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# Integrating Lean Data and Digital Sobriety in Digital Twins through Dynamic Accuracy Management

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**Abstract.** In this paper we focus on the design, development, and responsible use of the flagship technology of Industry 4.0, namely the digital twin (DT). After a brief review of the literature on industrial applications of the digital twin in a smart manufacturing environment, we look at usual misconceptions about this emerging concept, which often hinder the democratization of the digital twin or pushes to put too many resources at stake compared to the needs. Therefore, we propose to integrate lean data and digital sobriety at the design phase of the DT through a generic architecture including dynamic accuracy management. We present here the principle of our approach, an application example, as well as some adjustment capabilities.

**Keywords:** Digital Twin, Digital Sobriety, Dynamic Accuracy Management, Smart Manufacturing Systems.

## 1 Introduction

The advent of the fourth industrial revolution has led to the emergence of new technologies, each one as disruptive and innovative as the next, like the digital twin (DT) often considered a pillar of the smart factory. The notion of DT was originally introduced in 2003 at Michael Grieves' executive training on product lifecycle management (PLM) [1]. Even though the literature has more than 50 distinct definitions (Julien & Martin, 2021), the one provided by the new ISO standard 23247 [2] appears to be the most thorough and exact for manufacturing applications "a fit for purpose digital representation of an observable manufacturing element with a means to enable convergence between the element and its digital representation at an appropriate rate of synchronization". The digital twin is considered in a sense to be the spearhead of Industry 4.0, as it is transversal in terms of the tools, technologies and skills implemented (AI, Internet of Things, Data, as well as electronic engineers, automation engineers, data scientists, psycho-ergonomists, etc.) but also in terms of the issues dealt with (maintenance, control, product quality management, supply chain management, prognostic and fault detection, etc.). In this paper, we focus on this technology and the methodologies for its

development in line with the objectives of sustainable growth and human-centered technological development of society. Through this work, we look at the contribution that dynamic accuracy management of digital twins can bring to the sober development and use of this technology, as well as the means and methods that can be used to achieve this.

## **2 The Digital Twin, a polymorphic technology**

The digital twin is clearly distinguished by its capacity to address a broad range of issues and in a variety of application domains. Indeed, in the various fields that aim to upgrade technologically by keeping pace with the global technological revolution, the digital twin receives an unparalleled interest. In what follows we present the different applications of the digital twin in these areas to address various concerns.

1. Healthcare: Healthcare 4.0, which refers to the capability of customizing healthcare in real time for patients, professionals, and caregivers, is perfectly suited to the digital twin. DT health applications may be found in a variety of settings, including (i) digital patients, (ii) the pharmaceutical industry, (iii) hospitals, and (iv) wearable devices [3].
2. Smart cities: Due to the extensive use of information and communications technology (ICT) to monitor municipal operations, cities have become smarter during the past several years. These operations (including traffic and transportation, energy production, utility provisioning, water supply, and trash management) generate a large amount of data that can be used to build data-based models and use data-driven decision support tools as AI solutions to regulate and optimize city activities [4]. A number of governmental initiatives and academic research initiatives are working to create digital twins of cities with various levels of complexity (Dublin's Docklands area [4], the "Virtual Singapore" [5], the Zurich city digital twin [6]).
3. Transportation and logistics: A number of logistics-related issues, including those involving internal logistics (like warehousing and material handling) [7] and external logistics (like air traffic management, railway management systems, elevators and vertical transportation systems, and even pipeline DTs) [8] [9] [10], are being studied for their potential application of the digital twin.
4. Energy: When it comes to energy production, transit, storage, and even consumption, digital twins can offer a disruptive edge at several levels (control, optimization, and conception). A number of useful applications and use cases can also be found here, including energy-efficient manufacturing systems [11], energy consumption optimization [12], the implementation of digital twins in energy cyber-physical systems [13], DT based development of smart electrical installations [14].
5. Smart manufacturing: Even if the digital twin has been exported to different domains, the fact remains that its adopted home is in industry, which is why the most notable advances for this technology can be found there. In the following, we briefly present the essence of digital twin applications in smart manufacturing.

The applications of the digital twin in industry are very varied, however they can be classified into four DT lifespan phases: design, manufacturing, service, and retirement as proposed by Liu et al. [15].

