Application of MBSE and AI for developing a 3D printing system

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Abstract

The present work describes the combination of *Model Based System Engineering* (MBSE) with *Artificial Intelligence* (AI) during the development of a 3D printing system. It comprises a robotic positioning system, an additive manufacturing head and a quality supervision module. In order to handle the complexity of the final product, with different elements interacting and distinct operation modes, and to keep track of the design evolution with the product requirements, a MBSE approach is followed. Compared with traditional *Document Based System Engineering* a model encapsulates the complete description of the system and it is continuously updated for tracking the effects of modified requirements and including the progressive updates of the design. *SysML* is used as modelling language as it has been adapted to the needs of the methodology at Technological Institute of Aragon with specific stereotypes and standardized blocks for handling different product variants. In this work, the model is also the basis for the development of two AI-based functionalities: a quality supervision system for monitoring the quality of the part and a user support module that recommends the process parameters for assuring the quality of the printed parts.

The main contribution described in the present work is the methodological combination of MBSE and AI for the development of system functionalities. In the last years, active research is ongoing for combining the potentialities of both disciplines in the framework of the *Knowledge Based Engineering* (KBE) for acquiring the fundamental knowledge of a system and using it in design activities, further developments or product variants. As described by Kulkarni et al [1] SysML has attracted attention as knowledge model in the KBE framework as it is a natural language for system engineering, it is compact, it includes relationships between requirements, product and processes, and it is compatible with commercial and open software tools. The requirements described in the model can be automatically converted into conditions for special optimization processes as it is described by Baan et al. [2] for a potential *Process integration and Design Optimization* (PIDO) tool. Similarly, the

knowledge model can also be used for generating basic 3D geometries as proposed by Aramburu et al. [3]. Unfortunately, this is still an open research activity and partial solutions comprising different modelling, translation and design tools are normally developed *ad hoc*. This is the case described by Rimani et al. [4] where SysML is used as knowledge base for describing different robot concepts using AI planning solutions. In this case, the code is automatically translated from the behaviour description of the system model. Commercial solutions are mostly restricted to some integration module orchestrating the tasks done by specific software applications, which normally change depending on the industrial field. The present work describes the application of MBSE for the development of AI functionalities in a printing system.

The developed 3D printing system appears in Figure 1. It has a delta robot which places the additive manufacturing head at the required position, and a quality measurement system based on a laser line sensor Geocator 2340 mounted on a linear actuator for obtaining a 3D measurement of the printed layers. The application of the AI functionalities for the quality supervision and user support modules permits the optimization of the additive manufacturing process for increasing dimensional accuracy, efficiency and improving the sustainability. Combined with the use of sustainable materials, the integration of these technologies can lead to zero-defect manufacturing, significantly improving the environmental impact of the processes. More than 70% of additive manufacturing applications are focused on the industrial sector, where the non-quality costs include material waste, energy consumption and spent time. Through the designed system, it is expected to reduce this rejection to a minimum, even being able to rework or recover defective parts.

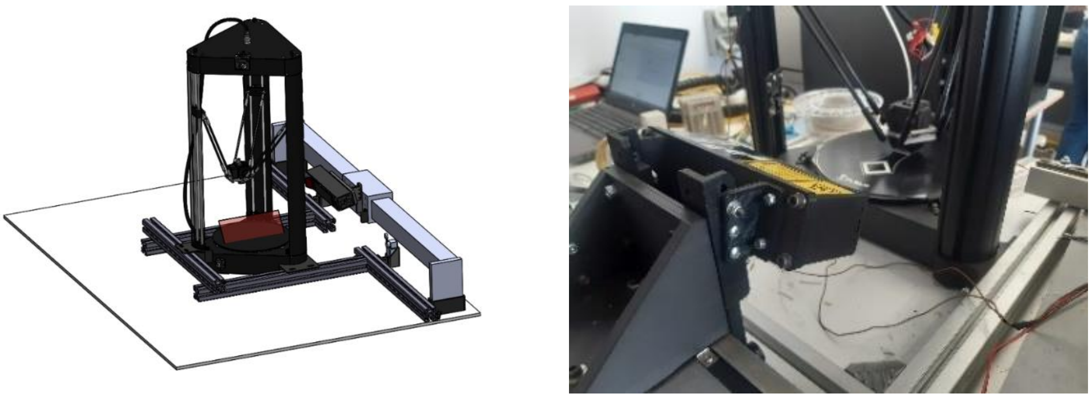

Figure 1: 3D printing system (-left- general view; -right- detail of the Geocator sensor)

The present work fucuses on the development of the AI models. The quality supervision system is based on a digital twin which takes information from the laser sensor and identifies deviations and anomalies. And the user support module models the relationships between the process parameters, material, reference geometry and resulted quality to predict the best parameters for minimizing the printing error.

