Stamping process analysis in an industrial plant and its limitations to obtain an industrializable Continuous Twin

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Abstract

This article aims to define the problem of the development of a "Continuous Twin" in any stamping process installed in an industry. A "Continuous Twin" is a modeling concept using the information available in both worlds, the virtual twin (simulation) and the digital twin (real-time data) of the process. There is currently a trend in the industry related to IIoT (Industrial Internet of Things) and linked to Industry 4.0. IIoT is the collection of sensors, instruments and autonomous devices connected through the internet to industrial applications. However, filling with sensors the entire industry and channelling all that information through industrial networks is a utopia. In our previous works, a new concept for generating industrializable IIoT applications has been presented, *Industrializable Industrial Internet of Things* (*I3oT*). The purpose of the *I3oT* is using the installations available in factories to develop IIoT applications from them. This article aims to analyse all available and accessible information from the parameters accessible from the stamping process PLC, material properties, FLD, to the measurement of the operators corrections after detecting part failures. This is information that could be included in the model in order to develop an industrializable "Continuous Twin".

1 Introduction

Throughout history, humanity has undergone several industrial revolutions. The first one began in the second half of the 18th century in Great Britain. This revolution promoted the transformation of the rural economy, based fundamentally on agriculture and trade, to an urban, industrialized and mechanized economy. The Second Industrial Revolution refers to the interrelated changes that occurred approximately from 1870 to 1914. During this period, technical changes continued to occupy a central position. New sources of energy appeared such as gas or electricity, new materials such as steel and oil; and new systems of transportation, airplane and automobile, and communication such as telephone and radio. The Third Industrial Revolution, also called STR (Scientific-Technological Revolution), was proposed by Jeremy Rifkin, and endorsed by the European Parliament in a formal declaration approved in June 2006. The third revolution favoured the conjunction of the advancement of communications technologies, together with the great development and use of the Internet, as well as renewable energies.

The Fourth Industrial Revolution concept, also known as "Industry 4.0" was coined by Klaus Schwab, founder of the World Economic Forum, in the context of its 2016 edition. This fourth stage was marked by emerging technological advances in a number of fields, including robotics, artificial intelligence, blockchain, nanotechnology, quantum computing, biotechnology, Internet of Things (IoT) or Industrial Internet of Things (IIoT), Big Data, 3D printing, autonomous vehicles and digital twins. The Fifth Industrial Revolution, known as "Industry 5.0" was coined in early 2021 by the European Commission. This is a new technological revolution that aims to enhance the transformation of the industrial sector in smart spaces based on the Internet of Things and cognitive computing. It is about putting artificial intelligence at the service of people, uniting machines and humans.

It is unclear when Industry 4.0 ends and the fifth revolution begins. Many authors state that this fifth revolution will begin with the deployment of emerging technologies that appeared in Industry 4.0.

However, we are still far from achieving that deployment, mainly due to the industry's ability to absorb the proposals for IIoT applications currently developed and the real situation in the factories.

1.1 How far are we from having massive IIoT applications in the industry?

When the industry, or the responsible managers, have to decide whether to install IIoT applications in their companies on a massive level, this decision can be slowed down by several factors:

1. *Energy efficiency*: Most IIoT devices are battery powered, so IIoT must deal with high power consumption, [1], [2], [3]. The expenses related to the service and/or replacement of such devices are a serious concern due to the fact that a large number of sensors are needed. Without proper maintenance and life-cycle assessment consideration, sooner or later they can become electrical garbage, [2].

2. *Interoperability*: Connecting so many devices is a serious challenge for IIoT. 30% of the organisations surveyed in [2] are against adopting IIoT for this reason. A lack of common connectivity, standard data formats, and common software interfaces complicate the implementation of IIoT. Interoperation and standardization of proposals is one of the major barriers, [2], [1]. The systems provided by different companies, even if they use Iinternet Protocol (IP) for routing packets of data across networks, do not guarantee that they can be connected to each other [2].
3. *Security*: Another barrier to IIoT and IoT adoption is the concern of companies management about information security and privacy, [1], [2], [3], [4]. 29% of the companies surveyed in [2] show that the risks outweigh the advantages that the implementation of IIoT tools can offer.
4. *Scalability*: Scalability is another barrier that is holding back the proliferation of IIoT applications. IIoT is made up of a huge number of devices and these are usually connected to each other in hierarchical subdomains. This in turn results in the number of connected objects being significantly greater than the current Internet, [2].
5. *Maintenance and updates*: When building the IIoT we need to take into account its future updates and maintenance. IIoT, which is a tangled network of interconnected devices, poses a considerable challenge for system operators. They will not only have to manage the original system, but also manage all new systems. Training engineers takes a lot of time, especially since most user interface management systems (UIMS) are not intended for industrial automation, [2], [4]. According to [2], the latter fact causes 26% of the companies surveyed to decline the implementation of IIoT solutions.
6. *Information Technology (IT) and Operations Technology (OT) Integration*: In [4] they also indicate that the integration of the OT network with the information coming from the IT network is another of the challenges for achieving the development of IIoT applications. These IIoT-enabled systems require the convergence of OT and IT, so integrating data from both can provide a comprehensive view of industrial processes that allows companies to optimize operations and increase efficiency, [4].
7. *Cultural change*: Also in [4] Babayigit and Abubaker state that another barrier is cultural change. Many industries resist change because they are afraid and do not understand the technology associated with IIoT.