- Regarding the first phase, they identified iterative optimization; data integrity; and virtual evaluation and verification as the main applications: automated flow-shop production system customization [16], optimal-selection in product design [17], Virtual validation in electronics [18].
- With regard to the second phase, they have instead identified seven main usages: real-time monitoring; production control; workpiece performance prediction; human-robot collaboration & interaction; process evaluation & optimization; asset management; and production planning. These can be declined according to different applications: autonomous manufacturing [19], DT implementation in Manufacturing Execution Systems (MES) [20], start-up phases acceleration through DT based product modifications management [21].
- Concerning the third phase, five applications for Digital Twins were identified: predictive maintenance, fault detection and diagnosis, state monitoring, performance prediction, and virtual test. The work in the literature supporting this deals with concerns as time-based maintenance (TBM) policies optimization [22], Remaining Useful Life (RUL) assessment [23].
- Finally, Liu et al. considered that the fourth and final phase was generally not considered. Knowledge of a system's or product's behavior is frequently lost when it is decommissioned. When a system or product is developed upon, it usually suffers from the same flaws that might have been avoided with the use of past knowledge. In the retire phase, the DT may be inexpensively kept in virtual space since it possesses the physical twin's whole lifespan information [15]. We can however mention the work of [24] who identified disassembly, reuse, disposal, retrospect, and upgrade as five major applications in the retirement phase.

This ability of a digital twin to fit into very diverse application domains and to deal with a variety of problems, requires it to have a very important capacity for adaptation. Hence the need to set up models and standards, or even generic development and deployment methodologies, which without taking away the adaptive characteristic of the twin, allow it to be correctly sized and dimensioned to the needs of the different situations it may face. It is for this reason that we are interested, in this paper, in the appropriate dimensioning of the digital twin, either at the level of the technologies brought into play in the DT during the design process or at the level of the operation modes. Here, we will discuss the integration of lean data and digital sobriety in digital twins through dynamic accuracy management

### **3 Usual Misconceptions about the Digital Twin**

Not only is the digital twin an emerging concept, but, because the lack of standards and formalization, it is often accompanied by implicit assumptions that fluctuate depending

on the speaker, making its definition and design very application-specific and technology-dependent.

Among these assumptions, we identify several usual misconceptions that lead the designer to over-size the architecture of the digital twin, making its deployment unnecessarily complex, consuming, and expensive.

- Big Data and Cloud Computing

Generating, processing, manipulating, storing, and transferring large amounts of data requires significant material and financial resources, which can be very distressing for a company and a brake on its development. Turning to data warehousing solutions may seem like a logical next step for any company that wants to upgrade technologically and keep up with the digital revolution, but it can be largely counterproductive considering the technical constraints and financial burdens whether it is done via cloud computing technologies or even via local servers. It is often necessary to opt for digital sobriety and lean data instead of big data by knowing how to properly size the means to be put in place in relation to established needs and available capacity.

- Real time

The digital twin is often associated with real time computing which implies a very high level of synchronization. However, this is usually not necessary and sometimes not even feasible. In some cases, feedbacks at longer intervals may clearly be sufficient, as well as asynchronous updates (when the value or state of some variable changes, or even when some thresholds are exceeded).

- High fidelity and 3D Model

Another misconception about the digital twin is that it must be represented graphically (mainly via a 3D model). This is clearly not necessary, and may even be inadvisable, as it requires a considerable amount of time and computational resources, as well as the use of often very expensive proprietary software. This without bringing any real added value apart from the aesthetic aspect. With the exception of cases where the digital twin must be visualized graphically by a human operator (clearly expressed need, and clearly identified added value) the integration of a 3D model is certainly not recommended, it is quite sufficient to implement models adapted to the needs (Tao et al. [25] have proposed different types of models to be implemented in a digital twin).

- IoT and over instrumentation:

It is also necessary to properly size one's instrumentation needs so as not to over-instrument the installations (except for sensitive installations governed by regulations which require certain redundancy in equipment and measurements), a good needs sizing is necessary, in order to correctly identify the data to be collected, the collection points, the sensitivity of the measurements as well as their precision and reliability (it is not necessary to use a microscope when a magnifying glass can do the job).

Moreover, the excessive use of IoT can only disrupt the objectives of digital sobriety and the costs incurred by the digitization process of any installation. For if there is no

need to implement a distributed architecture of computing resources or a strong horizontal and transversal interconnectivity (or even DT networks [26], there is clearly no need to excessively use IoTs when simple sensors may suffice.

