Energy-aware resources in Digital Twin: the case of injection molding machines

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Abstract. Many initiatives aim at describing the objectives and functionalities of the so-called digital twin of manufacturing systems. Considering the assets, the twin is meant to be able to both exhibit the actual and current states of the resources, and provide some estimates about the future behavior of these resources. To target the sustainability pillar of future industrial systems, the energy monitoring and management are critical issues. Consequently, the integration of multi-physics models helping to model the resources inside the twin is a major issue to deal with. This article intends to introduce a framework integrating the models inside the twin of the ARTI architecture, propose a methodology to implement the twin on a resource and illustrate these on a case study on injection molding machines.

Keywords: Digital Twin, ARTI, Multi-physics simulation, Discrete-event simulation, Energy management, Energy monitoring, Intelligent being

1 Introduction

Currently, the management of production in industry is based on performance indicators and only productivist objectives. The digitization of companies, the mainstay of the Industry 4.0 paradigm [1], should make it possible to organize production according to indicators on the energy performance of equipment [2].

The notion of digital twin (DT) is currently being introduced in the control architectures controlling the production activities. It becomes a key element between the decision making and the assets, able to trigger, monitor and forecast the behavior of the physical twin. Two main classes of DT can be exhibited:

- Digital Twin of products, digitalizing, structuring and monitoring the data related to a product all along its lifecycle. The first definitions and applications of DT were developed by NASA towards the realization of aircrafts DT, for diagnosis and prognostic. Sensors data and near-real-time information fed different simulators with the needed inputs in order to correctly mirror the behavior of the aircrafts [3, 4];

- Digital Twin of organizations, mirroring and forecasting the behavior of systems during their utilization. Domains like health care, logistics or manufacturing are typically addressed by this class. The purposes are multiple, from virtual reality to conditional maintenance, from intelligent control to knowledge management.

The remainder of this article focuses exclusively on the DT of manufacturing systems. Therefore, the expressions “Digital Twin” and “DT” will be used to refer to Digital Twins of organizations, namely manufacturing systems.

For inclusion in the DT, assets (or resources) behavior models must be developed in order to predict the evolution of performance indicators of all types and ultimately decision-making at the production control level. In a goal of energy performance, the models to develop are then of two kinds. First of all, multi-physical models of each process allow, thanks to the level of detail taken into account, to evaluate the behavior of each equipment under given conditions. These conditions are strongly impacted over time by the production activities, for example through a change of series on the machine or the evolution of the surrounding conditions. As a result, behavioral models are also needed to simulate these logistics activities. They thus make it possible to define the evolution of the conditions related to the choices of organization of the production to be provided as input data to the multi-physical models of each asset, which in return feed the behavioral model into estimated consumption data. .

The main objective targeted in this article is to introduce a generic framework of an energy-aware digital twin of an asset. This framework enables the coupling between multi-physical and behavioral models for both real-time virtualization of the asset and look-ahead behavior forecasts for the decision making.

Second section introduces in details this problem and identifies the hypotheses made in this study. Then the framework is presented and commented. Some implementation issues are also discussed, before the presentation of the application of the framework on a case study based on injection molding machines.

2 Problem statement

Digital Twin in manufacturing is a key element for the development of future industrial systems. It is meant to become the main middleware between the physical twin and any other applications of the IT infrastructure, offering a global view of the actual state and behavior of the systems. This would constitute a major breakthrough for many applications, from control to predictive maintenance, virtual reality or online simulation. Using this concept induces then the creation of an in-depth interoperability between the elements of the architecture. In the field of intelligent manufacturing, an innovative reference architecture was recently introduced and clearly exhibit the existence of DT in the architecture. This architecture is denoted as ARTI (Activity Resource Type Instance)[5] and represented as a cube (see Fig. 1). In comparison to other CPS oriented frameworks, such as 5C [6] or C2PS [7], this reference architecture is best suited to manufacturing systems (without being exclusive) and integrates natively the concept of DT.

The DT in itself is located in the blue layer of ARTI. The blue cubes are directly connected to their physical counterpart in an embodied way, i.e. in a one-to-one relation but not necessarily using an embedded implementation.

