Data-driven digital twin and digital shadow applied to brazing, additive manufacturing, and welding

by Nicola Gramegna[1], Giovanni Paolo Borzi[1], Domenico Stocchi[2], Silvia Tiberi Vipraio[2], Alberto Chiarello[2]
1. EnginSoft - 2. Gruppo Ecor International

Digital transformation is making revolutionary history in industry. Industry 4.0 technologies are spreading at an unexpected pace and sectors are consolidating around areas where the necessary tools can be used more effectively thanks to processes that more easily capture data directly (automation, robotics, CNC machines, etc.).

Thermal process simulation is well known and used in many industries for tool design and product optimization. The results of process simulation usually remain in the CAE department, although some limited possibilities can be used on the production line, even if the process setup has also been optimized virtually. The simulation-based digital twin is a new approach to linking the physical domain with the reduced order model (ROM) to quickly gain benefits in the product life cycle.

In this context, there is a need to integrate the real world with digital models using an increasingly popular digital twin methodology. Real-world manufacturing data, collected from different sources, can be structured and developed using different approaches. This paper introduces and describes a data-driven Digital Twin (ddDT) and Digital Shadow (ddDS) approach where a web-based monitoring platform can be functionally tailored to industrial applications based on processes and data received in real time. Each industrial case presented in this paper has specific objectives, but all share common challenges represented by the requirement to manage real-time data to support human monitoring, traceability and decision making. The ddDTs and ddDS connected to the thermal metalworking system allow a continuous and just-in-time monitoring of the process and are a valid method to track the events and quality indices of the component to be produced. A machine learning approach integrating supervised or deep learning models can be applied to the acquired data set, extending the data analysis with advanced meta-models.

The AGILE and AMQ_TOOLS research projects applied the ddDS approach to brazing thermal treatments and manual welding processes, the ddDT to additive manufacturing L-PBF. In all these cases, the thermal process transforms metals by influencing their microstructure, quality, and mechanical performance. A common technological approach was implemented using virtualization and digitalization with monitoring, modelling, and simulation.

In addition, process results can depend not only on the machine involved and the process parameters, but also on human variables.

For example, an innovative augmented reality environment has been developed for the manual welding process to monitor the human process variables. This virtual industrial space allows the integration of the operational setup and human gestures, generating useful data to monitor, visualize and configure the process, to support the analysis and development of the most appropriate process parameters, and to support operator training. This demonstrates a new paradigm of Industry 5.0, in which digital technology is used to improve the skills of human resources.

Introduction

Differential equations are often used to describe the fundamentals of mathematical modelling of phenomena occurring in thermal processes. The finite difference method (FDM) and finite element method (FEM) solutions to differential equations are well known, well established and implemented in simulation tools using computational solutions managed by workstations and, in some cases, high performance computing (HPC).

Some challenges remain in the CAE modelling of time and materials to represent multi-scale transformations in thermo-mechanical processes. Recent advances in emerging topics in modelling and simulation of advanced thermal processes find fertile ground in the development of advanced modelling of innovative materials and processes. While these sometimes remain at the laboratory or pilot demonstration level, they capture a current context of strong digital transformation of the factory environment where these processes are actually used. This context creates the need to integrate the real world with digital models, using an increasingly prevalent digital shadow methodology.

This paper focuses on manufacturing and thermal processes, which are often an integral part of the production chain and which use thermal energy to transform matter and product into the designed object. Where analytical or differential equation solutions are available, using the reduced order model (ROM) for fast response, simulation-based digital twins can be used to study the evolutions of material to achieve maximum quality and performance. In parallel, the real monitoring data of the production processes and their correlation with the qualitative results measured in the field also constitute a wealth of information of considerable value when managed and processed by a monitoring system such as a data-driven digital shadow. The acquisition of large amounts of data, now possible thanks to the connectivity of Industry 4.0 machines, and its processing with machine learning (ML) algorithms, makes it possible to identify the impact of deviations in the process that can lead to defects and production inefficiencies.

Recent research carried out by EnginSoft and Ecor International on metalworking processes has focused on virtualization and digitalization through monitoring, modelling and simulation, techniques that have been developed and implemented to study different processes such as brazing, additive manufacturing, and manual laser welding.