1.2 Factories in the fourth industrial revolution. Welcome to *"the Jungle"*

The governance of factories, such as the ones in the automotive sector, is extremely complex. They use thousands of robots, grippers, cylinders, conveyor belts, etc., each with its components, electric motors, gears, chains, and each applied to different processes, such as welding, stamping, painting, etc. In addition, all this machinery interacts with the operators involved in different phases of the process, such as the assembling of components, verifying the quality of the parts, and, in some cases, with the ability to modify machine parameters to guarantee the productivity and quality of the parts. The goal of automation is none other than to try to eliminate dependence on that human factor. However, some machines are not able to adapt to plant situations, which calls into question whether a complete automation of a factory without the human presence would be the most efficient approach, see for example, [5], [6]. Thus, the fact that operators can modify certain parameters of the machines responds to a reality in the manufacturing processes and is none other than variability. This variability can come from different sources, such as;

- *Two identical machines actually behave differently:* Many times machine or component manufacturers may provide curves to choose certain machine parameters that have been calculated under homogeneous laboratory conditions and as an average of tests with different components. In real situations, two identical machines or components may not be subjected to the same working conditions and in critical processes this cannot be extrapolated.
- *Lack of in-depth knowledge of the process:* There are processes, such as stamping, where there is no in-depth knowledge of how all the parameters may affect the process. This means that, although manufacturers provide curves and parameters to adjust them, these are only indicative and need human intervention, the operators' intuitive skills and learning based on experience, which can finish fine-tuning those types of parameters in order to achieve the right quality.
- *Technologies from different generations co-existing in the same factory and machine:* When a company buys an asset, whether it is a machine, robot or press, it will try to make it profitable over the years. When the machine breaks down and the broken component is replaced, the new component is usually of a more up-to-date technology, which means that the machine will not behave the same.

At Ford factory in Valencia, the daily production is around 2,000 units. Any delay or quality failure that generates rework or scrap can result in large losses, since it will directly increase the cost of manufacturing the product. This will cause a very high level of pressure on both managers and other plant personnel since poor management that generates losses can be a ground for dismissal. When something goes wrong and you have to look for the cause, it may not be entirely clear where it comes from and this is when human intervention, with its intuitive skills and experience-based learning can unlock the problem. For all the above, employees call the factory by the nickname of *"the jungle"*.

1.3 The twin continuum. From Virtual to Digital twin

Although, as previously mentioned, the technological development of IIoT tools needs significant improvements to become a reality in the industry, the development of digital twins or virtual twins at algorithmic level is indeed very advanced. The digital twin is a technology with many applications in the fourth revolution (Industry 4.0). In general, it is about having a virtual replica of the process or machine and using this to improve it, [7]. Digital twin and virtual twin are two different concepts. These two concepts can be defined as:

- *Virtual Twins*: They are basically based on known physics and their simulation by software through numerical methods. They tend to have complex systems and a very high cost in resources, including computation time. The results obtained have variability and uncertainty with the actual process.

- *Digital Twins*: They are based on data and not on physics. Being based exclusively on data, their operation is difficult to explain and therefore certifiable. They often use machine learning techniques to learn a model. Their main problem is that they depend on data and need a lot of it to be able to estimate appropriate behaviours. Unfortunately, data in the industry is highly expensive. What data should be collected?, where can we find the data?, and when and how to collect the data are questions to be solved in these cases. The model obtained is useful within the trained data range but extrapolating and working outside it may not give the expected results, so it is risky.

Between these two extremes, there are intermediate approaches that try to solve the problems of the digital or virtual twin, and this is what is known as *"twin continuum"*. The intermediate approaches can be divided into two large sections:

- *Physics informed learning*: For instance PINNs (Physics-informed neural networks), which are a type of approximators that can include any physical law that can be defined as a PDE (Partial Differential Equation) and that manages the learning process. This type of network, as it contains physics, does not need as much data as the Digital Twin and its operation is explainable.
- *Physics augmented learning*: In this case, the purpose is to try to learn the discrepancy between the virtual twin and the real world. This Gap is usually called "ignorance" since, as in the digital twin, it is not explainable. Machine learning techniques are often used for this type of learning. It usually needs less data since it is only intended to approximate the discrepancy.