The methodology follows the V-Cycle approach using the SysML model as reference repository of the design (Figure 2). The objective is that the model becomes the source of truth containing the current status of the development and so it is the reference for the different activities. Initially, the requirements, expected behaviors (ideal and error cases) and result of the functional analysis are included in the model. After that, this information is used for the design of the general architecture and the different modules. During the process, the technical features are refined and included in the model. Similarly, the requirements, functionalities and behaviors are the basis for the verification and validation activities.

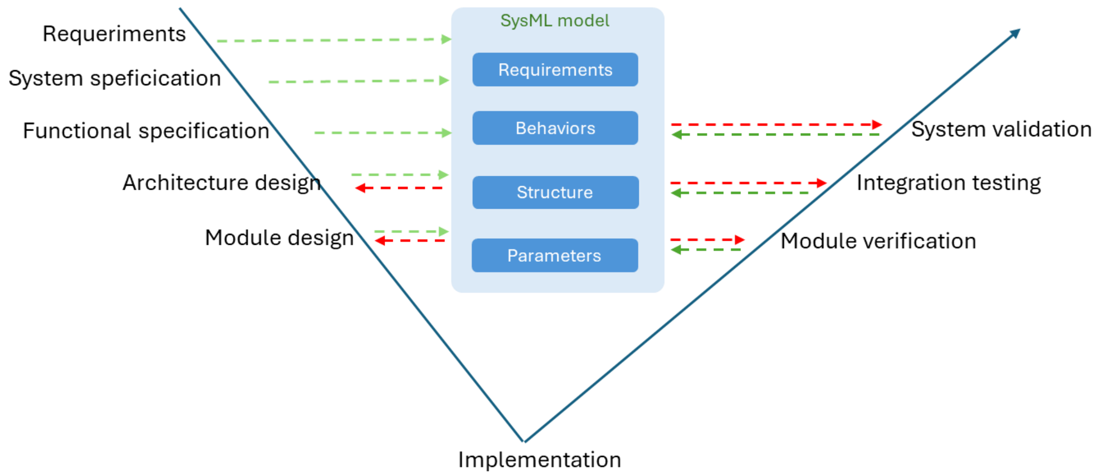

Figure 2. MBSE combined with V-cycle methodology

The specific approach followed for the design of the two AI modules is described in the Figure 3. The expected behaviors and parameters are used for defining the experiments which will produce the data required for building the AI models. The requirements are used for evaluating the obtained results and formatting the data. The detail of the final module is included in the SysML model. In this connection, different SysML models can be generated depending on variations of the product (e.g. one version using neural networks and another one using a random forest for a certain AI module). The detail of the data treatment is given in the following and it can be extended to other printing processes with different materials and geometries.