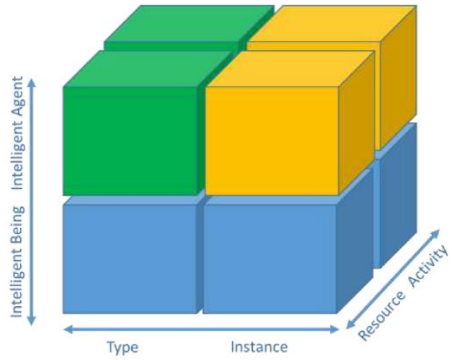

Fig. 1. ARTI reference architecture [5]

The definition of an energy-aware DT is based on the definition of some energy-aware blue cubes in the whole Intelligent Beings layer. Especially, the Resources are the first cubes to define, as they are embodied with the production and consumption points of the physical twins. This energy-awareness relies on the evaluation of the energetic performance of the resources. This performance is related both to the physical process running and to the parameters related to the environment of the resource. As a matter of fact, two types of models need to be considered and coupled: (i) a multi-physical model, able to describe the physics of the process and provide some energy consumption estimates based on the parameters of the process, and (ii) a behavioral model able to describe the logistic activity of the resource and its connection to the environment.
The inner composition of each DT cube is furthermore relatively complex because of the following issues:

1. The DT is intended to both monitor and forecast the behavior of the physical twin. These two functionalities have different dynamics and horizon;
2. The behavioral model needs to integrate the actual data sensed from the physical twin and the data of the control system in order to synchronize the activity of the DT and the physical twin (case of human operations for example);
3. Several multi-physical models can be used all along the operation of the asset. Indeed, the behavior of the physics can be completely different from one product handled by the asset to another for example. The models need to be switched dynamically in the DT;
4. Each multi-physical model is based on parameters that are related to the asset and its environment. Considering the variability of the environment, the values of those parameters might evolve during the life of the asset. A mechanism needs therefore to evaluate and adjust the value of the parameters in real-time.

The objective of the proposition described in the next section is to provide a framework able to cope with those issues.

3 Framework proposition

The framework is presented in Fig. 2. The top yellow layer corresponds to the intelligent agent cubes of ARTI. The red bottom layer corresponds to the connection with the physical pieces of equipment, for example robots, CNC, AGV or portable connection devices for human operators. The framework is intended to define the inner composition of the Resource instances blue cubes.

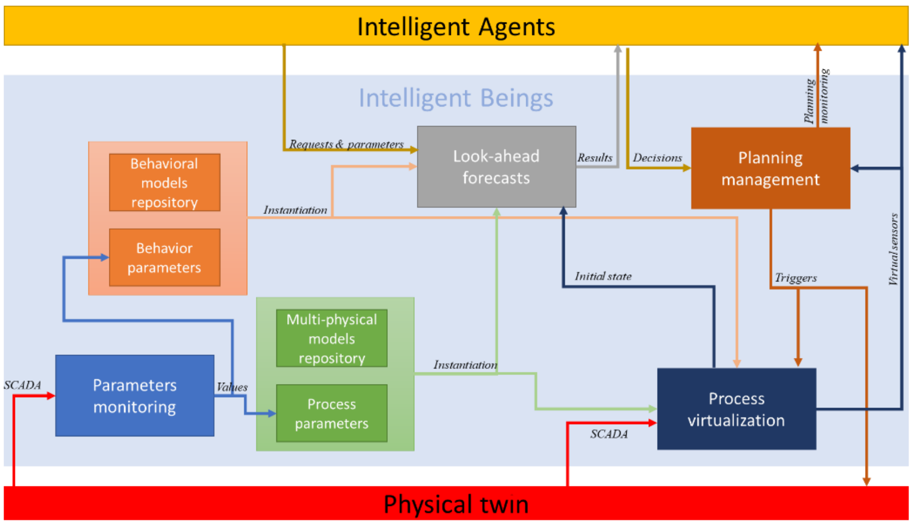

Fig. 2. Energy-aware resource framework for Digital Twin

There are 6 functions to be described in the framework. Next subsections describe each function.

