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ANALYSIS OF THE STATISTICAL DATA GENERATED BY AN ADAPTIVE STRETCH FORMING PROCESS

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Abstract: Constant industrial processes improvements represent a fundamental step in the evolution of efficient processing. Due to physical or financial limits, there is a limit to how the mechanical or electronic side can be optimised. A solution for improving industrial processes can come in the form of complex machine algorithms that analyse the process in real-time and decide, with each step, what is optimal. To put this statement into practise, we have designed and implemented a fully operational self-adaptive stretch forming process controlled with the help of a dedicated statistical analysis algorithm. The foundation of the algorithm lies in the deformation theory of metals. In its simplest form, it can be summarised that if a sheet of metal is stretched, its length will increase as the force acting upon it increases until the ultimate tensile strength limit is reached; after this limit, failure occurs. Therefore, the algorithm analyses the material strain controlling the bi-axial nature of the stretch forming process by constantly adjusting for axial force and die speed. It does this through complex computer-vision image analysis techniques for strain measurement and stretching pressure readings as input data. The readings are analysed using the ANOVA method, providing R-squared and p-values for stretching pressure and die speed. The decisions that the algorithm takes are based on the statistical analysis of its previous decision, aiming to improve the overall process R-squared. The overall results are validated by measuring the obtained stretched parts' deviation to the die shape. Therefore, the measurements were taken using a GOM 3D measuring system. This paper aims to explain the methodology of the algorithm using how the measurements are taken, how the statical analysis generated decisions for controlling the industrial equipment, and to analyse the statistical data generated by the self-adaptive stretch forming algorithm for the experimental study by comparing the decision it takes for each for the 20 processed 1050 aluminium alloys blanks. The results indicate the ideal succession of decisions and which path should be taken to improve the decision-making for both elastic and plastic domains.

Key words: statistical data, adaptive forming process, ANOVA method, computer-vision image analysis, ultimate tensile strength limit.

1. INTRODUCTION

The amount of data that a system can generate, store, and use in the current industrial context reflects a high level of digitisation that the manufacturing sector has achieved. This performance was achieved in terms of the Industry 4.0 standard implementation with concepts that include IoT (Internet of Things), II (Industrial Internet), Smart Manufacturing or Cloud-based Machining [1]. As expected, generating this large volume of data led to the development of complex algorithms that can understand this information. When analysing types of algorithms that are currently used in manufacturing processes, it can be noted that two main categories emerge: algorithms that analyse data using mathematical equations that are based on a hypothesis (Statistical Analysis) and algorithms that analyse data without a programmed hypothesis (Artificial Intelligence, Machine Learning and Deep Learning) [2]. In terms of solution delivery time, the statistical analysis algorithm is the fastest (the data is tested for significance); AI algorithms must find patterns between data, which is done through numerous iterations until a confident solution is found. Regardless of the type of system that analyses data, the outcome can be a prediction, an indication or a decision [2-5]. This paper aims to analyse the data generated by an adaptive stretch-forming process based on computer vision and statistical analysis [6] regarding statistical process measures of fit (R-squared) and p-value.

2. METHODOLOGY

The complex nature of the stretch-forming process implies biaxial control to be achieved for obtaining complex shapes characterised by severe plastic deformation. The authors have developed a complex computer vision algorithm that takes control of a hydraulic press using statistical analysis-based decisions (Adaptive Stretch Forming Process python-based algorithm), as can be noted from figure 1. The starting point of this paper is represented by published results [6], more precisely the data behind the decisions taken by a self-adaptive process that stretch-formed 320 by 100 mm, 1050 aluminium blanks, with a thickness of 0.5 mm. The schematic representation of the software logic can be noted in figure 2; it highlights the close loop path that the data follows from the industrial process to statistical analysis to decision making to controlling the industrial equipment. It does this by using input data, represented by material strain, stretching pressure and statistical data results while controlling the die speed, stroke and stretching pressure; this loop works until the system achieves a user input strain limit.

The algorithm controls the industrial process in terms of changing the die speed, stroke and stretching pressure; changing these values occurs as a result of the statistical analysis conducted on the input data. The system is designed to take decisions and evaluate them; it does this at a speed of $4x10^{-7}$ calculations per second, but a complete decision is implemented on average every 0.287 seconds, as the industrial process must implement the commands received. The main logic of the ASFP algorithm is the following: an analysis of variation (ANOVA) is made and if the current decision offers improvements for the process R^2 no action is taken, otherwise, the algorithm tries a comeback by adjusting the die speed, stroke and stretching pressure. Each value for the strain, pressure, stroke, statistical result (process R^2 and p-value) and decisions are written in .csv files.