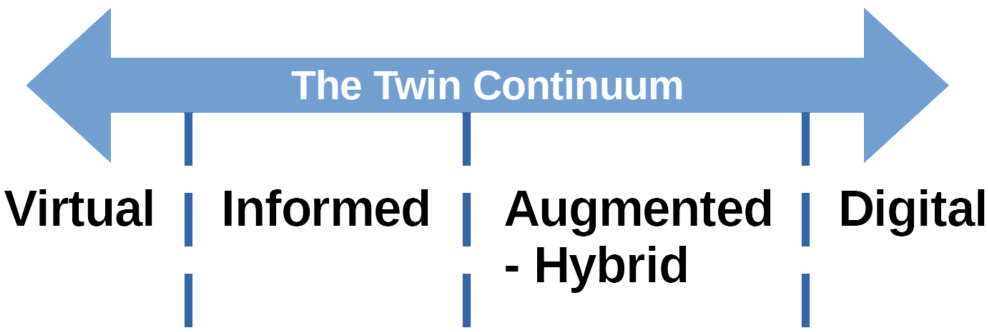

Fig. 1 The twin continuum

1.4 Digital Twins in the stamping process

The literature offers very few proposals regarding digital twins for the stamping process, mainly because it is a complex process with a large number of parameters, some unknown and very difficult to measure such as the coefficient of friction, see for example [8]. In [9] we can see the first work where the digital twin concept was applied to the incremental deformation process. In this paper, laboratory tests with a CNC machine and a 3D vision scanner are developed, along with sensors of punch force and its speed. The results show the benefits of using digital twins in this process but as the authors comment in the conclusions, in a real shop floor of large dimensions, all the information of all the available devices would have to be taken into account in order to achieve an effective DT in the production line. More recently, in [10] a digital twin is developed in which the actual punch force and the simulated punch force must match. To do this, they use the Particle Swarm Optimization with Differential Evolution (PSO-DE) algorithm. The adjusted model is used to optimize the process, reducing the maximum thickness of the final part by 14.35% and also reducing the energy consumed by 8.9%.

1.5 Goal of the paper

In [11] a new concept to generate industrializable IIoT applications is presented, *Industrializable Industrial Internet of Things (I3oT)*, with the main objective of solving the limitation that is slowing the implementation of Industry 4.0 technologies, including digital twins. The installation of sensors, their wiring and data extraction through the IT network to the OT network, and adding the increasing number of machines or components to be sensorized, means that the proposed solutions do not end up being implemented in the industry in a massive way, due to the high cost involved in their implementation. The goal of the *I3oT* is to use the installations available in factories to develop IIoT applications from them.

On the other hand, the literature shows that there is sufficient technology to investigate the development of digital twins within the *"twin continuum"* space by combining virtual physical models and data, either in the *informed* version or in the *augmented-hybrid* version. However, it is necessary to determine what data is available in the industry so that a digital twin of the stamping process can be developed that complies with the *I3oT* concept. This article aims to lay the foundations of how the actual stamping process is carried out, what parameters, from material properties, process data and quality measurement and output parameters are currently viable and what parameters could be introduced in an industrializable continuous twin.

2 Stamping process in autotomive industry

2.1 Process description. Ford Almussafes Press Shop case

At Ford factory in Valencia there are 11 stamping lines and 4 cutting lines with manufacturing capacity for up to 5 models, where each of them can be composed of more than 50 pieces, with a stamping cycle time of between 6 and 8 seconds.

The work carried out at the plant is divided into two phases, the blanking process and the stamping process. In the blanking phase, the steel coils are placed on a roller where the material is sent to the line to be cut according to the desired geometry, see figure 2. The phases of this process shown in figure 2 are as follows:

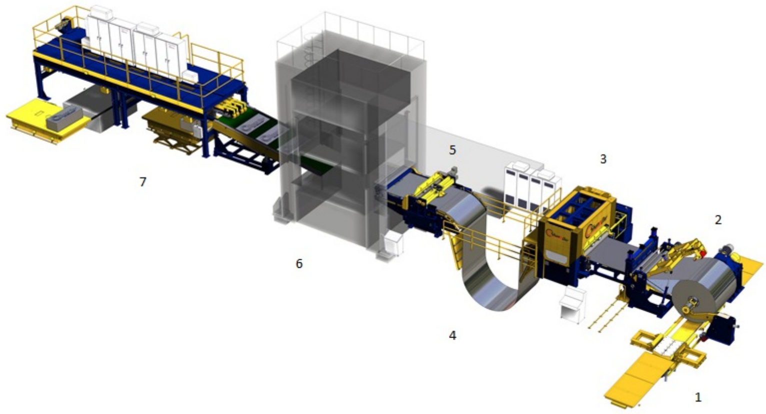

Fig. 2 Blanking process

1. Loading Cart.
2. Decoiler.
3. Straighteners with rolls to remove residual stress.
4. Loop pit to guarantee supply to the cutting machine.
5. Encoder that measures the distance of the sheets to be cut. Cutting press
6. Stacker.

The cutting presses are very fast and able to make up to 80-100 parts per minute when working at maximum capacity. At the end of the line the parts are stored on pallets for later use in the stamping process.

In the second phase, the stamping process, higher tonnage presses are used, up to 2500 tons of force, with lines of between 4 and 6 presses depending on the operations necessary to manufacture the final part of the chassis. Figure 3 shows a line with 5 presses. Presses are large machines composed of multiple mechanical elements to carry out the process. In figure 4 we can see an example of a single-action press with a hydraulic cushion, generally used in the first operation, and the different elements that make it up.

