related to the hole measurements, descriptors of the signal and test conditions. The output variables are the fastener's measurements and the group of the fastener (variable "Group" of Table I.).

Before the analysis, some pre-processing of the monitored signals was performed by: filtering the signals, lining them up, normalizing the $X$ and $Y$ axis and extracting descriptors. Fig.1. (a) shows one of the torque-angle curves monitored.

The torque-curved signal was split into six segments, in which different descriptors were extracted. These sections correspond to the different stages of the blind fastener installation: 1- installation start (change on the slope), 2- stop of sleeve rotation (calculated as the maximum of the detrend signal), 3- sleeve contact (change on the slope positive values), 4- sleeve formation (slope increasing), 5- installation completed (maximum torque value) and 6- spindle turn off (torque value reaches almost zero). Table III. shows the extracted descriptors per segment, as they are six segments and 15 descriptors, in total 90 descriptors are considered.

Concerning the holes, the average diameter, the depth of the drill and the depth of the countersink are measured. On the other hand, as far as the final quality of the fastener is concerned, it is evaluated by measuring the dimensions (diameter and height) of the formed head, as well as the steam's break-off that stands out from the front face of the assembly. Fig.1. (b) and Fig.1. (c) show the representation of a blind threaded fastener as the ones used for the study after completing the installation, where the measurement $J$ indicates the diameter of the head from the back face, and measurement $K$ indicates the length of the head from the back side.

| | Group of variables | Number of variables | Variables |
| --- | --- | --- | --- |
| Input variables | Test conditions | 4 | Plate thickness |
| | | | Fastener type |
| | | | Fastener grip code |
| | | | Batch |
| | Descriptors from the monitored signal | 90 | Details in Table III |
| | Hole measurements | 3 | Hole diameter |
| | | | Hole depth |
| | | | Countersink depth |
| Output variables | Fastener's measurements | 3 | Head's diameter |
| | | | Head's height |
| | | | Steam's height |
| | Fastener's groups | 1 | Details in Table I |

Table II. Classification of the variables used in the analysis.

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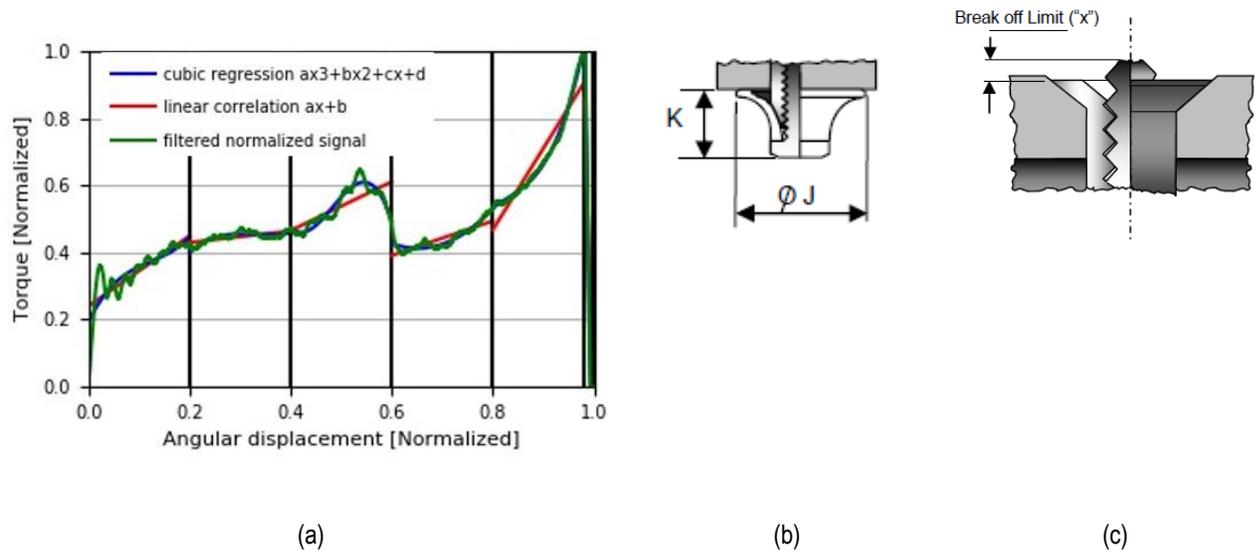
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(a)          (b)          (c)

