

International Conference on Changeable, Agile, Reconfigurable and Virtual Production

FMU-supported simulation for CPS Digital Twin

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Abstract

Manufacturing companies are experiencing the fourth industrial revolution characterised by the introduction of new technologies into production equipment, such as the Cyber Physical Systems and the Digital Twin simulations. Companies are then challenged by the digitization of products and production systems information, which leads to new potentials for digital continuity – i.e. information available and continuously updated for the decision makers – along the lifecycles. A semantic data model, that structures and stores physical and operational data from the field, can support the digital continuity to be used in production system simulations in a Digital Twin paradigm. This work proposes to model specific aspects and behaviours of the production system separately from the core simulation, in order to flexibly decide whether to activate the replica of the specific behaviours only when needed. The modules interact with the main simulation run through standard interfaces, allowing an easy reusability of the single modules also in different simulation environments.

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Peer-review under responsibility of the scientific committee of the International Conference on Changeable, Agile, Reconfigurable and Virtual Production.

Keywords: Digital Twin; Cyber Physical Systems; FMU; simulation; Ontology; Industry 4.0

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1. Introduction and objectives

In the last decades, simulation has evolved from a tool limited to very specific topics used by experts to a standard tool commonly used by engineers. It is used for design decisions, to validate and test components or even complete systems [1]. Its use has changed during the years and new possibilities are enabled thanks to the Industry 4.0 that leverages on the use of Cyber Physical Systems (CPS) in production systems. These allow building a copy of the real process in a digital world, thanks to computation, communication and control capabilities [2], [3]. With the development of CPS, simulation models might progress to so called “Digital Twins”, i.e. an integrated simulation of a complex product/system that, through physical models and sensor updates, mirrors the life of its corresponding twin [4]. Thus, Digital Twin simulation is relevant to answer needs emergent with the product or the asset life cycle simulation; to this end, information must be stored in a structured way through the use of appropriate data models [5], [6]. It is necessary to grant the “digital continuity” of the production system data throughout the plant lifecycle, meaning the capability to store and retrieve digital information about the production system and products for different purposes along the production system lifecycle. Semantic models seem the right way to represent and structure field information to be fed to the Digital Twin simulations, since they offer a unique and standard description of the CPS virtual information that the different tools can use to run. In this way, they support the digital representation of factory operations and enable interoperability and integration among multi-disciplinary simulation tools [7].

This work contributes to the development of Digital Twins by proposing to add black-box modules to the main simulation model. They simulate different behaviours of the system (such as energy consumption, availability, kinematic behaviours, to name a few) in addition to the main simulation model and are activated only when needed. The main simulation becomes in this way more flexible. The main objective of this paper is to present and discuss the application of such simulation modules, each of which simulates in real time a single behaviour of a production line (or equipment) that gives specific information on its state or on specific indicators. The structure of this paper is the following: in section 2 the use of Functional Mock-up Units in the Digital Twin paradigm is illustrated, in section 3 the semantic data model behind the simulation is discussed, section 4 reports the practical application of the proposed approach and section 5 proposes some concluding remarks.

2. The use of FMUs for the Digital Twin

From literature emerges that a Digital Twin is a coupled model of a real system, that is stored in a cloud platform and represents its status based on data analysis and physical sensory information [8]. Since authors are not implementing the Digital Twin in a unique way, one possibility is to build different simulation modules that simulate different behaviours of the system that must be replicated in the digital environment. The core simulation model is built with the representation of the pieces of equipment of the production system. Each of these pieces will be connected to one or more modules that represent the specific behaviour of interest. The behaviour modules are black-boxes that take standard input data from both the simulated and field environments and that output computed data also in a standard format, like in the general case described in Fig.1. Functional Mock-Up Interface (FMI) standard (<http://fmi-standard.org/>) is used for the black-box modules, creating Functional Mock-up Units (FMUs). The chosen standard allows the function to be exported to different simulation environments, in this way granting the independence of the FMU modules from the single simulation tool and allowing them to be reused with little arrangements (Fig. 2). This standard has already been successfully used in CPS-based systems, as shown in [9], [10].

The FMU modules are created to be recalled by Discrete Event Simulation (DES) and constituted by a unique FMU zip-file composed of three main parts:

- an XML file to define the variables inside the FMU;
- the equations used by the model (which is a set of C functions);
- other data, such as tables or comments about the model.