- Artificial Intelligence

One of the disruptive contributions of the digital twin is to be able to offer decision support tools to human agents in order to make the best use of their assets (control, optimization, maintenance, safety and security, etc.). This implies the presence of an "intelligent" element in this technology. However, this does not necessarily imply the presence of complex artificial intelligence algorithms that require a lot of data, resources, and computing time. In some cases, simple statistical models can be sufficiently accurate and reliable to achieve the fixed objectives, again it is all about precise dimensioning.

- Autonomous Digital Twin

An implicit inference from the assumed characteristic of the digital twin cited above (high intelligence) is that the digital twin must have a high degree of autonomy. Here it is not only a question of evaluating the resources to be brought into play in relation to the needs, but also of the allocation of decision-making and cognitive operations between the human agent and the technical agent (the digital twin). The human must necessarily be in the decision loop (closed, open, or mixed [27]), Kamoise et al. [28] presented a work that proposes the use of CWA (Cognitive Work Analysis) for the allocation of decision-making tasks between the human agent and the digital twin in maintenance related applications.

The first step to digital sobriety is to be aware that all these misconceptions may lead to DT oversizing (in design and use). This leads designers to provide the DT with useless functions, wasting more energy and producing more - irrelevant - data, more processes and calculations, supplemental tools, and even external expertise that is not really necessary for the actual requirements and needs. Such significantly, that one could state that the soberest Digital Twin is the one that does not exist! However, we assume that in some cases and provided that the cost of development and operation of the Digital Twin is controlled, it can globally reduce the overall consumption of a system. We therefore propose to size the digital twin as accurately as possible according to its uses, especially by integrating into its architecture a device that can adjust its precision through DAM (Dynamic Accuracy Management).

## 4 Dynamic Accuracy Management

Our research approach is to develop a DT design methodology based on genetic architectures. These architectures are defined through a typology characterizing the used needs via various parameters [29].

The DAM (Dynamic Accuracy Management) is an approach to integrate in the generic DT architecture from the design stage associated with policies suited to the

application and its usages as represented on Figure 1. It is inserted between the Physical Element (PE) and the Virtual Element (VE) that is the set of models.

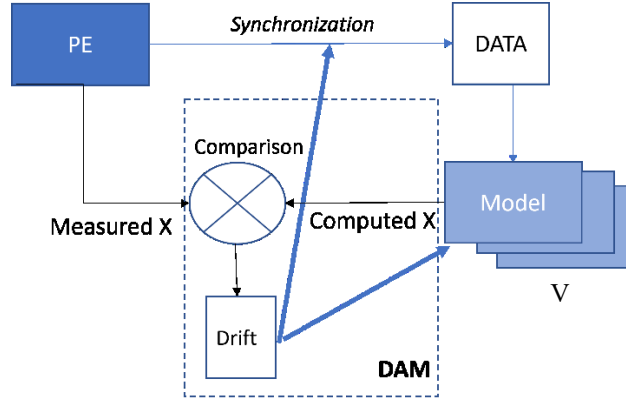


Fig. 1. DAM in the generic architecture

#### 4.1 Principle

We decide to act on two parameters of our generic architecture: synchronization (data acquisition rate) and models, both having a direct impact on the volume of data to be processed by the digital twin.

It is therefore necessary, for the application under consideration, to list the different models by order of precision and data volume as well as the different possible synchronizations (Table 1). To define the accuracy policy, we first determine the various states corresponding to the operational modes characterized by a pair (model, synchronization) as represented on Table 2.

Table 1. List of models and synchronizations

List of Synchronizations			List of Models		
Synchroniza-tion	Frequency	Accu-racy	Models	Parame-ters	Accu-racy
Asynchronous	$F = 0$ (event-based)	Low	Model 1	Few	Low
Synchronous 1	$F_1$	Medium	Model 2	Several	Me-dium
Synchronous 2	$F_2 > F_1$	High	Model 3	Many	High
Synchronous 3	$F_3 > F_2$	Best			

**Table 2.** Operational Modes

States	Model	Synchroniza- tion	Data volume
State 1	Model 1	Asynchronous	Least consuming
State 2	Model 1	Synchronous 1	
State 3	Model 1	Synchronous 2	
State 4	Model 2	Synchronous 2	
State 5	Model 2	Synchronous 3	
State 6	Model 3	Synchronous 3	Most consuming

We then need to precise the transitions between these states i.e., the condition to pass from one operational mode to another. To do this, we must define which physical variable  $X$  to monitor, and to which are compared the variables computed by the digital twin. The transitions are defined as thresholds qualifying the difference between the physical value and the virtual one, these drifts representing the correctness of the digital twin. This threshold can be expressed in absolute or relative value, as the example given on Table 3, considering that  $\Delta X$  is the difference between the measured and computed values.

