# From Static Models to Control-Oriented Digital Twins: Towards Virtual Learning Factories for Manufacturing Innovation

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***Abstract*— The increasing digitalization of manufacturing systems has highlighted the potential for Digital Twins and model-based simulation to support control, decision-making, and innovation in next-generation factories. However, while virtual and remote learning factories are frequently discussed as a training and experimentation paradigm, existing literature and industry feedback reveal that concrete implementations remain scarce. In this work, we investigate the transition from static virtual models to control-oriented Digital Twins within the context of a Smart Mini Factory, as a means to bridge this gap. We propose a model-based integration framework that incrementally integrates kinematic, dynamic, and synchronization aspects of manufacturing resources into a virtual environment, enabling simulation and what-if analysis relevant to decision-support tasks. This framework is aimed at supporting manufacturing innovation by offering a protected simulation environment in which alternative configurations, process designs, and operational strategies can be explored without interrupting real systems. We discuss the role of Digital Twins as both modeling and decision-support tools within Virtual Learning Factory settings, and we identify key challenges in making such environments useful for practitioners. A Smart Mini Factory case illustrates the potential of the approach and highlights directions for future research in control-oriented Digital Twins for manufacturing systems.**

***Index Terms*— Digital Twin, Automation, Robotics, Manufacturing Innovation, Learning Factories**

## I. INTRODUCTION AND BACKGROUND

Manufacturing systems are increasingly characterized by high variability, frequent reconfiguration, and growing pressure to introduce process and organizational innovations while maintaining operational stability. These challenges are particularly pronounced for small and medium-sized enterprises (SMEs), which often operate under strong resource constraints while facing the need to adopt new technologies and manufacturing paradigms. In this context, model-based approaches, simulation, and Digital Twins (DTs) are gaining attention as enabling technologies for analyzing system behavior, supporting decision-making, and reducing the risks associated with experimentation in real production environments [1], [2].

Learning Factories have emerged as an effective paradigm for training, experimentation, and knowledge transfer in manufacturing systems by providing environments that replicate industrial processes in a controlled setting [3]. In particular, Learning Factories play a crucial role for SMEs by enabling hands-on learning, skill development, and experimentation with new manufacturing concepts without disrupting ongoing operations. Through learning-by-doing and experimentation-based approaches, they support both technical learning (e.g., process understanding, system behavior) and organizational learning related to manufacturing innovation management.

However, most existing Learning Factories are primarily physical and are often complemented by static Digital Models (DMs) used for visualization or layout planning [4]. Although such representations are useful in the early stages of design and training, they provide limited support for analyzing dynamic behavior, exploring alternative operational scenarios, or enabling systematic, decision-oriented learning activities. As a result, the potential of Learning Factories to support continuous learning remains only partially exploited.

Recent research has highlighted the potential of DTs to overcome these limitations by coupling virtual models with behavioral and temporal representations of complex systems [5]. Existing DT frameworks mainly focus either on monitoring architectures, cyber-physical synchronization, or process-level optimization. In contrast, the proposed approach emphasizes the progressive evolution of virtual factory models toward decision-oriented DTs within VLF contexts, with a specific focus on learning-through-experimentation and SME-oriented manufacturing innovation scenarios. Nevertheless, fewer works address how DTs can be systematically designed as decision-support and experimentation environments that explicitly support learning processes. Moreover, despite increasing references to Virtual Learning Factories (VLFs) in the literature [6], [7], concrete and reusable methodological approaches for their design remain scarce. Industrial practice further confirms this gap, as virtual factory models are rarely used beyond visualization or isolated simulation tasks, particularly in SME contexts.

In response to these challenges, this paper proposes a model-based integration framework for VLFs that emphasizes decision-oriented experimentation and progressive model evolution. The contribution focuses on structuring the transition from static representations to dynamic and control-oriented DTs that support learning and manufacturing innovation activities in SME-oriented environments. The proposed approach is illustrated through a Learning Factory case study and preliminary simulation-based results are presented to demonstrate its applicability and implementation potential.

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## II. METHODOLOGY

### A. Proposal of a methodological framework

This work adopts a model-based methodology for the design of VLFs aimed at supporting manufacturing innovation through simulation and decision-oriented analysis, defining general principles and procedural guidelines for virtual factory environments that can be used as structured experimentation and analysis tools.

An overview of the methodological framework is provided in Fig. 1. A central assumption of the proposed approach is that VLFs should enable active experimentation, rather than passive visualization. Learning and innovation activities are therefore formalized as iterative experimentation cycles, in which system configurations, process parameters, or resource interactions are systematically modified and evaluated through simulation.

As illustrated on the left side of Fig. 1, each experimentation cycle consists of defining analysis objectives, configuring scenarios, executing simulation experiments, and evaluating system responses in order to support informed decision-making. From a modeling perspective, the methodology follows a purpose-driven abstraction strategy. Instead of prescribing a fixed level of detail, the model fidelity is selected according to the objective of the analysis and the context of the decision. The structural, behavioral and temporal aspects of the manufacturing system are treated as distinct modeling dimensions, allowing the complexity of the model to increase only when required by the intended analysis. This principle supports repeated what-if analysis while keeping models interpretable and computationally efficient.