*Fig. 1. (a) Example of a monitored torque-angle curve; (b) diameter of the formed head (J) and height of the formed head (K); (c) breaking-off length of the steam (X).*

| Number | Type | Name |
|---|---|---|
| 1, 2 | Maximum and minimum of the torque in the segment | $Tmax_i$-$Tmin_i$ |
| 3, 4 | Angular displacements corresponding to the maximum and minimum torque values in segment $i$ | $AngDispMax_i$, $AngDispMin_i$ |
| 5 | Area under the torque-angle curve within segment $i$ | $AUC_i$ |
| 6-10 | Parameters associated to linear correlation (slope, intercept, R, $R^2$, mean square error (MSE)) | From $[ax+b]_i$ a, b, R, $R^2$ and MSE |
| 11-15 | Parameters associated to third order polynomial correlation (parameters of the model and MSE) | From $[ax^3+bx^2+cx+d]_i$ a, b, c, d and MSE |

*Table III. Descriptors extracted from the torque-angle signals.*

## 3.2. RESULTS AND DISCUSSION

To study the critical variables in the blind fastening three different scenarios are proposed: 1) The influence of hole measurements in the quality of the fastener; 2) Influence of the monitored signal in the quality of the fastener; 3) Influence of the test conditions in the quality of the fastener.

### 3.2.1. Hole measurements

In this section, the influence that have the three variables related to the hole's measurement (hole diameter, hole depth and countersink depth) in each of the variables related to the quality of the fastener's installation (head diameter, head height and steam break-off) is performed. As the three variables are quantitative, regression models are built and corresponding measurements to perform the quality of the models are used. Table VI. shows the measurements obtained for the generated models for each variable. As can be observed, the R² is lower in the models regarding to hole measurements than the models related to test conditions, being the highest for the head's diameter (0.53). That is, the variables related to the hole's measurement can predict better the head's diameter than the head's height and steam's height.

The RMSE indicates the standard deviation of the residuals (prediction errors), being the lowest for the head's diameter (0.31 mm) continued by head's height (0.5 mm) and steam's height (0.53 mm). From these results it can be concluded that despite the low $R^2$

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values the measurements of the hole have some influence in the final quality of the installed fastener, in particular on the formed head values.

| | Hole measurements | | Test conditions | |
|---|---|---|---|---|
| | $R^2$ | RMSE | $R^2$ | RMSE |
| Head's diameter | 0.53 | 0.31 | 0.75 | 0.2 |
| Head's height | 0.42 | 0.5 | 0.64 | 0.36 |
| Steam's height | 0.46 | 0.53 | 0.67 | 0.36 |

*Table IV. $R^2$ and RMSE measurements for the three models generated regarding the installed fastener quality checks, using as predictive variables hole measurements and test conditions.*

Regarding to how the input variables affect to the output variable, a similar pattern was found in the three built models. Fig.2. a) shows the importance of the predictive or input variables for the head's diameter. As it can be seen, the order of relevance is: the depth of the countersink, depth of the hole and diameter of the hole. That is, to have a suitable head's diameter, a bigger emphasis must be put on the depth of the countersink and depth of the hole. This pattern is repeated for the steam's break-off, however, for the head's height, the drilling thickens has more influence than the depth of the countersink. In order to have a better understanding of the quality of the predictions, Fig. 2. b) shows the real values versus the predicted values for the fastener formed head diameter. Those points that are closer to the regression line, were predicted more accurately than the others that are farther.