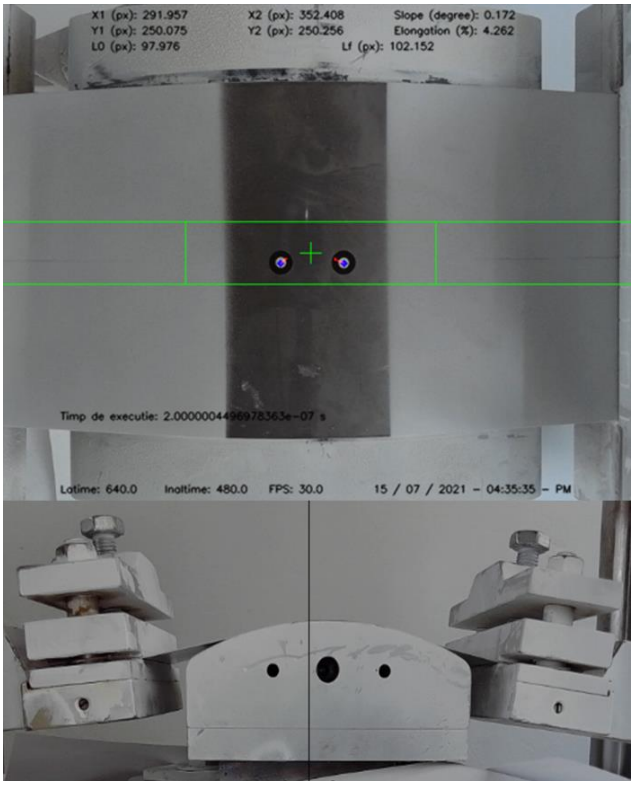

Fig. 1. ASFP video frame strain analysis along with the side view of the stretch forming process

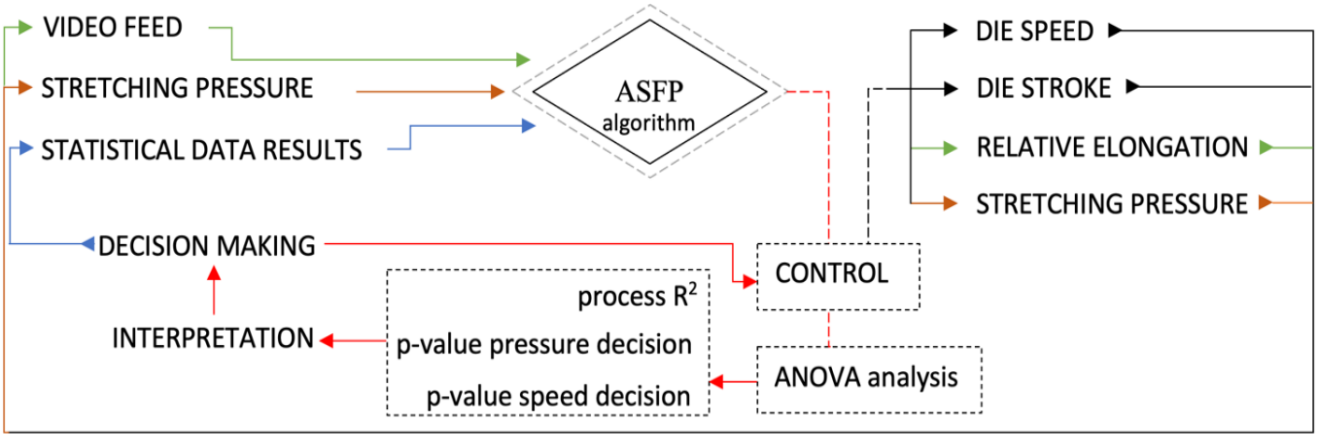

Fig. 2. ASFP algorithm logic

3. RESULTS AND DISCUSSIONS

Considering that the final point of any industrial process is represented by the final part agreeing with the requirements, the stretched blanks were compared by rank, obtained by dividing their measured radius to 150, which is the die radius in mm; this calculated subunit coefficient will be referred to as "ρ", with the complete set of calculations given in Figure 3, along with the distribution of R^2 values. When analysing the statistical data distribution, multiple patterns appear. It can be noted that, on average, 8% of the R^2 values are above 0.95, with values ranging from 0.2 to 17.5 %. Parts that are closer to this average values offer are also