The built FMU in the application case (Fig.1) is created for a Discrete Event Simulation (DES) model and takes as an example of behaviour module the energy consumption computation. The energy consumption highly depends on the actual state each equipment piece is in at each moment, as shown in Fig. 1 where the FMU is connected to the

field to get information on the updated machine states [11].

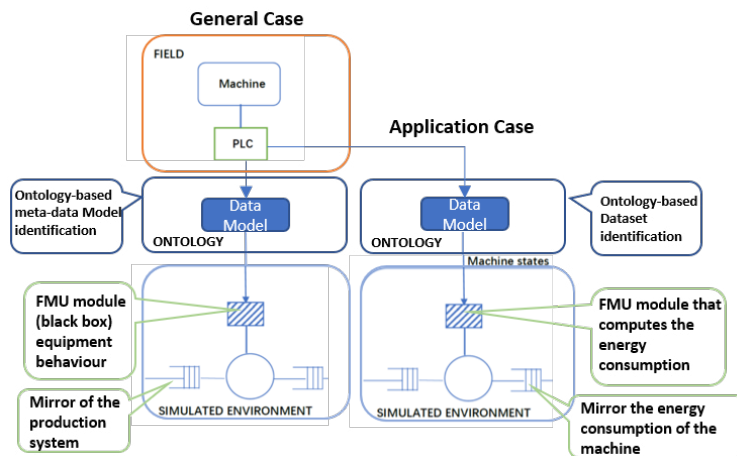


Figure 1- Relationship between field, ontology and simulated environment

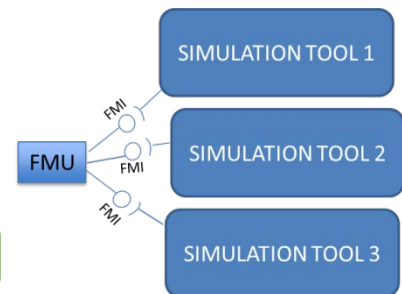


Figure 2 - FMU module reuse in different simulation environments through FMI standard

3. Ontology

Among the key enablers to bridge between the digital and real worlds, ontologies play a relevant role, together with the Service Oriented Architecture (SOA) of the CPS-based system. In particular, ontologies are needed to structure and store information to be retrieved by automated systems [12]. In industrial applications, different modules of the manufacturing equipment and the relationships between them are represented in a machine-readable way through semantic objects [13]. At the same time, the definition of the relative positions and movements, roles and relationships specifies how objects can interact and gives rules and constraints according to which machines can perform automatic reasoning and decision making [14]. This means that single production CPS are not only self-aware, but also aware of the system thanks to the system's semantic representation, and are therefore able to adapt their behaviour according to other components [15]. The hierarchical structure, or the links between objects, might be changed in a flexible way, allowing a continuous update of the knowledge base to reflect the real system.

The present research work is based on a semantic meta data model, that supports the representation of both static and dynamic information of different aspects of product, process, production system for the simulation of the production system during design, planning, implementation and operations. The semantic data model was developed in AML (Automation Markup Language), which is an XML-based data format, available as open standard (IEC 62714), within the MAYA EU-project (www.maya-euproject.com). The ontology consists of various sub-models, representing prototypes, resources, projects, product routings and security aspects. The standard ISO 14649-10 *Data for CNCs* (Computer Numerical Control) has been chosen as a conceptual reference for the development of the semantic data model, in order to grant the interoperability between simulation and automated systems as it specifies the process data, which is generally needed for NC programming in any of the possible machining technologies. In practical terms, a number of entities of the standard were used as objects in the ontology model development, in particular regarding workpiece features, operations and sequencing.

The purpose is to make sure that the Digital Twin of the production system is continuously updated according to information coming from the real plant, in this way mirroring the real world into the digital one, and that decision-making and optimization processes can be made locally and digitally. The used semantic meta data model is thus the underlying support schema according to which data are collected, elaborated and employed. Consequently, the Digital Twin design and plant configuration are based on a shared understanding of objects, functions and relationships, as defined in the ontology.

The semantic data model is stored on a platform that communicates with the physical system through: i) a communication middleware that supports real-time exchange of information; and ii) an architectural framework that allows for information exchange among different-purpose multi-vendor simulation tools. Supporting a CPS-based production system, the semantic model has to represent a big amount of information to define different aspects of

the CPS equipment to run the simulations. In this sense, it acts as an integration enabler that reduces the effort of simulation tools to retrieve production data, by adding meta-data to the specific data available from the field.