In the first press of the line, the deep drawing operation is carried out which is considered the most critical. This is because in this operation the steel sheet is deformed into the desired shape. Depending on the type of part, the deformation will be more or less complex and if the process has not been adjusted properly, defects may appear such as cracks and wrinkles that will make the part to be classified as bad and therefore sent to scrap. Subsequently there are the processes of drilling, folding and surface finishing where the final shape of the part is carried out by cutting all the excess material. These processes are often less critical.

We can consider the cutting area and the stamping area as two different plants, where one of them works on the stock manufactured by the other. The stamping process is more complex than the cutting process and therefore it has a shorter cycle

Fig. 3 Stamping process

time than the stamping process. That is why for the supply of the factory, only 4 cutting lines are needed compared to 12 stamping lines.

2.2 Overview of the stamping process in the industry

One of the major problems in the daily production of the stamping process is the generation of scrap. This can be caused by various factors, such as, for example, the replacement of some element of the press (or the die) due to maintenance or breakdown. It can also be caused by the human factor, since the technicians who control the line can make adjustments to the press configuration due to production demand and this may cause some mistakes. Other common examples of process mismatches are poor lubrication of parts, die modifications and mechanical wear of the elements involved in stamping. On the other hand, we have the material, the supplier may provide the steel with certain characteristics but within tolerances, which are not usually homogeneous in the same roll batch of material.

All of the above shows how dynamic the stamping process can be in a real production plant. There may be cases of a batch of consecutive parts broken due to a mismatch and therefore an action must be carried out on the line so that the defect does not appear again, but there may also be the case of a single defective part found in a random manner and even the case of a batch with a reduced number of parts broken intermittently, but it is important that this defect does not appear again without adjusting anything.

Quality control is vital in the stamping plant. If the defective part is not detected at the end of the line, it will be moved with the rest of the batch to the following vehicle manufacturing processes. The cost of the waste generated by that defective

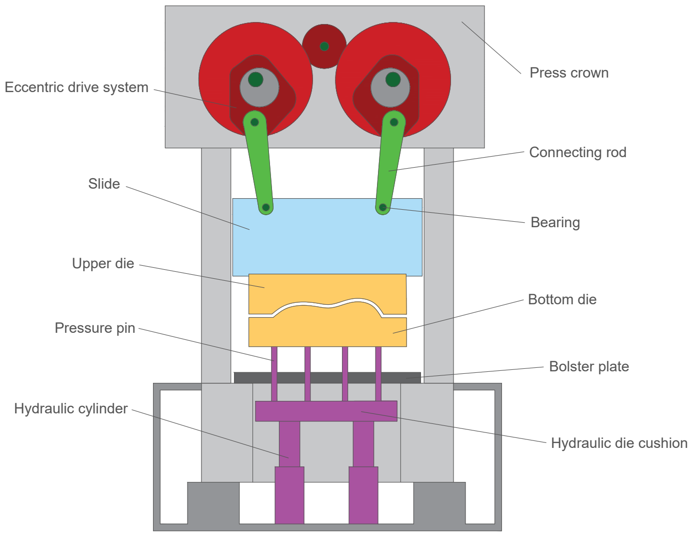

Fig. 4 Single-action mechanical press

part will increase when it is later detected. In the automotive sector, entire assembled and painted bodies have been discarded or even after the vehicle just manufactured. This is something that the automotive industry wants to avoid at all costs, due to the high losses that these situations entail. However, reviewing the quality of manufactured parts is an arduous task due to the level of precision required and the number of parts manufactured per minute.

Currently there is no automatic defect detection technique, the parts are checked by visual inspection by technicians working at the end of the stamping line, and this is not usually done for all manufactured parts. The inspection is carried out only for the most problematic parts, or periodic reviews carried out by quality personnel, with a periodicity that can vary from 1 hour or carrying out reviews at the beginning of each production. Many attempts have been made to automate defect detection in the past. Multiple proposals have been made such as the use of non-destructive tests, analysis of working parameters, etc., but without success at the industrial level, where a high detection rate is sought and the requirements of the process cycle time must be met, see for example [12], [13]. In [14] a promising system is presented by analysing audio signals emitted when a crack appears but without showing the type of cracks detected and the percentage of detection. They are systems that, when applied to the industry, can show a false positive result and lose reliability when automating the detection of defects.

3 Conceptual model of digital twin

As presented in [15] the new concept paradigm of the Hybrid Twin comes from combining both worlds, the data obtained from the process in real-time and the physical knowledge of the process. There may be simpler cases in the industry in which physical modelling is not necessary to obtain a virtual copy, being able to obtain a good result directly with the monitored data of the real process, but the most common case that we are going to find in many industrial sectors is the opposite, without the knowledge obtained from the physical model we will not be able to have enough information in order to give a solution that can be implemented. We are going to address how to implement the information we have in the real world to formulate the fundamental equation that defines a Hybdrid Twin applied to the cold stamping process. This equation would be as follows;

$$\dot{\mathbf{X}}(t;\nu) = \mathbf{A}(X,t;\nu) + \mathbf{B}(X,t) + \mathbf{C}(t) + \mathbf{R}(t). \tag{1}$$

Donde:

- $\mathbf{A}(x,t;\nu)$: refers to the result obtained from the physical problem in real time thanks to the use of reduced order models, which we will call physical prediction.
- ν: refers to real-time data measured directly from the process.
- $\mathbf{B}(x,t)$: refers to the deviation between the actual solution and the estimated solution using $\mathbf{A}(x,t;\nu)$, also defined as model error, i.e., the difference between the result of the physical modelling and the actual result.
- $\mathbf{C}(t)$: defines the adjustments that are made during manufacturing, as it is a dynamic process, adjustments and modifications that are made on the fly must be entered into our model for the result to be correct.
- $\mathbf{R}(t)$: refers to the noise that may appear in the process that has traditionally been addressed by applying the appropriate filters. This also includes external actions that cannot be predicted.