closer to the die shape, as in the case of parts 18, 2, 14 and 11, with values for ρ ranging from 0.982 to 0.999 and percentage of R^2 values of 8.2, 7.7, 8.7, respectively 8.0 %. At the other end, parts with larger deviation (parts 4, 19, 10, 17 have a ρ coefficient between 0.789 to 0.813) are obtained in processes that resulted in a distribution of the R^2 value closer to the marginal limits (16.7, 10.8, 13.5, 2.8 %). The number of R^2 values distributed between 0.90 and 0.95 shows a sudden decrease, on average 2.3% of decisions fall within this range. From this point on the values are falling freely with average distributions of 0.7 and 0.1% until the 0.70 ÷ 0.75 range, from which average values increase above 2%. In this interval, the system tries to correct the R^2 value by adjusting the stretching pressure and die speed. The corrections can be observed in the p-value indicating that 71% are below 0.01 and 74.5 % are below 0.05. In addition, it must be considered that, on average, the R^2 value drops below 0.7 after 305 decisions. If the average number of decisions of 887,4 is considered, then the system offers the best possible outcome for 30% of its decisions. A high percentage of its decisions are taken early in the stretch forming process since it is capable of generating mathematical models that indicate a high connection between elongation and stretching forces. This only occurs in the elastic domain, where the material deforms proportionally, following Hooks law. From the analysis of the alignment of the data with each step of the process, it can be noted that the algorithm has an affinity for the elastic domain, due to a simpler mathematical model. Once the deformation exceeds this limit, plastic deformation occurs, and the system struggles to find a meaningful mathematical connection between the input data. This is also indicated by data generated towards the end of each process where, with no exception, the values for the R^2 drop below 0.4.