4. Laboratory application

The proposed FMU modules approach, supported by a semantic data model, was tested in a laboratory environment: the Industry 4.0 Laboratory (I40LAB) at Politecnico di Milano. The production line installed in the laboratory showed in Fig. 3 has been designed to assemble a Mobile phone.

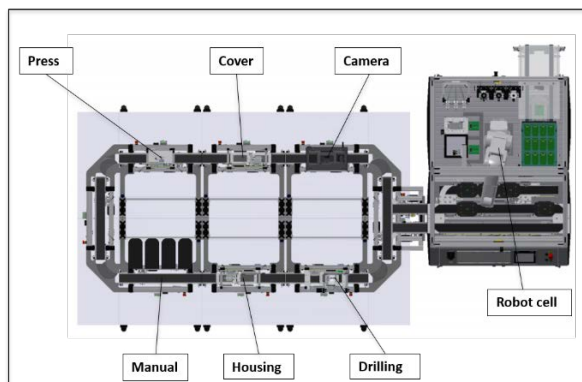


Figure 3 - Production line installed in the I40LAB

The production line in Fig. 3 is composed of six stations: Manual Load/Unload Station, Housing, Drilling Station, Robot cell, Camera check Station, Back Cover Station, Press Station. In this system, a certain number of carriers moves around the line and are stopped in each module to read/write the information about them using the RFID (Radio frequency Identification) Technology. Each machine in the I40LAB is equipped with a PLC server, that uses the Open Platform Communications (OPC) Unified Architecture (UA), a machine to machine (M2M) communication. To enable the communication with non-Windows computer applications, the new OPC UA specification introduced in 2009, published as an IEC 625414 standard, was used [16].

The laboratory gives the opportunity to realize a first implementation of a Digital Twin environment. The MATLAB Simulink environment was chosen to construct the FMU modules, and the OPC UA toolbox of MATLAB is used to establish the server/client connection and extract data from the system. The starting point is a single station of the production line in laboratory, since the embedded sensors are the same in each station. The next stations simulation will be obtained by replicating the first one. As said before, the energy consumption computation is based on the sum of the energy consumption in each machine state. The identified states of the machines in the laboratory are: Idle, Working, Energy Saving and Fault mode.

The first step is to model in the simulation environment the single states and their energy consumption curves in the FMU module. Then, through the OPC UA standard, the client/server connection can be established with the PLCs (Programmable Logic Controllers) of the line. The established connection allows to construct the ontology-based dataset used for the laboratory application (ref. to Fig. 1), that is fundamental to restrict the variety of the data present in the laboratory (i.e. at PLC level) into the relevant set of data used to replicate in a virtual environment the machine state. Once identified the dataset, the signals from the field that are part of it can be read directly in the simulated environment and their combination reconstructs the actual state of the machine. Both the reconstructed machine states and the signals read directly from the PLCs can be used as an input of the FMU modules. In this way it is possible to replicate in real time both the states of the station and its energy behaviour in the virtual copy of the physical system. The connection with the PLCs of the line and the reconstruction of the machine state for each station are the basis to build a function that computes the energy consumption of the station. The FMU block of the application case built in the simulation environment is shown in Fig. 4. The inputs of the module in Fig. 4 are the reconstructed states of the station, the sample frequency of the simulation and the instantaneous power at each sample time. The outputs of the function are the energy consumption for each of the machine states (Energy Idle, Energy Work, Energy Saving, Energy Failure) and the total amount of energy consumption, as the sum of the energy consumed in each state. In fact, the function stores the amount of time in which the station was in a

determinate state and, according to the equation (1), computes the energy consumption for each state and the total one will be the sum of all E_m . (In the equation E_m is the consumed energy in the machine state m [J], P is the instantaneous power [kW], P_{avg} is the average power of the machine state m and T_m is the initial time instant at which the machine state starts [s]). This function can be then extracted from the simulated environment through the FMI standard and be used as a black box function that computes the energy consumption in different simulation environments.

$$E_m = \int_{T_{m-1}}^{T_m} P dT = P_{avg} * (T_m - T_{m-1}) \quad (1)$$

The procedure was initially validated for a single machine inside the laboratory. Following several MES (Manufacturing Execution Systems) production orders launches, multiple assembly production cycles were performed, creating the conditions to have also the presence of faults, according to the reliability behaviour of the system. In this way, it was possible to verify the energy consumption computation also in faulty state. Then, the same procedure was repeated for the other stations of the production line in Fig. 3. The results in Fig.5 show a validation scenario, in which a fault occurred during the drilling operation and during the positioning of the back cover on the product. Moreover, the developed FMUs are connected to the semantic data model to store data of the computed energy consumption and to the main simulation model. These data represent part of the digital description of the real system: in fact, they are computed in the simulation environment and are based on updated field data about machines' states and the actual time intervals of these states.