The lower contribution of the hole diameter can be explained by the fact that the fasteners used do not expand radially along the installation. Hole diameter should not be therefore a critical variable for the resulting installation. Regarding the other two variables analyzed, countersink depth and depth of the hole, they define together the grip length which determines the fastener grip code to use, so they should be expected to have an influence on the quality of the installed fastener.

From the results shown in this section, it is worth noting that the drilling process has an influence on the union in terms of its static resistance and fatigue as suggested in [35], but also that it significantly affects the correct performance of the fastening process.

### 3.2.2. Descriptors of the monitored signal

In this section the influence that have the 90 descriptors obtained from the torque-angle monitored signal on the variable group is analyzed. This variable differentiates the fasteners in 9 classes or categories depending on the type of installation and the quality of the installation. As the variable is qualitative, classification models will be built and corresponding measurements to perform the quality of the models will be used. In this case, the $R^2= 0.78$ is higher than the $R^2$ scores obtained from the previous section, though it is usual to obtain better results in classification models than in regression models for Decision Trees. The accuracy obtained is of 86%, that is, 86% of the fasteners were classified in the correct group that they belong. It is noticeable that the monitored signal corresponding to a fastener has a big influence on its quality.
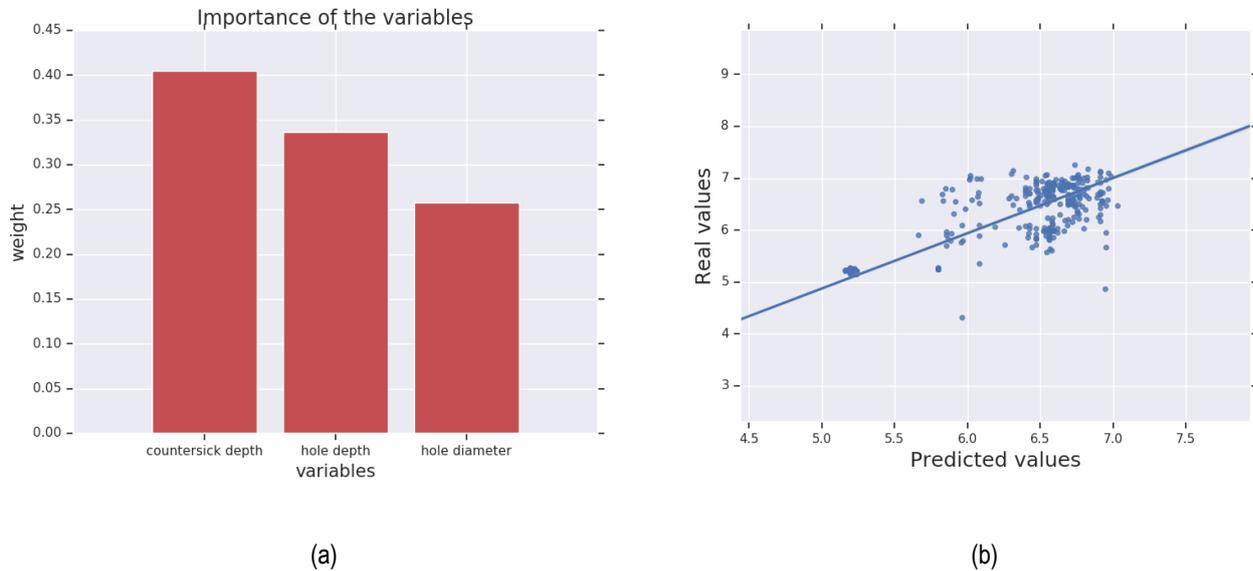
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(a)                                                                 (b)

Fig. 2. (a)The weight of the input variables, depth of the countersink, depth of the hole and the hole diameter, in the generated model for the fastener formed head diameter; (b) Real and predicted values in the model generated for the fastener formed head diameter.