The following subsections show the information that we currently have digitized, by monitoring press data strategically thanks to the *(I3oT)* architecture implemented, [16] and other parameters found in the production process that could be incorporated.

3.1 Available process data (ν)

The vector ν of the model parameters $(\nu_1, \ldots, \nu_N)$ for the stamping process is composed of a large number of parameters, some of them more critical than others. Next, we will list the parameters that could be part of the ν vector and that could be monitored in real time in the plant for the development of our hybrid modelling based on the *(I3oT)* rationale.

3.1.1 Stamping press

Table 2 shows the variables accessible from the PLC of a stamping press.

In order to extract this information, a routine was designed in the automaton that controls the press. Each value collected by each sensor throughout the cycle is

Process Value	Sensor Quantity	Units
Tonnage Force	4	Tm
Cushion Cylinder Pressure	8	bar
Cushion Cylinder Position	2	mm
Counterbalance Pressure	1	bar
Overload Pressure	2	bar
Main Motor Speed	1	rev/min
Main Motor Power	1	kW
Main Motor Intensity	1	A
Press Speed	1	hit/min
Slide Position	1	mm

Table 1 Press Data in Real-Time

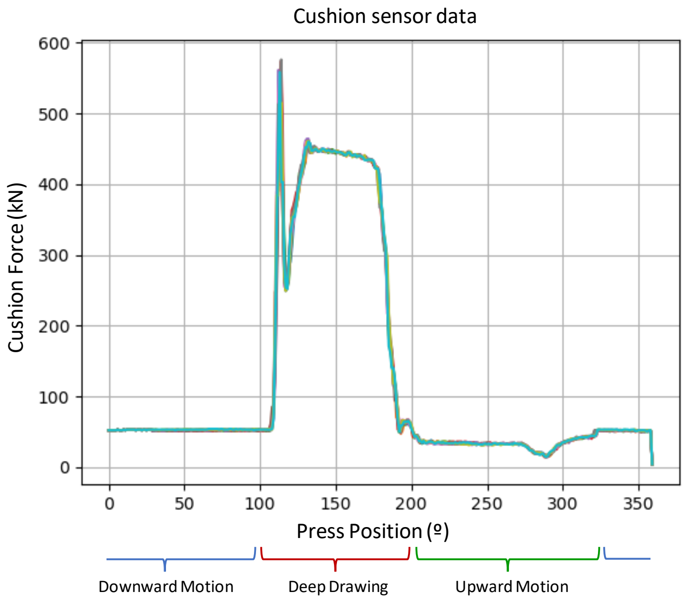

Fig. 5 C360 cushion pressure (bar) data

associated with the press position, defined in a range of 0-359, and which is associated with the degree of rotation of the main shaft of the eccentric transmission system. As one complete turn corresponds to the complete cycle of movement of the press, we are able to determine at which point in the cycle we are observing the data. Thus, the total data for a sensor that we measure in a cycle is 360 and the number of sensors from which we obtain data amounts to 15. In picture 5 we can see the monitored data of the cushion for a cycle.

This information is stored in the database thanks to the developed IoT architecture that allows connecting the OT network with the IT network where we have developed several worker service applications running in our servers to make the data available in real time from any user device.

The routine that allows us to have such an amount of information from the line has been named Criterion-360 (C-360).

3.1.2 Material

The properties of the material, both as input to the stamping process, and of the manufactured parts is a handicap and information that could be decisive for the development of a digital twin.

From the input materials to the stamping process we have all the material information provided by the manufacturer with its respective tolerance (*Type, Geometry, Thickness, Coating, Yield Strength, Tensile Strength, Elongation %*). There are variations in the material properties for the same coil, apart from the tolerances provided by the manufacturer. The accumulated experience of line operators shows that a part formed at the beginning of a coil is not the same as the one formed in the middle or the end of the coil. Having a more pronounced winding angle at the end of the coil than at the beginning, residual stresses may remain in the steel sheet that can cause problems when deforming. Unfortunately, we cannot currently measure each and every sheet that is fed into the stamping line.