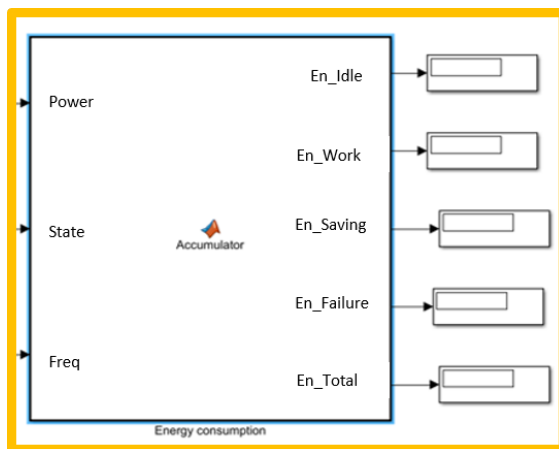


Figure 4 - Input and output signals of the FMU module

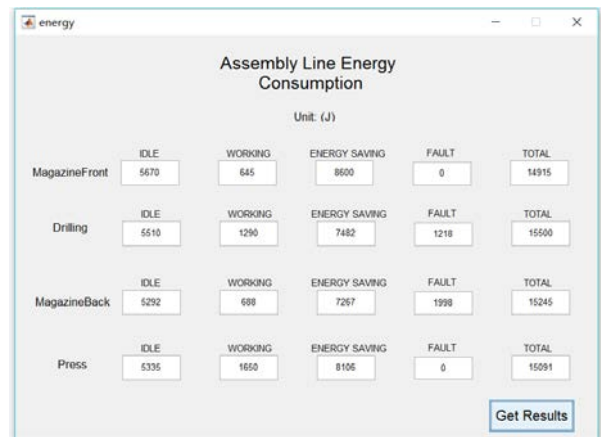


Figure 5 - Laboratory energy consumption results

5. Conclusions

This work focused on the use of Digital Twin simulation for production systems. The Digital Twin paradigm leverages on an appropriate communication infrastructure to guarantee a consistent digital representation of the factory floor [17]. In this infrastructure, this work developed simulation modules, i.e. the FMUs, to replicate specific behaviours of the manufacturing equipment (such as the energy consumption, as presented in the example of this paper). The Digital Twin can thus be used to understand, in real-time, different aspects of what is happening on the shop-floor, and to update the real system with improvements that may be obtained in the digital model. Being environment-independent modules thanks to the standard interfaces, a single FMU module can be activated by different simulation tools, in this way supporting simulation throughout the whole production system lifecycle.

In order to enable digital continuity along both the product and the factory lifecycles, the Digital Twin simulation also relies on an ontology that provides the semantic representation of the necessary information to integrate, and allows interoperability among different simulation software tools. The calculation of realistic performances/performance indicators, also inside the FMU module, is supported by the data collection and

elaboration, even in real-time. This is backed by a solid ICT infrastructure: a cloud computing platform, that stores the ontology and elaborates data; a communication middleware to communicate with the physical field; distributed intelligent CPS components; an architectural framework that guarantees the integration among heterogeneous simulation tools.

The current paper provides a contribution in this direction basing on the experimental results obtained at the “Industry 4.0” Laboratory in Politecnico di Milano. More specifically, the current field of application of the results of this work is the manufacturing domain, where plant design and virtual commissioning activities are performed with multi-domain simulation and forecasting tools, thanks to the support of a continuously updated Digital Twin.

In the future, the whole ICT infrastructure will be tested on the real systems and tools at industrial demonstrators. The use of a Digital Twin / Digital Twin simulation can be enhanced in new applications: real-time decision making based on the digital representation of the system may be done for aspects like production planning, system configuration, maintenance planning, failure prevention, and the impact it will have on human operators.

Acknowledgements

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 678556, correspondent to the project shortly entitled “*MAYA*”, “*MultidisciplinArY integrated simulation and forecasting tools, empowered by digital continuity and continuous real world synchronization, towards reduced time to production and optimization*”.

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