A web-based platform called "smart prodactive", already used in Foundry4.0 and in plastic injection moulding, has been extended and applied to similar thermal processes.

The thermo-fluid dynamic simulation of a TAV heat treatment furnace, such as the brazing case study in the AGILE project, is certainly not new, but the data-driven digital shadow, based on advanced sensing and real-time data collection to track any deviations from the ideal setup, introduces an innovative solution that makes it possible to predict the impact of such deviations on the various parts inserted into the treatment grid of the entire batch.

An important transformation from melting to solidification of metal alloys occurs in the additive manufacturing L-PBF process, which is managed by increasingly powerful, automated and sensor-rich machines. The 3D printing process provides layer-by-layer temperature-time results depending on the laser path, power and speed, and the monitoring platform collects data from the machine and in-process sensors. Again, even small variations in the many process variables can affect the quality of the product, which is sometimes unstable and unrepeatable even with identical machine configurations. The same data-driven digital shadow platform used for the TAV oven was then connected to an EOS M290_OT machine as part of the activities foreseen in the AMQ_TOOLS project supported by HubCup.

It is not always easy to monitor the process variables of a manufacturing process, especially when the human-machine combination is critical. This was the case for the manual welding cell, digitized by tags on the operator's hands, used in the AGILE and SMACT projects, where monitoring via a VR system is synchronized with the laser source signals and the operator's execution times.

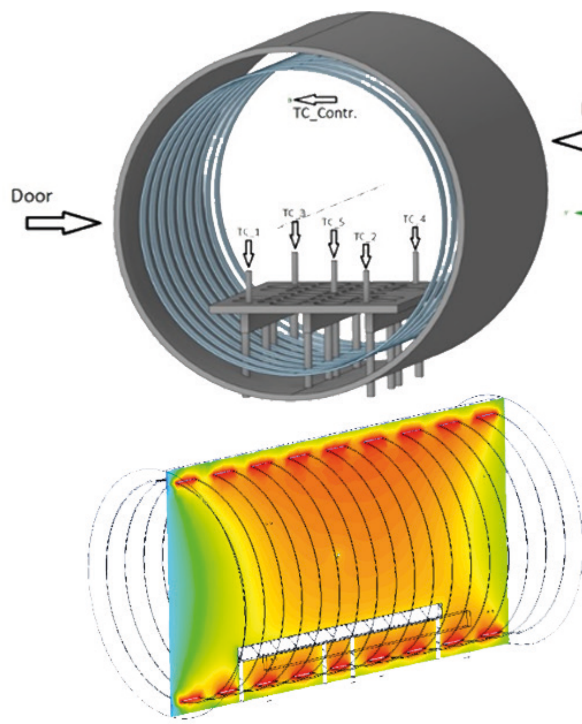

Fig.1. Diagram of the digital platform and its integration into the production line.

Fig.2. Diagram of the digital platform and its integration into the production line.

All this is integrated into a digital shadow platform that processes the data and provides the right information to support decisions. This benefit is further enhanced by the tracking of welding processes, which are highly operator-dependent.

The optimal paths can now be used as best practice to standardize and plan the training of new resources.

Digital Shadow Case Studies

Case study 1: Brazing furnace monitoring and simulation

Brazing is a well-known technological process for joining two or more materials by melting and adding a filler metal, called braze, which is a eutectic alloy that melts at a lower temperature. The feedthrough is a special type of electrical capacitor consisting of conductive elements (copper/steel) and other insulating elements (typically ceramics). As with any mass production, quality control is a very laborious task and does not always understand the causes of defects. A possible improvement could be achieved by fully tracking the processed parts to identify process variations that could cause defects in individual parts.

The first step towards digitalization was the creation of a virtual study of the oven which made it possible to identify the furnace zones of maximum efficiency and stability, both in a steady state (static) and transient (dynamic) situation (Fig.1). The CFD modelling of a TAV oven now makes it possible to analyse the different usage scenarios with even the smallest deviations and allows the possible creation of reduced order models (ROMs), useful for a future simulation-based digital twin. The static and dynamic simulations confirm the temperature uniformity in the oven, suggesting the study of possible deviations in the positioning matrix and in the geometric conformity of the assembly.