Fig.3 shows the importance of the input variables depending on the weight that they have in the generated model. As can be observed, there are 5 variables that predominate over the rest of the variables: maximum time (segment 5), coefficient *b* of *[ax+b]* (segment 6), *MSE* of *[ax+b]* (segment 5), area (segment 5), coefficient *a* of *[ax+b]* (segment 6), minimum angular displacement (segment 5) and *R* of *[ax+b]* (segment 5). It can be concluded that segment 5 and 6 are more important to determine the quality of the fastener, that the other segments. Certainly, segments 5 and 6 should be expected to provide the highest amount of information on the quality of the installations, since it is within the period, they cover that the plastic deformation takes place, so the fastener head forms and the steam breaks off.

### 3.2.3. Test conditions

In this section, the influence that have the variables related to test conditions on the measurements of the installed fasteners is studied. As the three variables are quantitative, regression models will be built and corresponding measurements to perform the quality of the models will be used. Table IV. shows the $R^2$ and RMSE measurements for the three generated models. In this case, the $R^2$ scores are higher than the ones obtained for hole measurements. Also, in this case, the highest one is for the head's diameter (0.75) followed by steam's break-off (0.67) and head's height (0.64).

Regarding to the RMSE, the lowest one was obtained for the head's diameter (0.2 mm), while for the head's height and steam's height the same measurement was achieved (0.36 mm). Regarding to the input variables relevance, similar pattern was obtained for the three generated models: plate thickness, fastener type, fastener grip code and batch. Above all, the plate thickness and the fastener type are the most critical ones as can be observed in Fig.4.a), as they have much higher weights than the rest of the variables. Fig. 4.b) shows the predicted versus real values for the fastener formed head diameter.
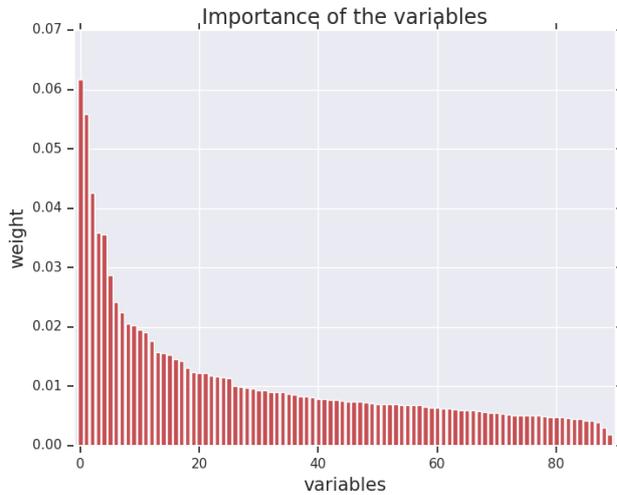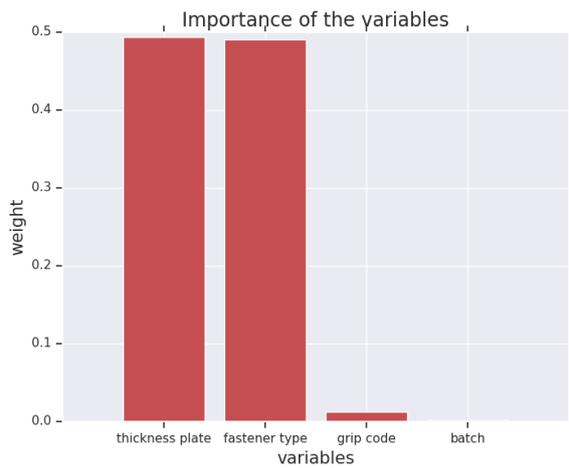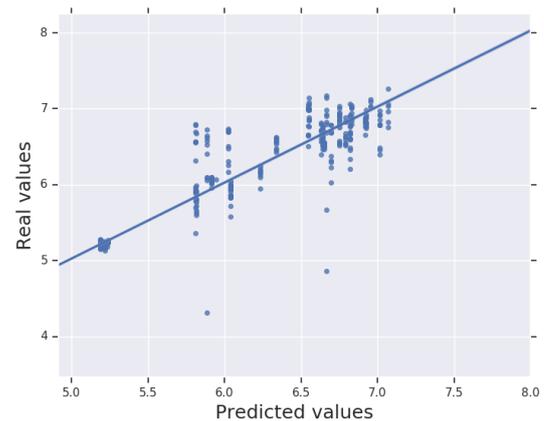
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*Fig. 3. The weight of the input variables in the generated model. The first two variables correspond to coefficients a and b of the equation ax+b of the segment 6.*