With regard to the physical properties of the output material, we encounter the following drawbacks:

1. *The size of the blank sheets:* In large parts they can be up to $20m^2$ with irregular polygon geometry. These dimensions make it impossible to accurately measure the state of a part at the end of the line in order to obtain a good process output.
2. *The geometry of the parts to be manufactured:* With the evolution of technology and the improvement of vehicle designs, more and more complex geometries can be achieved where, when deforming the material, unwanted events may occur that are beyond our control.
3. *The thickness:* With the advancement in the research of materials and the reduction of weight in vehicles we have been able to make them more sustainable and safe. A thickness up to 0.5 mm can be used. When we work with less thickness, it is easier to reach the neck-in effect.
4. *Batch change:* This may give random quality problems. This is mainly due to the part of the coil to which those sheets may belong. As of today, this phenomenon has not been monitored or classified and cannot be verified at the moment.

3.1.3 Lubrication mapping

One of the most critical parameters to consider in the deep drawing process is the coefficient of friction (μ). Assigning an erroneous coefficient of friction can lead to unsatisfactory results as explained in [17], where the FLD (Forming Limit Diagram) result of the simulation gave a satisfactory result but eventually the manufactured parts generated defects. After simulating the surface of the materials and obtaining a good coefficient of friction using the TriboForm tool in AutoForm, they managed to correct the design of the die to avoid these problems.

Actually, it is not possible to measure the coefficient of friction in real time and let alone over the entire surface of the die. In the literature there are many models that can obtain Pressure-Speed curves for a lot of materials and new methods are also proposed for [18] that approximate very well and obtain good results in simulations. However, their application in a real environment generates doubts and at most an average friction coefficient of the entire part could be achieved by using the available data. TriboForm has the option of providing different lubrication zones to obtain a better simulation result as evaluated in [19]. In addition, friction is also known to be variable throughout deep drawing. There is not the same coefficient of friction at the beginning of the deep drawing as at the end.

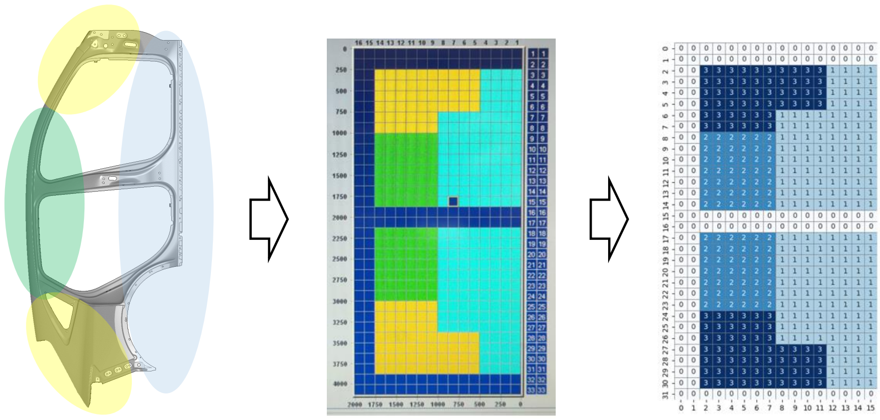

Fig. 6 Lubrication mapping of a car body part

In certain parts, especially those that have more deep drawing, the amount of lubricant applied has to be adjusted and for this there is a machine called Brush Washer that cleans and lubricates the blank at the beginning of the line after configuration. In picture 6 we can see the example of a part with different intensities of oil applied on the sheet in order to form it correctly. This is inserted in a mapping in the equipment in which we have the monitored information. This lubrication map is accessible by using the *(I3oT)* rationale. Knowing this information may be of special interest to build the hybrid model that includes friction with different values along the surface as carried out in [19].

3.1.4 Die

The tool used in the industrial stamping process is a set of dies with as many configurations as there are presses in the workshop. The weight of a set of dies can be very heavy, they can weigh about 5 to 40 tons depending on the size of the item to manufacture.

There are many tons of iron in a die and large tonnage industrial cranes are needed for transport within the press shop. As we can see in picture 7, the die is composed of the punch shown in green colour, the blank holders in red where we have the drawbeds and the spacer blocks. We have the blank centerers that are used to centre the sheet to be stamped correctly on the die. We have the brakes, in the green area around the punch that together with the spacer blocks are in the red area that will be the blank holder of the sheet before being deep-drawn. Both the force exerted by the blank holder and the height of the spacer blocks are critical to manufacturing a defect-free component. Then we have the external space blocks in the blue area where the upper die would rest. And in the centre, as we have already named the punch, in this die the punch is fixed and the deformation of the part is achieved by displacing the movable part of the die, the blank holder, once the upper die is supported and the sheet is held, in a downward direction. And when the press arrives at the bottom dead center (BDC), the entire press is resting on the ground and the deep drawing has been formed in the first operation of the stamping process. This is the most critical process where cracks and wrinkles appear that may cause quality defects if die and press parameters are not well adjusted or if there are any problems in the material.

Fig. 7 Bottom die. Rear door inner panel

The geometries of the dies are rarely modified. The most common change they undergo is the modification of the height of the spacer blocks in dynamic during manufacture and polishing where the radii are more pronounced for facilitating deep drawing. Maintenance work is also carried out and the coating of the surface in contact with the sheet is periodically changed to ensure the hardness of the die and prevent its wear. A wear of the die surface could lead to serious quality problems in the manufactured parts.