3.1 Behavior models repository

First, a repository of behavioral models is defined. It contains all the alternative models that need to be defined in order to take into account the various possible behaviors of the resource. For example, some machines can sometimes operate in full automation mode and sometimes with a human intervention during the cycle. To cope with these different operative modes, several models can be defined and called whenever necessary. In addition, some parameters need to be defined and evaluated offline and eventually reevaluated online. Those parameters are stored in the set of behavior parameters. For example, the operating time of the operator can be evaluated prior to the execution of the resource, and then reevaluated online when monitoring the actual performance of the operators.

3.2 Multi-physical models repository

A second repository needs also to be defined, containing the multi-physical models to be considered. Same as before, a set of parameters, mainly concerning the physical process, needs to be defined and reevaluated online. As an example, different models can be defined when changing the tools and the product on injection molding machines. The sets of parameters for every configurations of the machine can be evaluated offline, prior to the production. These sets can be used to initialize the virtualization and the process tuning function. If the parameters are modified during the production, the parameters monitoring function will help to tune them.

3.3 Parameters monitoring

As mentioned before, a function of parameters tuning and monitoring needs to be defined. This element is connected to the physical twin and gather data of various origins: discrete I/O on the PLCs, energy consumption measurement or physical sensors such as temperature, pressure or moisture. This also concerns the inputs of the system. As they are subject to potential inaccuracies and/or high variability, the forecasting functionality could be highly impacted. Therefore, this function is meant to analyze the evolution of these data and provide an estimate behavior forecast function in order to adjust the parameters in the forecasting phase.

3.4 Process virtualization

The multi-physical models and the behavioral models are used online for a process virtualization function. This function aims at defining a global view of the whole process, able to provide virtual sensors to applications requiring it. It instantiates one model of each repository for each configuration of the physical resource. This function is connected to the physical twin in order to correct the deviation induced by the errors and simplifications made in the models. Virtual or augmented reality applications dedicated to the representation of the process are meant to connect to this function to get updated in real time.

3.5 Look-ahead forecasts

In the same way, the models are also instantiated to predict the evolution of the process in look-ahead mode. The virtualization of the process is used to provide to the look-ahead function all the data needed for the initialization of the prevision. It has to be noted here that ARTI definition implies a recursive view and an aggregation ability of the resources. This means that the look-ahead function requires to be able to integrate simulations of single process as well as simulations of several different processes connected by logistic activities. This function is classically implemented using discrete-event simulation, especially when the logistic activities have an impact on the evolution of the process. In that case, the models repositories classically contain simplified versions of the models of each configuration in order to avoid slowing down the simulations.

3.6 Planning management

Finally, the connection between the intelligent agents and the physical twin is implemented with the function of planning management. This function is updated from the decisions made by the intelligent agents and triggers the execution of the planning on the physical twin. The information on the progress of the execution (acknowledgements of beginning and end of tasks for example) is retrieved through the virtualization of the process. Through these data, the planning management function enables a monitoring of the planning in order to keep the intelligent agents up-to-date about the execution on the physical twin. To close the loop, the virtualization also takes into account the planning in its normal working.

4 Case study: injection molding machine

The objective of this section is to illustrate, on a single machine, a simplified implementation of the framework. A methodology to implement the initialization and coupling of simulation models is proposed and applied in this work to a thermoplastic injection process. The methodology is based on six major steps

(i) Development of a multi-physical model of the injection process enabling to evaluate the profile of energy consumption in time;
(ii) Consumption measurements, on the actual machine in a given condition;
(iii) Tuning of the multi-physical model considering the measured parameters;
(iv) Development of a discrete-event simulation model of the machine;
(v) Generation of the sets of parameters for every configurations of the machine;
(vi) Tuning of the parameters in real time through the analysis of the data acquired in real-time with the measurements.

First, this section introduces the machine, then the models and their coupling. A complete equipment dedicated to the simultaneous measurement of energy consumption and events was developed and is presented. Finally, some ongoing works are presented.

4.1 Injection molding machine

The machine under study is sketched in **Fig. 3**. This kind of machine is for elastomers. The same machine for elastomers was already studied in [8], and an example of energy consumption profile of the whole machine was presented (**Fig. 4**). Analyzing this energy profile, no obvious pattern of energy consumption corresponding to the cycles of the machine can be identified. Therefore, it is necessary to split the machine into elementary consuming pieces of equipment in order to identify the corresponding models. **Fig. 3** exhibits several of those pieces of equipment for thermoplastics: barrel (containing the main heaters), motor, hydraulics, ejection and mold motion, etc.