(a)



(b)

*Fig. 4. (a) The weight of the input variables, plate thickness, fastener type, fastener grip code and batch, in the generated model for model for the fastener formed head diameter; (b)Real and predicted values in the generated model for model for the fastener formed head diameter.*

The methodology proposed in this article allows us to discriminate the variables that have the greatest correlation with the correct fastener installation in this use case. The influence on the process of the relationship between the thickness of the plate and the type of fastener is demonstrating its criticality as it has been discussed in previous works [35]. In other researching work, Camacho et al. [26] carries out a monitoring system based on the determination of the correct selection of the type of rivet for the sheet thickness in which the operation is to be carried out.

## 4.- CONCLUSIONS

In this research work, an analysis engine was developed to identify critical variables in a multi-stage industrial process using ML-based techniques. A blind fasteners installation process was used as a case study, as it is a multi-stage process, in which variables

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of different stages can affect to the final quality of the installed fastener. The analysis engine is divided into multiple categories, following a common workflow in ML. Moreover, it is user-friendly, and it is oriented to a non-expert user in data analytics.

Regarding to the studied use case, three different scenarios were posed to study critical variables in the process. In the first one, the measurements of the holes are related to the fasteners' measurements, that is, the influence that a previous stage of drilling has on fastening. It was found that the hole measurements from drilling do affect to the quality of the fastener, especially to the formed head's diameter, being the most critical variables the steam's depth and the thickness of the drilling part. The hole's diameter lower contribution to the model is related with the fact that the employed fasteners do not expand radially along the installation.

In the second posed scenario, the descriptors of the monitored signal were related to the final quality of the fastener, a single stage analysis. From this analysis, it can be concluded that the segments 5 and 6 are critical to classify which kind of fastener, depending on its quality, will be obtained. These parts of the segment are more critical because within that period, the plastic deformation takes place, so that, the fastener head is formed and the steam breaks off.

Finally, in the third scenario the influence that test conditions have in the fasteners' measurements is analyzed. It was found that variables related to test condition affects to the final quality of the fastener, and as it happens in the first scenario, especially, to the formed head's diameter. In this case, the most critical variables are the plate thickness and the fastener type.

## REFERENCES

[1] Lee J, Bagheri B, Kao HA. "A cyber-physical systems architecture for industry 4.0-based manufacturing systems". Manufacturing Letters. 2015. Vol. 3. p.18-23. DOI: https://doi.org/10.1016/j.mfglet.2014.12.001

[2] Murua M, Suárez A, López de Lacalle LN et al. "Feature extraction-based prediction of tool wear of Inconel 718 in face turning". Insight-Non-Destructive Testing and Condition Monitoring. 2018. Vol. 60. p. 443-450. DOI: https://doi.org/10.1784/insi.2018.60.8.443

[3] Ezugwu E, Fadare D, Bonney J et al. "Modelling the correlation between cutting and process parameters in high-speed machining of Inconel 718 alloy using an artificial neural network". Machine Tools & Manufacture. 2005. Vol. 45. p. 1375-1385. DOI: https://doi.org/10.1016/j.ijmachtools.2005.02.004

[4] Rangwala S, Dornfeld D. "Learning and optimization of machining operations using computing abilities of neural networks". IEEE Trans Syst Man Cybern, 1989. Vol. 19. p. 299–314. DOI: https://ieeexplore.ieee.org/document/31035