The FEM study contributes to the important goal of moving from traditional methods to a virtual approach where information can be managed in an integrated way. The availability of a predictive simulation tool increases the agility and speed of the design phase, for example for new products. To be competitive, it is necessary to know how to innovate the product quickly and adapt the production system accordingly. The tool can also support decision making.

In this case, given the efficiency of the furnace, a different approach was taken and implemented with a data-driven digital shadow that collects process data in real time via the OPC-UA protocol to create a control optimization algorithm, predictive data-driven control of the model, robust/optimal control, and a decision support system. This integrated quality-process management system is designed to manage both thermal data with possible historical processing and quality data from process controls in a single system (Fig.2).

The GUI integrates process data (pressures, temperatures, etc.) with production data (batches, product codes, etc.) and with quality data. The database allows searches and extractions to identify any problems in the process.

It is only with this information can that we can talk about process control and monitoring, component traceability, and the implementation of improvement actions to reduce waste (towards zero waste). The system developed allows an in-depth analysis of quality data and the production of a report with detailed process tracking.

As part of the quality study for the digital platform, quality and functionality analyses were performed on each component of the experimental campaigns. The tests were all non-destructive due to the small number of defects found and consisted of visual inspection, tomography, optical scanning, CMM inspection, and a leak test.

The measurement campaigns also included the analysis of a number of specimens with varying degrees of weld defect to which a specific misalignment (concentricity) value was assigned. A correlation analysis was then carried out between these two aspects. Preliminary information confirmed a relationship between the degree of defect in the components and the misalignment between the components of the assembly.

Optimization of the mathematical model using physical parameters, vacuum temperature laws and dynamic regimes under both static and dynamic conditions results in a good agreement with the experimental data.

As part of the agility concept, the main objective was to monitor, track and intelligently manage process data (part position, reference times compared to recorded times for each individual process, cell availability, tracking of any criticality and its resolution) with the digital platform.

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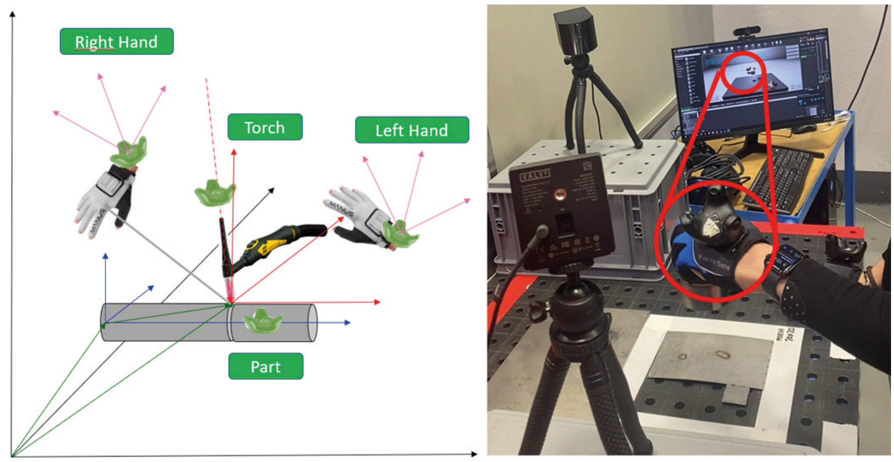

Fig.3. Human sensors for manual welding and system configuration.

Remote management of the system and design has been achieved, minimizing low-value human activities. The platform makes it possible to digitize and integrate quality data to perform searches and extracts to identify any problems in the process.

Case study 2: Virtualization and data management of the manual welding process

Controlling processes that are affected by direct human interaction, such as the manual welding process, can have a significant impact on continuous improvement by reducing defects. Predicting quality and controlling the joining process can greatly influence production efficiency, process repeatability and the reduction of production costs towards a "zero defect" approach.

Product development mainly involves the pre-assembly of the parts to be welded, spot welding, and then in manual Tungsten Inert Gas (TIG) welding of the joints. NDT and visual inspection are used for quality control and defects are classified into porosity, slag inclusions, bite edge, weld pit and linear defects such as incomplete penetration, incomplete fusion, etc. The quality problems encountered were related to process variables such as welding voltage, welding current, wire feed rate, welding speed, and bevel angle. A second set of process parameters were identified as human process variables. (Industry has shown that different technicians using the same set of parameters and welding procedure specifications (WPS) to produce the same specific part can produce results of varying quality.)