3.2 Gap between the two worlds: Real vs. Digital

We know that the result obtained from a simulation can give us a solution that is close to reality. These results have been very useful for designing a process, a product and knowing the feasibility of its development, saving large amounts of money for companies in trial-error tests where a large amount of resources would be invested.

Despite the accuracy of these results, there is always a deviation from what happens in the real world. The result of the simulation will hardly match with what happens in the real world. This deviation is one of the challenges that arise in the development of a digital hybrid model.

The simulation is used in the stamping process to give us an approximation of the parameters that would have to be used in the press when a new part is manufactured. However, when operators install that part on the line they know that specific adjustments are necessary. The operators verify that the part is correct through an actual FLD of the part. The actual deformation of the part can be obtained using the tool AutoGrid_comsmart developed by Vialux [20], where a large amount of deformation data is obtained over the entire surface of the part as shown in figure 8.

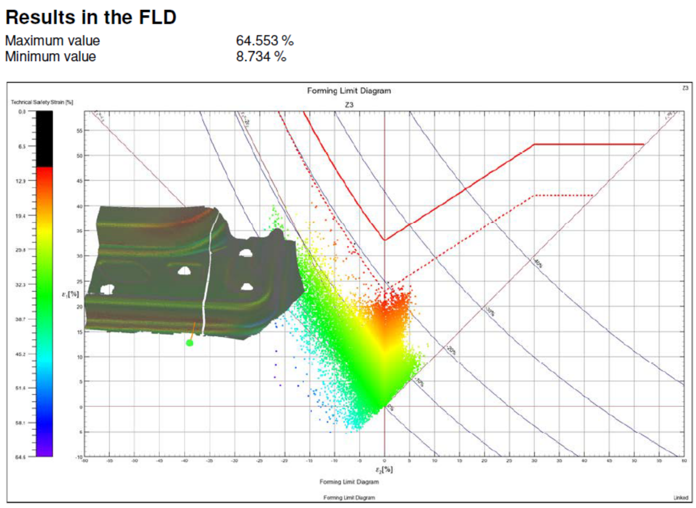

Fig. 8 FLD result

Unfortunately, this information is not available in real time since obtaining this information currently requires a long process, which is impossible to obtain in real time. The process consists of taking a blank sheet, printing a grid of dimension 2 by 2 mm by electrolysis along the surface, feeding the sheet into the line, performing the deep drawing operation, extracting the semi-product from the production line, taking it to the workshop and scanning it using an optical system with a four-lens 3D camera in order to obtain the result of the real deformation.

It is not common to use this technique during normal production although it would be possible to insert a part with the grid inside the continuous production and analyse it later.

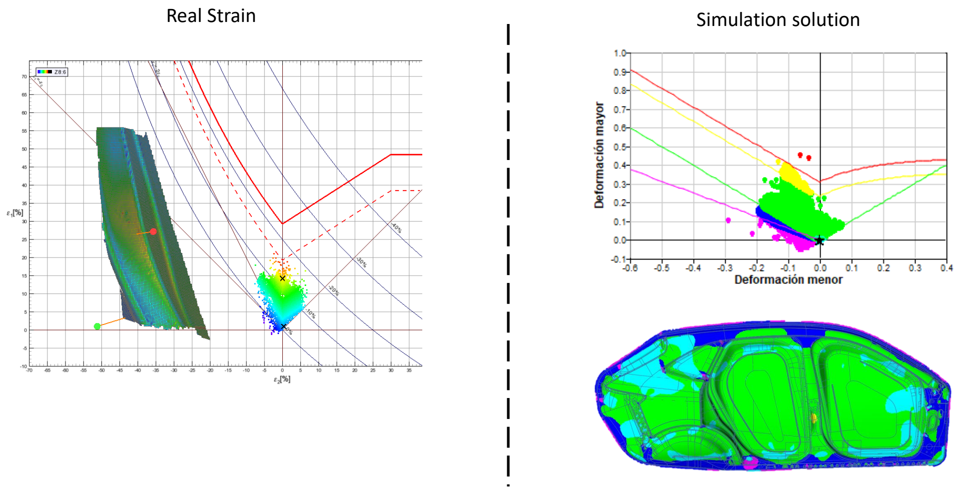

Fig. 9 Real FLD vs simulated FLD

3.3 Process dynamic adjustment. $C(t)$

Dynamic adjustment refers to how the system transitions to a new steady state when there are changes in the determining variables.

During the real process it is possible to know in real time the dynamic variation of the process. The adjustments that are made when quality problems such as cracks or wrinkles appear are usually adjustments of press speed, adjustments of the die spacer blocks and the pressure exerted on the blank holder.