[5] Feng C-X, Wang X-F. "Surface roughness predictive modelling: neural networks versus regression. IEE Trans. 2003. Vol. 35. p.11–27. DOI: https://doi.org/10.1080/07408170304433

[6] Sikdar S, Chen M. "Relationship between tool flank wear area and component forces in single point turning". Journal of Materials Processing Technology. 2002. Vol. 128. p. 210–215. DOI:https://doi.org/10.1016/S0924-0136(02)00453-3

[7] Correa M, Bielza C, Pamies-Teixeira J. "Comparison of bayesian networks and artificial neural networks for quality detection in a machining process". Expert Systems with Applications. 2009. Vol. 36. p. 7270–7279. DOI: https://doi.org/10.1016/j.eswa.2008.09.024

[8] Kilundu B, Dehombreaux P, Chiementin X. "Tool wear monitoring by machine learning techniques and singular spectrum analysis". Mechanical Systems and Signal Processing. 2011. Vol. 25. p. 400–415. DOI: https://doi.org/10.1016/j.ymssp.2010.07.014

[9] Shi D, Gindy N. "Tool wear predictive model based on least squares support vector machines". Mechanical systems and signal processing. 2007. Vol. 21. p.1799–1814. DOI: https://doi.org/10.1016/j.ymssp.2006.07.016

[10] Lavanya K M, Suresh R K, Priya A K et al. "Optimization of process parameters in turning operation of AISI-1016 Alloy steels with CBN using taguchi method and anova". Journal of Mechanical and Civil Engineering. 2003. Vol.7. p. 24-27. DOI: 10.9790/1684-0722427

[11] Baskar N, Asokan P, Prabhaharan G et al. "Optimization of machining parameters of milling operations using non-conventional methods". Int J Adv Manuf Technol. 2005. Vol. 25. p.1078-1088. DOI: https://link.springer.com/article/10.1007/s00170-003-1939-9

[12] Sahoo P. "Optimization of turning parameters for surface roughness using RSM and GA. Advances in Production Engineering & Management". 2011. Vol. 6. p.197-208.

[13] Chandrasekaran M, Muralidhar M, Krishna CM et al. "Application of soft computing techniques in machining performance prediction and optimization: a literature review". Int J Adv Manuf Technol. 2010. Vol. 46. p. 445-464. DOI: https://link.springer.com/article/10.1007/s00170-009-2104-x

[14] Abburi NR, Dixit US. "A knowledge based system for the prediction of surface roughness in turning process". Robot Comput Integr Manuf. 2006. Vol.**22**. p. 363–372. DOI: https://www.sciencedirect.com/science/article/pii/S0736584505000621

[15] Zhong ZW, Khoo LP, Han ST. "Prediction of surface roughness of turned surfaces using neural networks". Int J Adv Manuf Technol. 2006. Vol.28. p. 688-693. DOI: https://link.springer.com/article/10.1007/s00170-004-2429-4

[16] Nandi AK, Pratihar DK. "An expert system based on FBFN using GA to predict surface finish in ultra-precision turning". J Mater Process Technol. 2004. Vol. 155-156. p.1150-1156. DOI: https://doi.org/10.1016/j.jmatprotec.2004.04.408

[17] Wang ZG, Wong YS, Rahman M. "Optimisation of multipass milling using genetic algorithm and simulated annealing". Int J Adv Manuf Technol. 2004. Vol. 24. p.727-732. DOI: https://link.springer.com/article/10.1007/s00170-003-1789-5

[18] Vijayakumar K, Prabhaharan G, Asokan P et al. "Optimization of multi-pass turning operations using ant colony system". Int J Mach Tools Manuf. 2003. Vol. 43. p.1633-1639. DOI: https://www.sciencedirect.com/science/article/pii/S0890695503000816

[19] Meissner M, Schmuker M, Schneider G. "Optimized Particle Swarm Optimization and its application to artificial neural network training." BMC bioinformatics. 2006. Vol. 7. p. 1-125.