The method designed and developed to design and digitalize the manual welding process aims to create a mixed reality-oriented digital shadow (MR-DS) framework to detect defects and configure the process according to the most appropriate parameters.

Motion capture (MOCAP) was used to monitor the welding process. This system allows real-time monitoring and subsequent data storage. It was equipped with two cameras for a complete welding plate scenario. Trackers in wearable gloves and on the forearms of the operators tracked all their movements to detect the manual dexterity of the welders.

The same types of sensors are also found on the weld part, torch, and worktable. An offset was added to centre the table tracker. Details of the organization of the equipment to generate the virtual welder are shown in Fig.3, along with details of the sensors to capture the spatial variables of the entire welding environment. The complete set of variables monitored is reported in Table 1.

Data from the welding station is fed into a unique data management system (DMS). It is exchanged between the Unreal Engine tool and the data logger. Data from the physical and virtual systems needs to be stored and processed in the communication layer (Fig.4).

Item instrumented	Parameter monitored	Associated functionality
Welding unit	Current	Influence on seam heat input
Welding unit	Voltage	Influence on seam heat input
Right and left hand	3 translations and 3 rotation angles	Manual dexterity of the operator
Fingers	3 rotations for each finger	Manual dexterity of the operator
Welding torch	3 translations and 3 rotations	Management of the torch during welding
Welded part	3 translations and 3 rotations	Spatial position of the piece
Welding table	Reference plane	-

Table 1 – Set of parameters monitored to develop the virtual model.

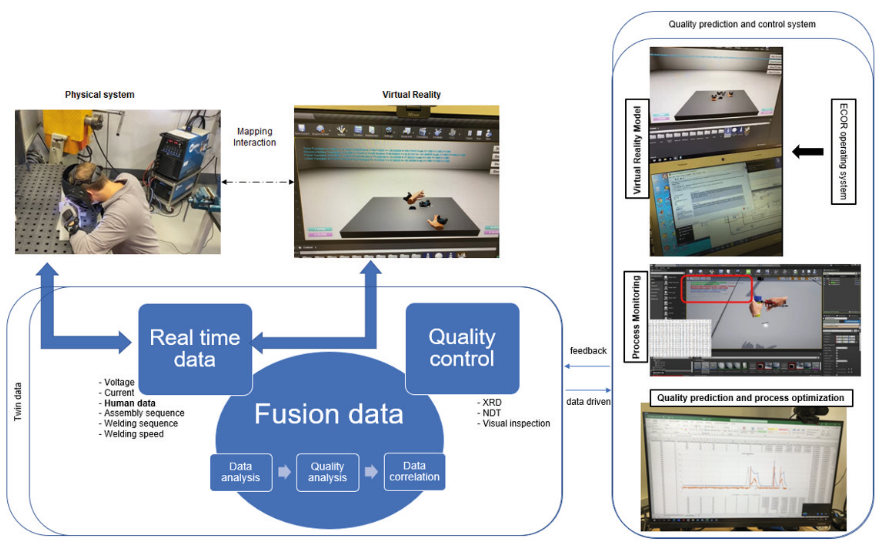

Fig.4. Digital Shadow model to predict and control manual welding quality.

Internet of Things (IoT) technology enables interactions between different layers of embedded systems for real-time data transfer. The IoT provides bi-directional synchronization of physical and virtual systems, providing data for virtual system updates. Real-time control commands are executed based on the past and present state of the physical system to ensure the consistency of the manufacturing process and the quality of the manufactured parts [1].

The main objective of the research is to improve the efficiency of the process by monitoring and controlling its variables in real time, and to achieve better and more consistent product quality. This will be achieved through a dynamic industrial virtual reality scenario in which the simulation will replicate the main variables of the production process. All the variables collected (big data) will be processed by a digital software platform.

The interaction between the physical entity and the hybrid twin data model is actually managed by a software structure and the process technologist and welding operator who distribute the sensor data represented by the welding process database. The tool used for this specific purpose is an intelligent cloud platform specifically integrated with the Enterprise Resource Planning (ERP) system.