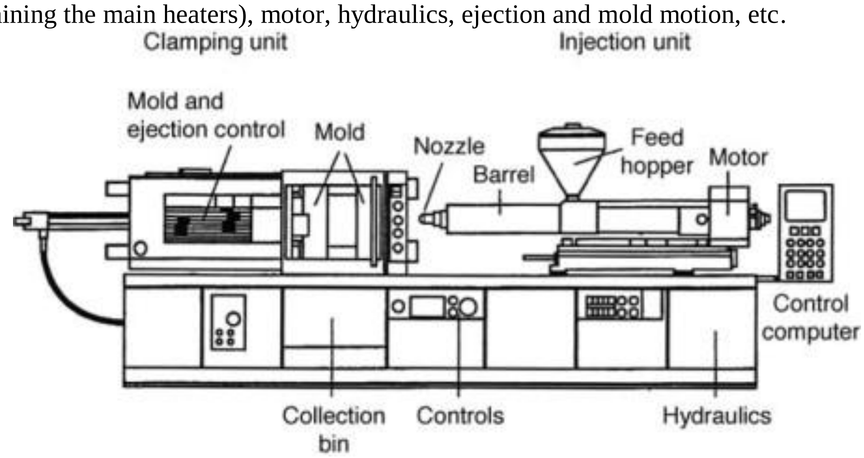

Fig. 3. Injection molding machine schematic [9]

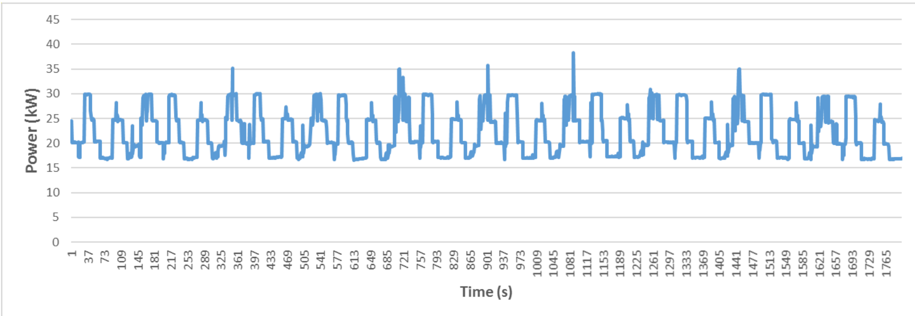

Fig. 4. Elastomer injection molding machine energy consumption

4.2 Models and coupling

First, behavioral models are developed with discrete-event simulation, using Rockwell Arena. The use of discrete-event simulation is classical in this field, and many studies already dealt with this problem [10–12]. A custom library enabling to integrate energy consumption together with logistic activities was used [13]. The main idea of this library is to define, for each resource of the system, a profile of energy consumption related to each activity the resource can perform.

This profile is based on the definition of sequences of energy blocks [14] representing a model of the actual consumption. The coupling between the behavioral and multi-physical models is thus performed through the energy blocks parameters definition. In practice, the parameters represent the length and power of each energy blocks. Both can be deterministic or represented with a statistic distribution. When a change in the process conditions occurs, the parameters might evolve. Some of them can be tuned through the SCADA thanks to the parameters monitoring function. However, the evolution is in some cases so important that a whole new set of parameters needs to be evaluated [15].

For example, when a new reference of product is to be produced on the machine, the mold is changed and consequently the energy consumption behavior of the machine. At this level, the multi-physical model of the process close to the mold is able to evaluate the new energy blocks that correspond to this new reference in this part of the machine. For the injection of elastomer, a complex model needs to be defined. Indeed, the mold is hot, and the modelling needs to take into account the curing of the polymer inside the mold. The thermal model is mainly based on the energy balance on the platen heaters, the mold and the elastomer which are each described by the equation of heat transfer (1):

$$(\rho . Cp)\frac{dT}{dt} = \nabla.(\lambda.\nabla T) + Q \quad (1)$$

with the term Q corresponding to heating source (the power provided by the heating devices in the platen heaters), ρ the density, Cp the heat capacity, T the temperature and λ the thermal conductivity. A standalone software was developed to provide a simple user interface for creating the various geometries of the molds. A screen capture of the software is provided in **Fig. 5**. It shows on the left side the graphic user interface for the design of the geometry of the product and on the right side the evolution of temperature in the mold (and in the product) according to the energy provided. This evolution is calculated thanks to the equation given above and is represented through a colored temperature field for clarity purposes.