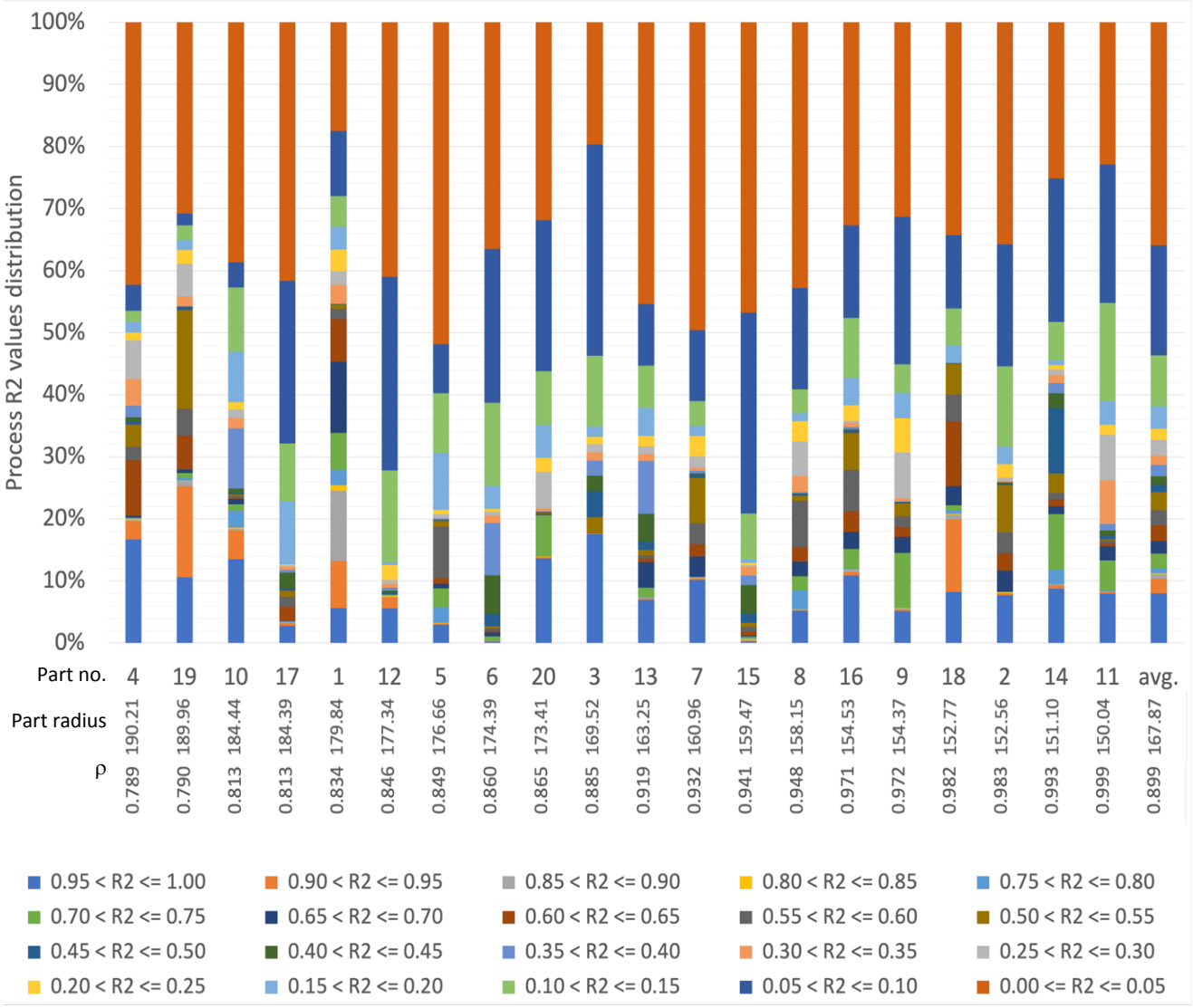

Fig. 3. R^2 values distribution for each part, sorted ascendent by ρ, and part radius

The significance of each decision is tested by the p-value; if the value is lower than 0.05 the decision is considered significant. Therefore, it is necessary to indicate that in the case of pressure, 60.893% of decisions are considered significant and 56.636% in the case of the die speed.

Although 30% of the overall decisions that the algorithm took are considered, from a statistical point of view, significant, the radius of the parts cannot be set aside from this discussion. The evaluation of these parts was made also, according to the previously published data [6], by comparison to parts obtained by a classical stretch-forming process; improvements are indicated and supported by 3D measurements, made on a GOM system.

To emphasize this study, a comparison between parts 11 (ρ = 0.999) and 4 (ρ = 0.789) highlighting the distribution of the process R2, p-value over each decision, correlated with strain, pressure and speed evolution. From figure 4 the process parameters that lead to obtaining part number 4 are highlighted. This is the worst result that the ASFP offered. Around decision number 200 a sudden drop occurs in the R^2 value; immediately the algorithm tries to correct it by raising the die speed; the solution raises the value from 0.4 to 0.65. Once the plastic deformation occurs the algorithm tries to correct the R-squared value by adjusting the pressure; as the solution does not offer the desired result it tries to vary the die speed, ultimately, the best option, in this case, is setting the stretching pressure to around 19 (bar) with the variation of the die speed from 0 to 6 (mm/s).

Part number 11 is, considering ρ = 0.999, the part with the shape similar to the die. From figure 5 it can be noted that around decision number 75 a sudden drop occurs in the R^2 value; as in most cases, the solution that worked was to raise the die speed. The ASPF algorithm tries to correct the R^2 value and manages three comebacks to values of 0.15, 0.1 and 0.2.