**Table 3.** Transition Table Example

State	State 1	State 2	State 3	State 4	State 5	State 6
$\Delta X$	$\Delta X < V_1$	$V_1 < \Delta X < V_2$	$V_2 < \Delta X < V_3$	$V_3 < \Delta X < V_4$	$V_4 < \Delta X < V_5$	$V_5 < \Delta X < V_6$
$\Delta X$	$\Delta X < 1\%$	$\Delta X < 2\%$	$\Delta X < 3\%$	$\Delta X < 4\%$	$\Delta X < 5\%$	$\Delta X < 10\%$

Therefore, all the elements characterizing the accuracy policy are defined. The application to a simple case of battery state of charge monitoring will illustrate our approach.

## 4.2 Battery Digital Twin

The application consists in monitoring a lithium battery through collecting its temperature, voltage and current together with its State of Charge (SoC) that is the physical value we want to predict with the Digital Twin. We can rely on two different models:



the Model 1 is a Thevenin model composed of 4 electrical elements; such a simplicity enables Edge computing as indicated in Table 4. The second model is more detailed with 12 electrochemical parameters and then requires Cloud computing.

**Table 4.** Models for Battery Digital Twin

Models		Parameters	Accuracy	Computing
Model 1	Thevenin	4 parameters	Low	Edge
Model 2	Electrochemical	12 parameters	High	Cloud

**Table 5.** Synchronizations for Battery Digital Twin

Synchronization	Frequency	Accuracy
Asynchronous	$F = 0$ (event-based)	Low
Synchronous 1	$F_1 = 1/10s$	Medium
Synchronous 2	$F_2 = 1/1s$	High

We choose to apply 3 levels of synchronization (Table 5) and 3 operational modes (Table 6).

**Table 6.** Operational Modes for Battery Digital Twin

States	Synchronization	Synchronization	Data volume
State 1	Model 1	Asynchronous	Least consuming
State 2	Model 1	$F_1 = 1/10s$	
State 3	Model 2	$F_2 = 1/1s$	Most consuming

Default, we are in the State 1 with the Model 1 in an asynchronous mode, so we are waiting to see a drift between the measured and computed SoC to act, as represented on Figure 2. This state typically corresponds to the monitoring when we are controlling that measured and predicted values are coherent i.e. less than 1%.

In case of slow variation with a difference of less than 5% (Drift 1), we switch to the State 2 by keeping the same Model 1 but commute the acquisition into a synchronous mode and collecting data at the rate of 10s to have more information and adjust the computed SoC; if the drift persists, we can modify the model parameters either manually or through Machine Learning.

In case of strong variation, if  $\Delta X$ , the relative difference between measured and computed SoC is more than 5%, we switch on the Model 2 and raises the synchronization rate to 1s to ensure the most detailed information and work onto the model parameters until the drift decreases under 5%. Such an approach also allows to tune the model along with the aging of the battery and environmental context. Of course, we can implement more elaborated policies with various models and frequencies, but it is important to guarantee that the architecture stay efficient with no useless complexity.