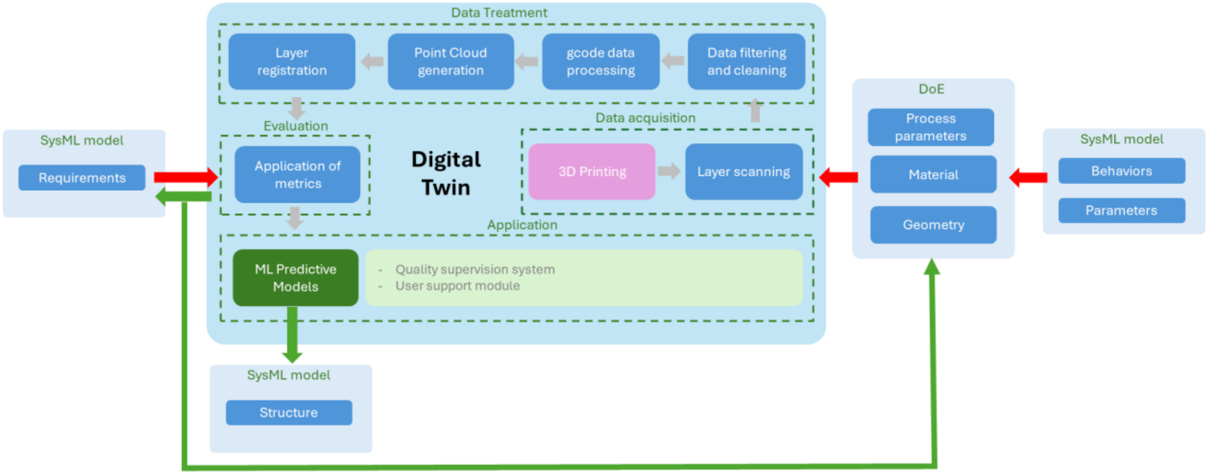

Figure 3. Process for obtaining the AI modules

Based on the system requirements and parameters, the AI models have been developed considering the geometries in the Figure 4, different materials and printing conditions (process parameters).

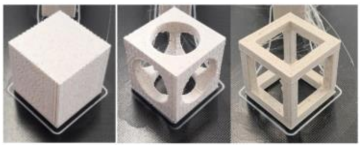

Figure 4. Geometries

For each experiment, the process starts with the data acquisition (Figure 5a). It is afterwards treated by a process of referencing, filtering and cleaning (Figures 5b and 5c). And finally, the treated data for each layer is compared with the theoretical model (CAD) to identify the anomalies (Figure 5d).

(a) (b) (c) (d)

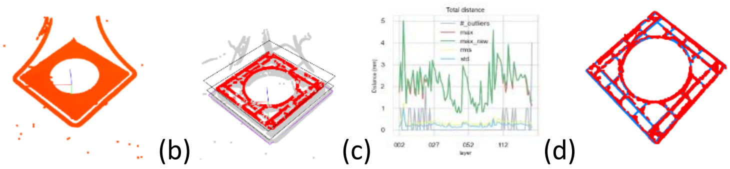

Figure 5. (a) Acquired data layer; (b) Data treatment; (c) Process control; (d) Model comparison

The anomalies are described in the SysML model as failure behaviours of the system. They consist of geometric deviations, printhead reference loss, lack of filament, loss of adhesion of the specimen or catastrophic failures (Figure 6).

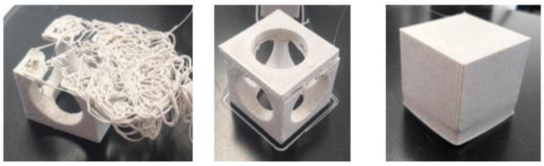

Figure 6. Examples of anomalies during the printing process

For the quality supervision system, the final design is based on a random forest model and it has been verified by comparing predicted deviations using the Hausdorff distance with experimental measurements (Figure 7). The resulting model can detect trends for small deviations, and it clearly identifies them for deviations larger than 0.5 mm.

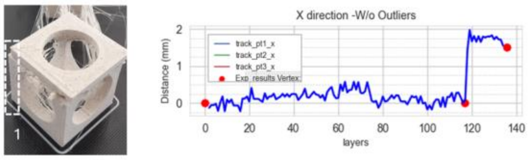

Figure 7. Verification of the quality supervision system by comparing predicted and measured dimensions

Regarding the user support module, 10 process parameters have been selected including temperature of the printhead, temperature of the base, printing speed or flow rate, among others. These parameters are dependent on the material chosen and the geometry of the specimen. The relationships between the process parameters, material, geometry and quality have been processed and used to build a KNN (k nearest neighbour) model to predict the best process parameter set to minimize the error printing.

The current work shows the status of the methodology developed at the Technological Institute of Aragón for linking MBSE and AI. The approach can be extended to other products, and it shows the potential of using MBSE for the design of AI based functionalities. Further activities are the automatic test generation, as the presented approach was done using standard Taguchi methods, and the refinement of the AI modules to consider a larger set of materials and geometries, as the current solution is focused on PLA with different contents of recycled material and the geometries in the Figure 4.

References:

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