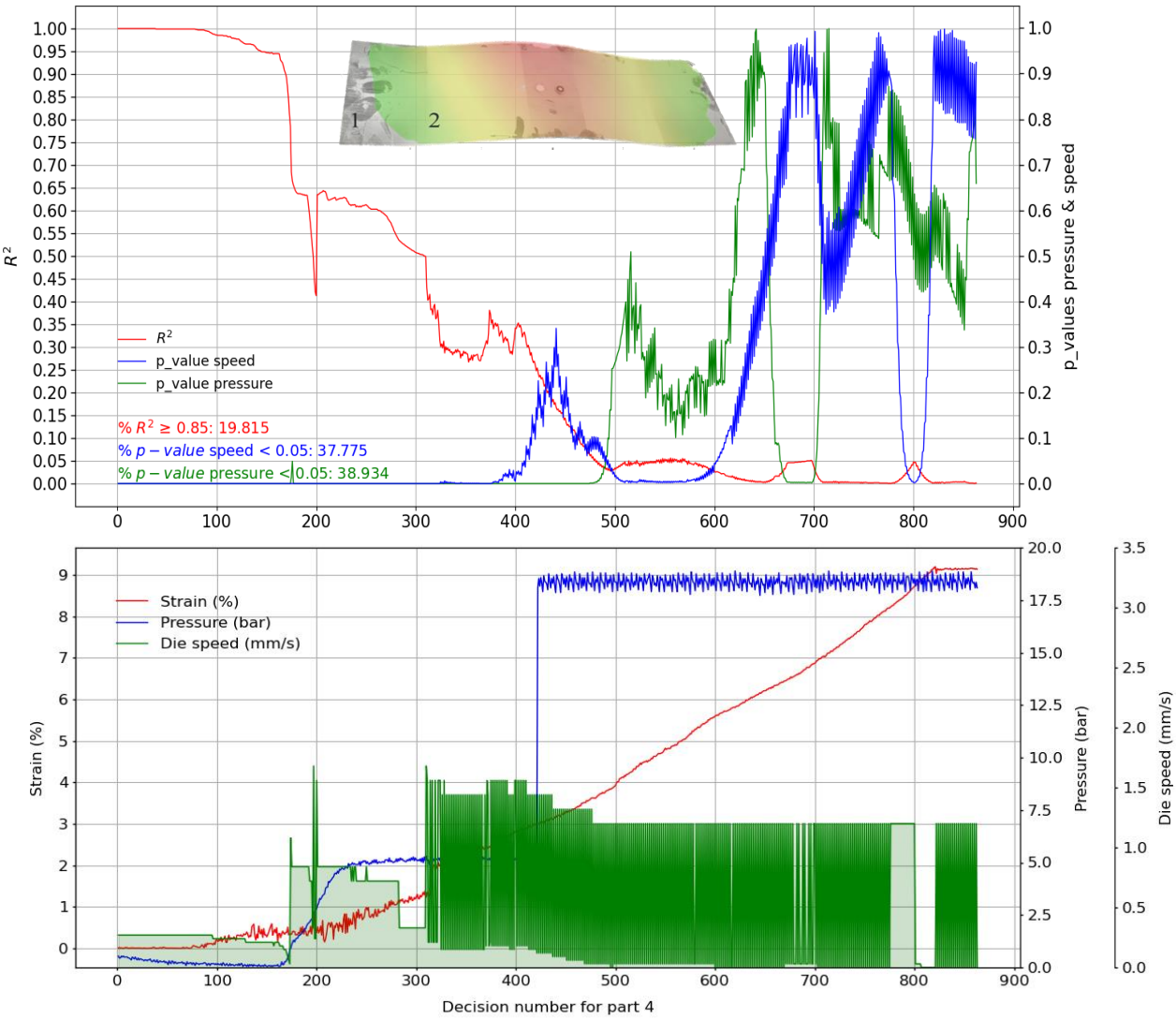

Fig. 4. R^2, the p-value for speed and pressure distribution across decision numbers. Deformed part (1) and 3D measurement overlay (2). Correlation between the evolution of strain, pressure, die speed and statistical data distribution for part number 4