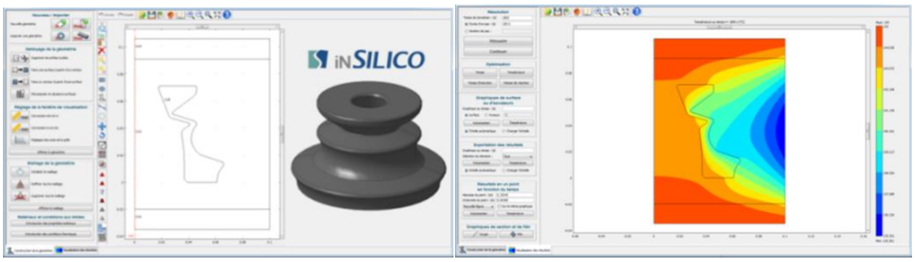

Fig. 5. Geometry design (left) and temperature fields obtained (right) with the multi-physical model

In the case of injection of thermoplastics, the mold is cold and the main heating consumption corresponds to the plastification of the polymer inside the screw. In the previous case, this was negligible and not modeled. Here, based on experimental consumption, a simplified model is currently under development to predict the consumption of those elements of the machine, only based on some process parameters and the thermophysics of the mold as inlets.

4.3 Measurement device and preliminary measures

To ease the parameter monitoring and analysis, a specific measurement device was developed. A schematic representation of the device is presented in **Fig. 6**. Thanks to measurement tores, the current is measured on each phase of the consumer elements of the machine. This choice of a non-intrusive measurement technique was driven by the opportunity to implement this more easily on legacy machines, already in production. Intrusive measurements imply drawbacks on security and warranties that could not be accepted.

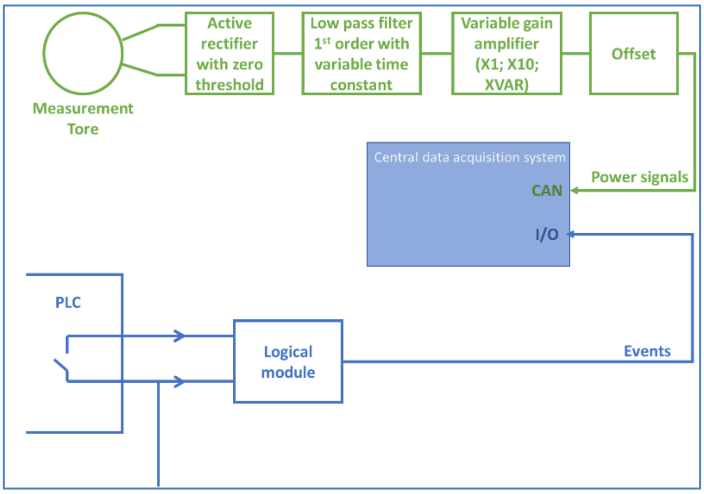

Fig. 6. Schematic representation of the measurement device

Several components were then added to filter the signals and obtain some clear representations of energy consumption evolution. **Fig. 7** exhibits an example of the obtained signals. The measurement noise was totally suppressed and the shape of the cycles is well identified.

In parallel, an intrusive module is added between the Inputs/Outputs of the PLC and the sensors/actuators. It enables to identify the relationship between the activity of the logic controller and the evolution of energy. This identification is important to put in perspective the evolution of consumption with the working of the machine both in the pre-analysis, in order to identify the cycles, and in the online phase, to ease the monitoring.

All these elements are connected to a single data acquisition system. This system is connected on ethernet or Wifi to an analyzer developed in Java, which is the one used to generate **Fig. 7**. It contains 8 slots of extension cards, accepting either digital or analogic I/O. The data of each slot are gathered through Modbus TCP.