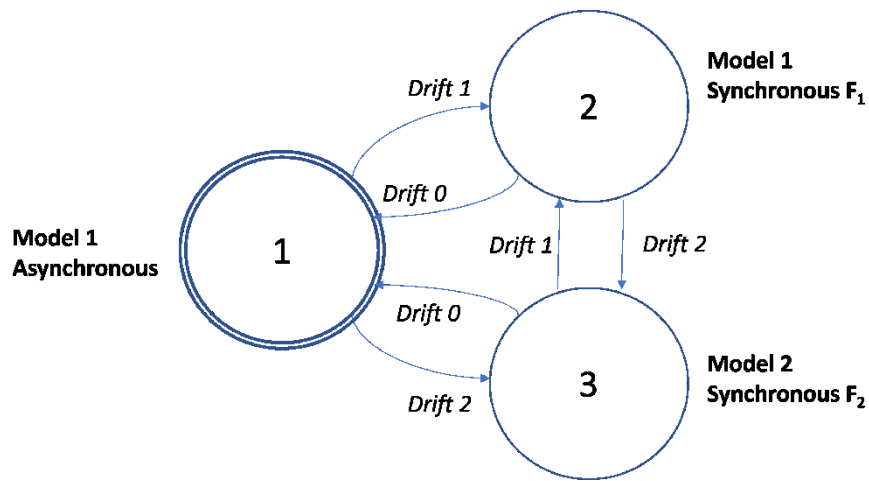


Fig. 2. State Diagram for Battery Digital Twin

Table 7. Transition Table for battery Digital Twin

State	State 1	State 2	State 3
Drift	Drift 0	Drift 1	Drift 2
$\Delta X$	$\Delta X < 1\%$	$1\% < \Delta X < 5\%$	$5\% < \Delta X < 10\%$

### 4.3 Dynamic Accuracy Adjustment

With the dynamic accuracy management, we can act on the data volume both on a temporal way by tuning the synchronization and on a spatial way by choosing the model along with its number of parameters and complexity. All this approach can be done either off-line where the DT user can set the application-specific accuracy required, or on-line to follow hazards and malfunctions, alert the user, and to modify the model along the physical element aging.

When doing health monitoring for maintenance of an equipment, you can first use a simple model with few parameters and a low accuracy; then, when the equipment is aging, you can raise the data number to better anticipate the warning signs of failure.

For example, if you are doing health monitoring for an engine conditional maintenance, you can first monitor the vibrations only (Model 1) as long as the engine does not show signs of aging, and then you can add the temperature (Model 2) to be more efficient in preventing the failure.

We also can define a policy depending on the data dynamics by raising the frequency rate to be more responsive to important variations while the model switching is more convenient to prevent unpredicted events.

Another way to use this approach as in Figure 3, is to first adjust the DT accuracy as close as possible to the physical element with the higher synchronization rate (State 4) and then to reduce it progressively while keeping the drift in the predefined threshold (State 3). If possible, we can also switch on a simpler model (State 2 or 1). Each time the drift is increasing, we can use spatial or temporal adjustment while modifying manually or automatically the model parameters.

Finally, the dynamic accuracy adjustment can be determined by the DT usage. For the same equipment, you can use a simple model (Model 1) for monitoring, a more precise model and synchronization for production optimization and the highest accuracy level for preventive maintenance.

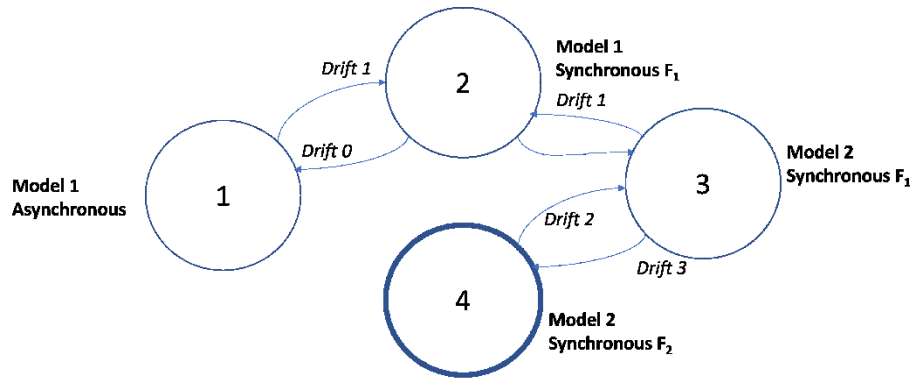


Fig. 3. Dynamic accuracy adjustment

## 5 Conclusion

Through this work, we have proposed some good practices to apply when developing a digital twin. These are based on dynamic accuracy management to ensure digital sobriety. This, while highlighting all the preconceived notions around the digital twin that encourage a certain digital gluttony when it comes to setting up a digital twin. As a complementary future work, we aspire to implement these operating mechanisms in real applications in order to evaluate their relevance and their actual impact under real conditions.

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