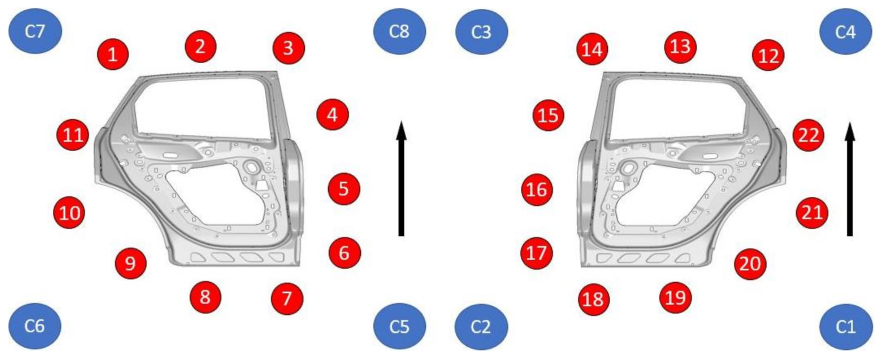

Fig. 10 Dynamic Adjustment Parametrs Map

In picture 10 we can see the sketch used to indicate which cylinder has had the pressure modified or the spacer block whose height has been modified. This decision is made by the line managers based on their experience. For example, if wrinkles appear in the lower right corner, the pressure of cylinder 4 will increase so that the blank holder increases the force in that area so that not so much material slips out. Table 2 shows a record of the modifications that were made during a production because defects began to appear during the palette change.

Coil	V start	V end	Spacer block	Variation	Cushion	F start	F end	Reason
003	16	14			C1	400	450	Wrinkle G9
003					C6	400	450	Wrinkle G2
003	14	16	9	-0,1				Wrinkle G2
003			20	-0,05				Wrinkle G9
003					C1	450	400	Wrinkle stabilized
003					C6	450	400	Wrinkle stabilized
003			9	+0,05				Necking G2
004								Palette change

Table 2 Press Data in Real-Time

This information can be entered into our system when a change is made immediately.

3.4 Unbiased noise. $R(t)$

This term includes external actions that we cannot predict or control, either human intervention in the system, or modifications in the material that cannot be detected at that time.

Here we could consider the changes in material properties. Throughout the plant it is easy to hear from any stamping technician, engineers, managers, etc., that the same coil will have different properties along its length, therefore, the sheets obtained from the cutting process may have different mechanical properties. This is the main reason why a new batch of sheets that is fed into the process can give random quality problems.

Many different batches can come out of a coil and these are stored for later use in stamping. These batches are not usually identified, we do not know if the batch is from the beginning or end of the coil and that is why suddenly a part may begin to fail.

Mechanical deterioration of both the die and the press, modifications in the die due to maintenance, changes in auxiliary equipment of the press due to breakdown, polishing of the die that modifies the coefficient of friction in a certain area, etc., could also be considered.

4 Discussion

This article aims to show what information is available in the stamping process to develop a "Continuous Twin" based on the *(I3oT)* rationale. The use of this rationale is essential to achieve developments that are industrializable. It is necessary to explore applications developed with this information in the first instance and in the event of not achieving the expected results, we should propose the use of additional sensors. At present, research and research centres are not based on developing applications that use available information, but rather based on proposing the use of their own sensors, thus limiting their applicability.

Within the stamping process there is a lot of information available and accessible. This article shows the information that can be obtained from the stamping process. With criterion C-360 we can measure the different parameters that may affect the drawing process in the press, such as tonnage, speed, compensation, etc., and these parameters are available in real time. However, to be able to include these parameters directly in the simulation code, it would be necessary to improve it. On the one hand, the commercial software does not allow to include variable parameters throughout the deep drawing and on the other, the simulation techniques that could include it, such as incremental deformation, are extremely time-consuming in computation time to be able to be put into production. The reduction of the model could be a solution to solve this problem.

Measuring the quality of the part at the output of the process is a very important handicap. The FLD information of real-time parts is not available with current technology and is only performed in the process of installing a new part. This process is very time-consuming and although parts prepared during production may be included, this is a changing process and by the time the FLD corrects the simulation, the process may have already changed. However, a corrected adjustment of the simulation when it is installed and the use of the rest of the information could provide the solution.

Batch changes and the fact that these can be from different parts of the coil sometimes will cause random failures to appear. The adjustments made are recorded and could be used in our "Continuous Twin" to correct failures. A correlation of these adjustments VS the position of the batch inside the coil could allow a "Continuous Twin" to correct the process parameters and avoid such defects.

5 Conclusion

This article tries to provide researchers who are developing "Continuous Twins" with the information available in the industry based on the *(I3oT)* philosophy, and the restrictions of the process that can be found when they try to industrialize it.

This article opens a reflection on which of the possibilities presented may be the most appropriate. If we take data from the actual FLD of the part, even if it is not in real time, we will quickly find the GAP between physical prediction and real solution, or on the other hand, if it is feasible to know the real state of the part when using the amount of data monitored so far. We have the possibility of using the two techniques, with the process data measured in real time to enhance the modelling and with the FLD tests to know the deformation that we have so that we can calibrate the system every X period of time in order to ensure that we do not lose accuracy in the solution and therefore contributing to long-term predictions.

On the other hand, the article tries to show how dynamic the process is but we must be aware that there is noise such as the wear of the mechanical components that will change the result of the physical prediction. Therefore, to adjust this error, the amount of data needed will be greater as the parameter t is increased compared to the initial amount of data with good physical modelling.

What is clear is that we are presented with many development options to find the solution. Our future work will be aimed at evaluating the different possibilities shown.

Declarations

Conflict of Interest: The authors declare that they have no conflict of interest.

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