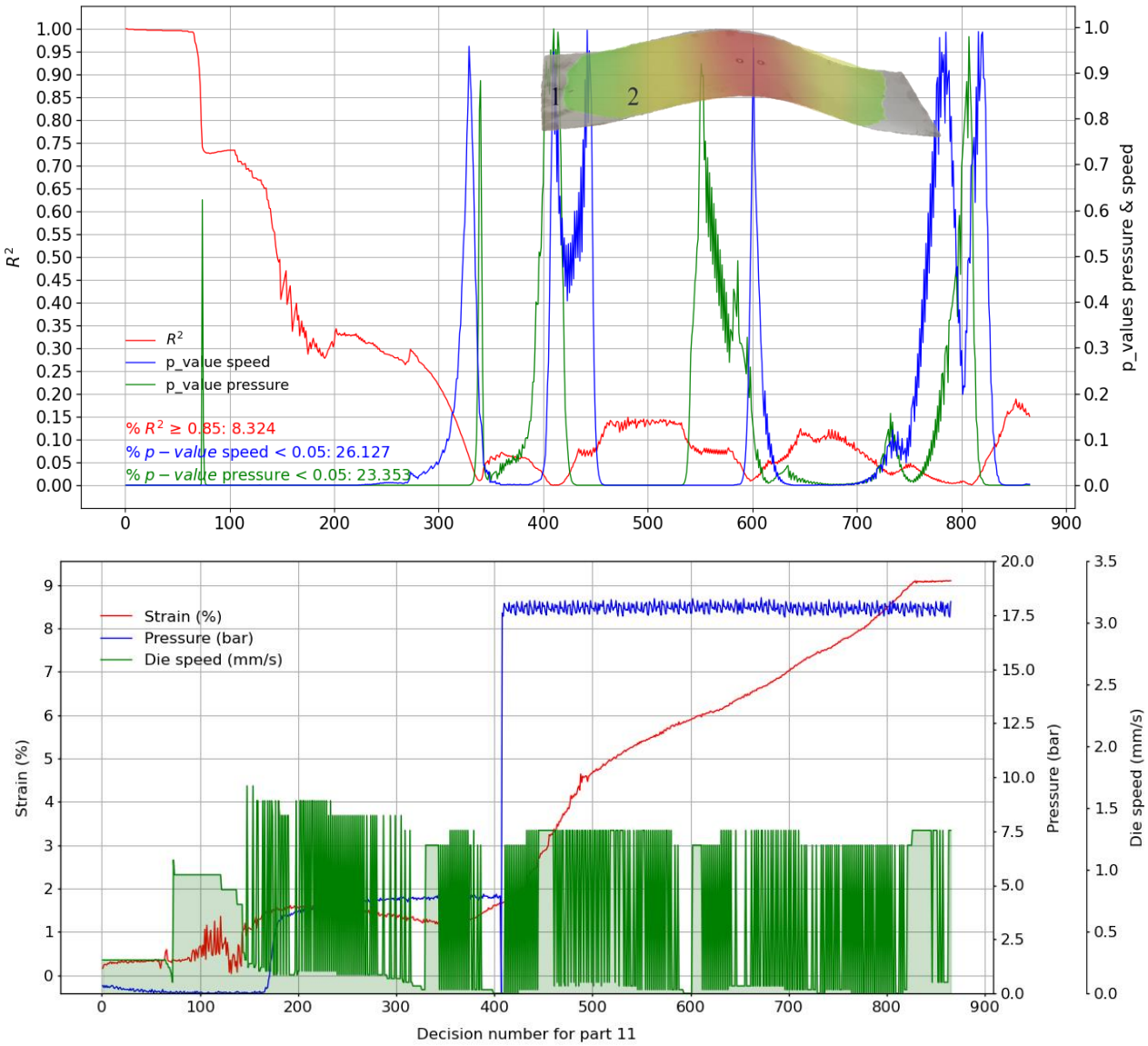

Fig. 5. R^2, the p-value for speed and pressure distribution across decision numbers. Deformed part (1) and 3D measurement overlay (2). Correlation between the evolution of strain, pressure, die speed and statistical data distribution for part number 11

4. CONCLUSIONS

The analysis of the data generated by the Adaptive Stretch Forming Process indicates that the algorithm recognises the transition from elastic to plastic deformation. This is important for future improvement as the data show that the current form can be used successfully in the elastic domain and an update may be required when analysing in real-time plastic deformation.

The data indicate that the process parameters offer the best results when the starting values obtained for the R^2 are average. If these values increase or decrease the part radius deviates. Also, it was observed that the frequency with which the die speed is changed, influences the end result. Another important aspect is that the algorithm takes the optimum decision when sudden changes occur.

5. ACKNOWLEDGMENTS

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6. REFERENCES

1. Vaidya, S., Ambad, P., Bhosle, S., (2018). *Industry 4.0 – A Glimpse,* Procedia Manufacturing, 20, 233-238.

2. Xu, K., et al., (2020). *Advanced Data Collection and Analysis in Data-Driven Manufacturing Process,* Chinese Journal of Mechanical Engineering, 33(1), 43.

3 Ismail, A., Truong, H.-L., Kastner, W., (2019). *Manufacturing process data analysis pipelines: a*

requirements analysis and survey, Journal of Big Data, 6(1), pp. 1.
4. Shang, C., You, F., (2019). *Data Analytics and Machine Learning for Smart Process Manufacturing: Recent Advances and Perspectives in the Big Data Era,* Engineering, 5(6), 1010-1016.
5. Sheuly, S.S., et al., (2021). *Data analytics using statistical methods and machine learning: a case study of power transfer units,* The International Journal of Advanced Manufacturing Technology, 114(5), 1859-1870.
6. Grigoras, C.C., et al., (2021). *Adaptive Stretch-Forming Process: A Computer Vision and Statistical Analysis Approach,* Machines, 9(12), 357.

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