The digital tool allows the process to be monitored in real time. Its configuration can support comparative analysis of the reference process and the current welding phase: quality data for each welding phase is stored to ensure process traceability of parameters and

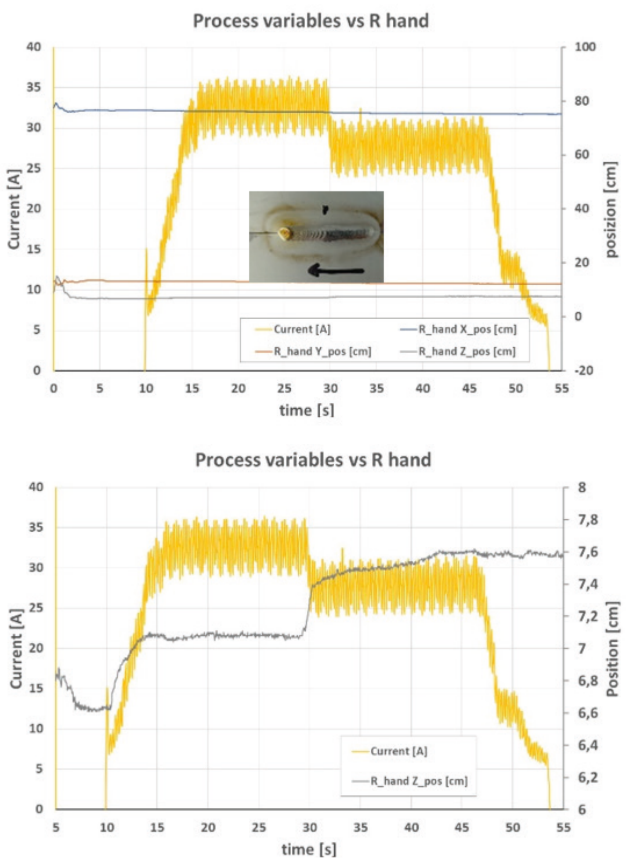

Fig.5. Reduction in bead size due to movement of torch hand in z-direction.

time-space variables. Prediction of process quality is then obtained by processing and analysing large amounts of data, which the platform supports by refining the pass/fail criteria.

There was a good correlation between the data and the real conditions in terms of physical changes being reflected in the virtual system. Fault detection and validation of the sensor data was carried out by inducing faults to assess both the ability of the virtual system to adapt to changes in the real environment and to measure its sensitivity.

Fig.5 shows the monitored data output (current, voltage, z-displacement of the torch hand) after the operator induced a reduction in the seam size. The operator's movement caused a z-displacement of 6mm, which is perfectly acceptable in the range of potential errors during welding.

The digital shadow is a digitalized, data-based system for smart decision making and quality forecasting. Once data from different part number jobs has been imported into the digital platform, the correlation between the influencing variables of the physical unit and the virtual model can be efficiently analysed for real-time information analysis and decision making.

The research framework is fully integrated into the Industry5.0 model. The (human) technician of the welding unit (the industrial machine) and the virtual machine work together with the common goal of improving industrial production efficiency and operator skills.

The training of human resources is managed by the data-based platform. The entire production team (consisting of the welding operator, welding engineer, and process technologist) is then involved in interactive upskilling sessions via virtual on-the-job training. Predictive quality can be achieved through the benchmarking phase for data-driven decisions.

In addition, young welders or engineers can be kept up to date through virtual training sessions that implement distance learning on real industrial cases. Instruction is provided through safe training that avoids exposing workers to unnecessary problems during these phases [4].

Traceability of process quality is ensured by the availability of data that can be analysed and processed efficiently and intelligently by the data platform. The data analysis experience has been greatly improved by the implementation of a customized tool for industrial welding.

A new concept of human efficiency and productivity is being developed. Skills are the driver of business productivity. Human resources are directly involved in improvement activities through the support of innovative digital technologies, and this can create a virtuous circle of engagement [5].