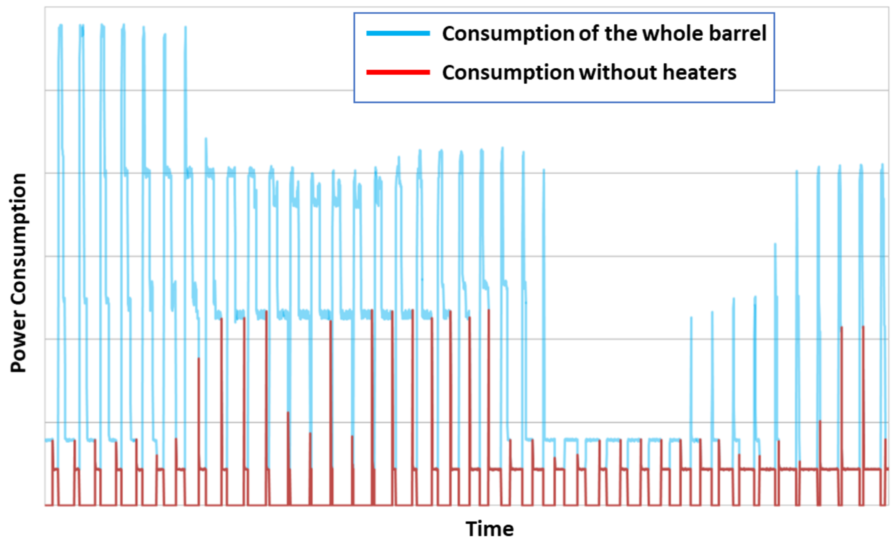

Fig. 7. Energy consumption profile example on 40 injected products

5 Related works

Many works deal with estimation of energy consumption and monitoring aside the DT paradigm. These estimations are generally made through metrological data acquisition using measurements devices, even if it can also be in some cases acquired through empirical models, mathematical model [16] or even technical documentation.
Simulation techniques are also used to evaluate the consumption. For example, [17] proposed a flexible and modular simulation framework in which they model the whole production system with all the interdependencies and dynamics of involved technical equipment. In addition to the total amount of energy consumed, the authors were interested in the load profile. This result is an important element to be considered when analysing energy costs, as energy is the only product which price increases when bought in big quantity. This is partly due to the energy supply contract (e.g. pick surcharge and time-sensitive prices of electricity). Swedish Iron foundry used simulation in this way in order to cope with the rapidly increasing energy prices in Sweden [18] and plan the production in a more efficient way.
The impact of product variety on energy consumption is another subject of study [19]. In order to optimize the energy consumption in multi variant production, [20] developed a simulation-based model to assess the energy consumption of a production station based on its operating conditions , considering electricity, gas and air.
On a global point of view, these studies are performing offline evaluations or online monitoring. However, the notion of DT implies both an online monitoring of the energy behavior of the system and an ability of prediction of this energy behavior. Therefore,

the proposed framework integrates the possibility of data acquisition, model-based reconstruction and model-based forecasts.

6 Conclusion

This paper introduces a framework for designing some energy-aware digital twin resources. This framework aims at providing the basic functionalities every resources of a digital twin should provide to be able to handle energy consumption information. In most of the applications, these functionalities are meant to address the major issues enabling to develop more complex energy oriented-functionalities. For example, it shall guide the development of the technological devices needed. This type of data is quite complex to handle, as it necessitates in most of the case either a large experimental study or a multi-physical modelling effort. This last case being the most generic one, this is the one that is addressed in the framework. The framework highlights the necessity to couple multiple models (behavior and process) at any time, and to be able to switch the models all along the lifecycle of the machines. Furthermore, it emphasizes the need for real-time parameters monitoring and evaluation for ensuring the quality of the models. All these elements are meant to be used for both real-time virtualization and look-ahead forecasts.

The presented case study is still under development. At the time being, the elementary bricks for the models development and coupling are in progress. The measurement devices are developed and validated. The next steps deal with the tuning of the parameters of the models to fit the initial measurements and the generation of the sets of parameters for all the considered configurations of the machine. The objective is to find a model of the multi-physical models parameters, enabling to estimate the consumption of unknown configurations with only predefined geometric parameters, such as mass of the mold, materials, setpoint temperature, etc.

Last step will deal with the real-time implementation of these models, and the demonstration of energy-aware look-ahead functionalities for a Digital Twin resource.

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