[20] Pawade R, Joshi S S, Brahmankar P. "Effect of machining parameters and cutting edge geometry on surface integrity of high-speed turned Inconel 718". Machine Tools & Manufacture. 2008. Vol. 48. p.15–28. DOI: https://doi.org/10.1016/j.ijmachtools.2007.08.004

[21] Peters H, Link N, Heckenthaler T. "Application of Data Mining Techniques to Find Correlation Between Quality Data and Process Variables". IFAC Proceedings Volumes. 2001. Vol. 34. p.193-198. DOI: https://doi.org/10.1016/S1474-6670(17)33205-6

[22] Hall M A. "Correlation-based feature selection for machine learning". PhD Dissertation. University of Waikato (New Zealand). 2009.

[23] X. Zuo, B. Li, J. Yan. "Error sensitivity analysis and precision distribution for multi-operation machining processes based on error propagation model". Int. J. Adv. Manuf. Technol. 2016. Vol. 86. p. 269-280. DOI: 10.1007/s00170-015-8154-3

[24] Chien C-F, Wang W-C, Cheng J-C. "Data mining for yield enhancement in semiconductor manufacturing and an empirical study". Expert Systems with Applications. 2007. Vol. 33. p. 192-198. DOI: https://doi.org/10.1016/j.eswa.2006.04.014

[25] Diez-Olivan A, Penalva M, Veiga F. et al. "Kernel density-based pattern classification in blind fasteners installation". In HAIS 2017: Hybrid Artificial Intelligent Systems. 2017.p.195-206.

[26] Camacho J, Rivero A, Veiga F et al. "A non-destructive quality assessment for blind-fastener installations based on the combination of ultrasound techniques and real-time monitoring of the fastening process ". The International Journal of Advanced Manufacturing Technology. 2016. Vol. 84. p. 1057-1066.  DOI: https://doi.org/10.1007/s00170-015-7795-6

[27] Camacho J, Veiga F, Penalva M L et al. "On-line monitoring of blind fastener installation process". Materials. 2019. Vol. 12. DOI: https://doi.org/10.3390/ma12071157

[28] Breiman L. "Random forests". Machine Learning. 2001. Vol. 45. p. 5–32.

[29] Wu D, Jennings J C, Terpenny R.X et al. "A Comparative Study on Machine Learning Algorithms for Smart Manufacturing: Tool Wear Prediction Using Random Forests". ASME. J. Manuf. Sci. Eng. 2017. Vol.139. p.1-10. DOI: 10.1115/1.4036350

[30] Zhang C, Ma Y. "Ensemble machine learning: methods and applications". Springer Science & Business Media. 2012.

[31] Seber G A, Lee A J. "Linear Regression Analysis". Wiley. 2003.

[32] "ForZDM – Integrated zero defect manufacturing solution for high value multi-stage manufacturing systems". Funded under H2020-EU.2.1.5.1 Technologies for Factories of the Future, call H2020-FoF-2016, contract No. 723698. https://forzdmproject.eu/

[33] Pedregosa F, Varoquaux G, Gramfort A et al. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research. 2011. Vol. 12. p. 2825–2830. DOI: http://www.jmlr.org/papers/v12/pedregosa11a

[34] Zitoune R, Krishnaraj V, Collombet F et al. "Experimental and numerical analysis on drilling of carbon fibre reinforced plastic and aluminium stacks". Compos. Struct. 2016. Vol. 146, p. 148–158. DOI: https://www.sciencedirect.com/science/article/pii/S0263822316301404

[35] Saygin C, Mohan D, Sarangapani J "Real-time detection of grip length during fastening of bolted joints: a Mahalanobis-Taguchi system (MTS) based approach". Journal of Intelligent Manufacturing. 2010, Vol. 21(4), p. 377–392. DOI: https://link.springer.com/article/10.1007%2Fs10845-008-0186-1.

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