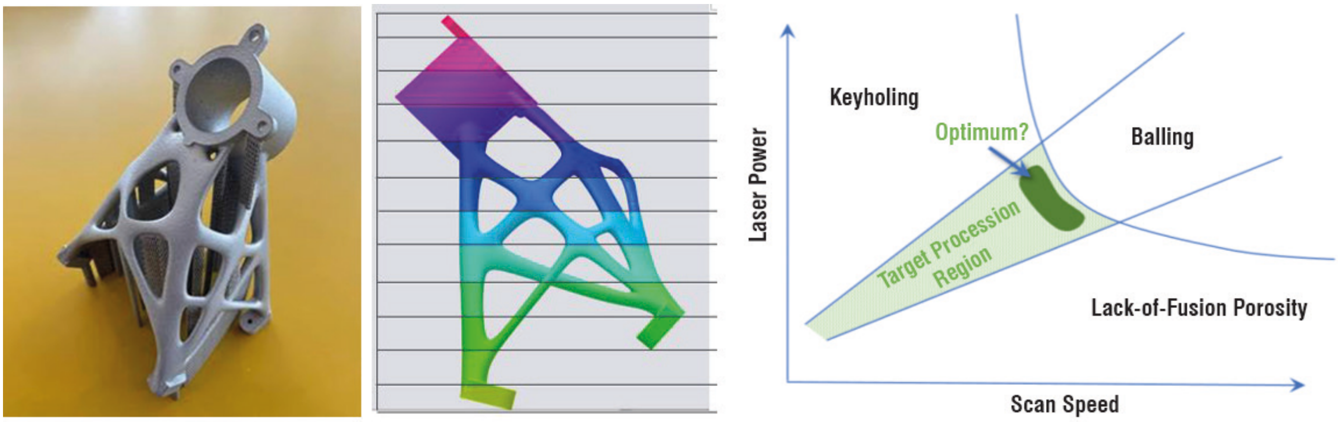

Fig.6. Final demonstrator with scan plan and typical AM defects with optimal setup.

Environmental control through smart, networked, and customized sensors that work together to provide a real-time picture of the industrial scenario from different angles. In the search for sustainable processes, the aim is to reduce production time and minimize material and energy wastage in re-manufacturing by minimizing defects resulting from poor production quality control. Corrective and preventive actions can be implemented by using the digital tool in the process optimization phases.

It also has a major impact on the productivity and business efficiency of the entire production system, as the process can be adjusted based on the direct results of the quality checks.

Digital twin case study

Case study 3: Monitoring and data management of the additive printing process

Metal additive manufacturing (AM) is a complex process that requires the fine-tuning of hundreds of process parameters to achieve repeatability and good design quality at the dimensional, geometric and structural levels. Among the key technology challenges, many recent reports have highlighted the need to achieve intelligent metal AM process control so to ensure quality, consistency, and reproducibility across AM machines.

A huge amount of data can be collected in metal AM processes, as most industrial AM systems are equipped with sensors that provide log signals, images, and videos. However, there are no consolidated solutions in industrial practice capable of analysing this data in real time for quality control. The HUBCAP programme (www.hubcap.eu) aims to develop and promote European cyber-physical systems (CPS) technology. Within this programme, the AMQ_TOOLS (additive manufacturing quality and monitoring control system) project developed a platform for technology providers and users to collaborate and access tools and services for model-based design (MBD) of CPS.

In particular, the validated quality control methodology consists of the combination of a) a model-based tool that adapts the design for additive manufacturing (DfAM) using a process simulation software solution (Ansys Additive Suite) based on technical and quality requirements (Fig.6) and b) a cyber-physical system that connects the EOS M290 machine with newly developed process monitoring software to control the quality of the parts during the printing phase.

The four key parameters, namely laser scanning speed (LSS), laser power (LP), hatch distance (HD), and layer thickness (LT), are directly related to the energy transferred to the powder bed, expressed as volumetric energy density (VED), by the equation:

$$\mathbf{VED} = \frac{\mathrm{LP}}{\mathrm{LSS} * \mathrm{HD} * \mathrm{LT}}$$

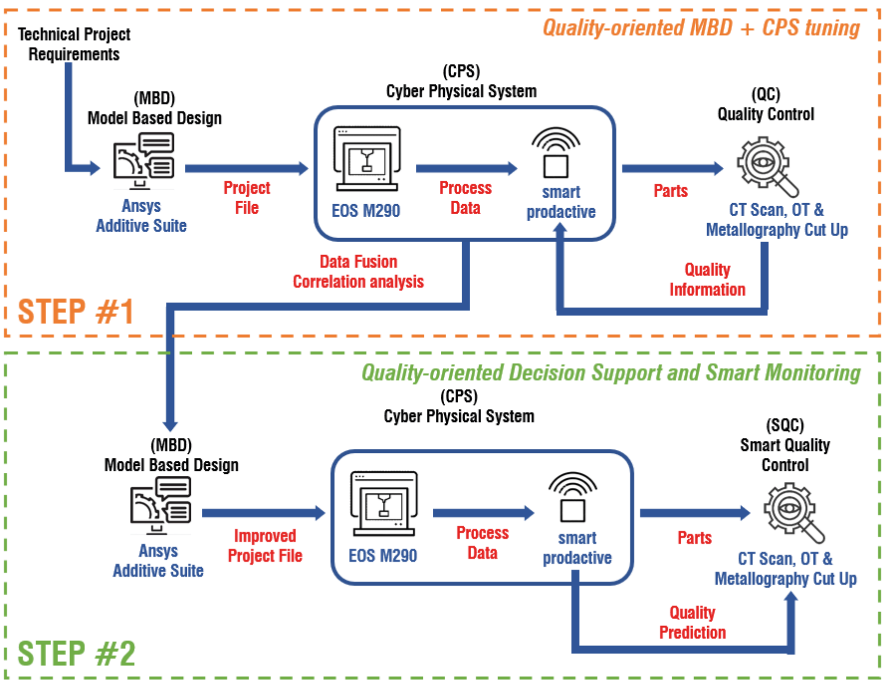

Fig.7. Quality-oriented approach with MBD and CPS tuning.

The VED is related to the measured density studied during the experiments.

Quality control in additive manufacturing involves a decision support framework that integrates a design for AM (DfAM) with the digital platform that connects AM machines (in this case an EOS M290) with quality assurance requirements and quality control data.

smart prodactive is a fully integrated system that links production processes with data sources (machines, sensors, HMIs) and uses traceability information to correlate this data with output quality. smart prodactive thus enables intelligent monitoring of additive manufacturing processes by applying quality-oriented predictive models and machine learning algorithms in real time. These models predict defects by category, area and quality. Process simulation identifies macro-scale defects, while advanced modelling with real-time process data is used to analyse, model, and predict meso- and micro-scale defects.

The overall solution proposed is based on a two-step methodology (Fig.7):

- **Step 1:** Defects are categorized and a catalogue is created. An MBD tool then translates the technical requirements into part geometry, machine and process parameters to identify defect risks. The AM process then starts and the CPS collects the process data. The OT and CT scan collects the quality information and links it to the relevant process step, batch and part number.
- **Step 2:** Process parameter optimization is applied to provide decision support for part and process design. The detailed information generated by the CPS is integrated into the MBD to define quality-oriented product and process design practices. The AM process is initiated, and data is collected and the model estimates quality compliance in real time.

The quality-focused AM solution supports quality compliance by estimating the real-time impact of:

- Monitoring DMQ (maximum density achieved/target density) quality improvement during the print phase.
- Reducing lead time by up to 20% using online quality process monitoring to reduce the number of the quality checks.
- Minimizing design complexity using simulation tools to validate process set-up.

Uses cases referenced

The use cases described are the results of the recent research projects AGILE (funded by the Veneto Region through the POR-FESR 2014-2020 programme), AMQ_TOOLS (funded by the HUBCUP programme), and the EFFIMEC – "Sistemi di produzione ad alta efficienza per componentistica meccanica speciale" (or high-efficiency production systems for special mechanical components) project funded by IT MIMIT within the framework of the "Accordi per l'Innovazione – 2019" (or innovation agreements).

Acknowledgements

The authors would like to thank Dr Shahram Roshanpour for his valuable contribution to the brazing furnace modelling research, which has significatively improved the depth and quality of this research by contributing to the availability of an industrial tool for the efficient optimization of the brazing process. We would also like to express our appreciation to the dedicated teams from the companies who provided unwavering support and direct involvement in all the research activities.

For more information:
Nicola Gramegna – EnginSoft
n.gramegna@enginsoft.com

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