To ensure that virtual factory models are suitable for decision-oriented analysis, the methodology explicitly considers a set of dimensions of technical specifications, summarized in the right column of Fig. 1. These dimensions include the definition of relevant system state variables (e.g., positions, modes), configurable parameters (e.g., speeds, rates, setup times), and the chosen level of model fidelity in terms of abstraction and granularity. In addition, the methodology accounts for the selection of appropriate simulation engines (e.g., discrete-event or continuous-time solvers) and the availability of interfaces for data exchange and model interaction. By explicitly structuring these elements, the methodology supports transparent and reproducible simulation-based analysis without imposing specific technological solutions.

To conclude, concrete DT realizations are treated as instances of the methodological framework, rather than as integral components. This separation ensures that the proposed approach remains transferable across different manufacturing contexts, while allowing individual case studies to be implemented for illustration and preliminary evaluation.

### B. From static models to control-oriented Digital Twins

Virtual factory models typically originate as static representations of manufacturing systems, capturing layout, resources, and logical process flows. Such models are well suited for spatial reasoning and conceptual understanding, but provide limited insight into system behavior and are insufficient for decision-oriented analysis.

To address these limitations, the proposed approach follows a staged model evolution in which static models are progressively enriched to capture dynamic system behavior. The first step consists of introducing the temporal structure and execution logic, which allow the representation of task sequencing, resource interactions, and dependencies between system elements. This transition allows the model to describe how the manufacturing system evolves over time, rather than simply how it is structured. As model capabilities increase, the virtual factory becomes suitable for simulation-based analysis of alternative operational scenarios. Different configurations, process variants, or resource allocations can be evaluated by observing system responses under varying conditions. At this stage, the model supports systematic what-if analysis, enabling a comparative assessment without interfering with real systems.

The final stage of this evolution leads to control-oriented DTs. In this work, the term control-oriented refers to the capability of the DT to expose interpretable states, parameters, and behavioral responses suitable for monitoring, what-if analysis, and decision-support tasks, rather than to the implementation of closed-loop control algorithms. By exposing these elements in a coherent and structured manner, the DT enables systematic reasoning about system behavior, sensitivity to parameter changes, and the potential impact of alternative operational or organizational configurations.

From a modeling perspective, control-oriented DTs emphasize transparency and causality, allowing users to understand how variations in input, configuration, or execution logic propagate through the system and influence performance-related indicators. This characteristic is highly relevant in manufacturing innovation contexts, where the objective is often to explore, compare, and assess alternative concepts rather than to optimize a single operating point.

Within VLFs, this progressive evolution of the model plays a key role in enabling learning through experimentation. Users can gradually move from conceptual exploration based on static representations to behavior-oriented analysis using control-oriented models. The staged increase supports different learning objectives and levels of expertise, enabling both exploratory and analytical interaction with the system. As a result, DTs remain not only technically meaningful, but also usable and effective as learning and decision-support tools in manufacturing innovation environments.

The transition from the methodological framework to the implementation of SMF can be interpreted as a progressive instantiation of its three main dimensions. The experimentation loop is realized through scenario-based simulation activities within the VLF; the staged model evolution is implemented through the enrichment of the SMF digital model from static layouts to synchronized kinematic/dynamic subsystems; the technical dimensions are instantiated through the definition of state variables, synchronization interfaces, and software engines within the simulation environment.

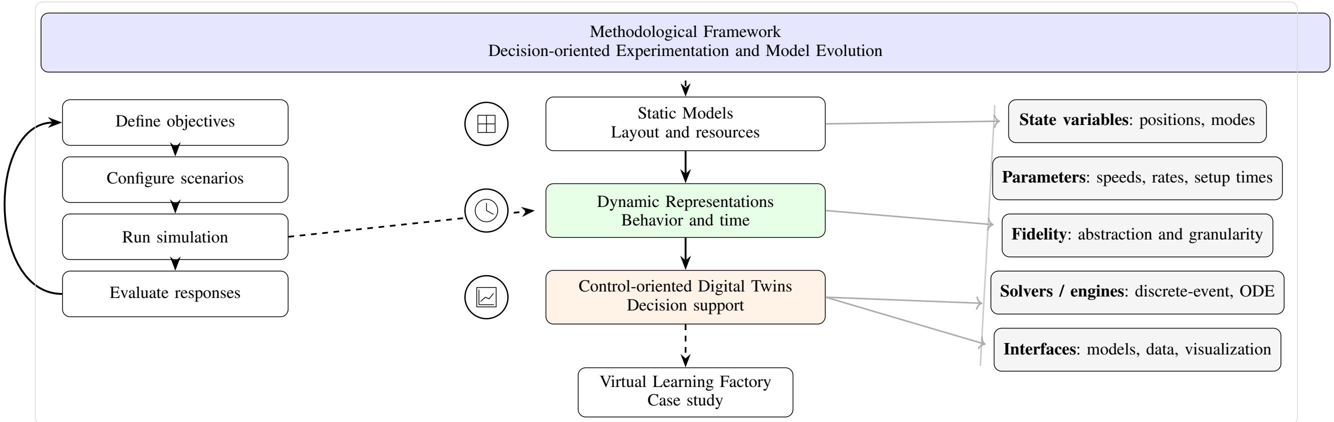


Fig. 1. Methodological framework for Virtual Learning Factories: decision-oriented experimentation and progressive model evolution from static models to control-oriented Digital Twins, complemented with technical specification elements

## III. LATE-BREAKING RESULTS AND DISCUSSION

### A. *Virtual Learning Factory case study*

This section presents a VLF case study used to illustrate the application of the methodological framework introduced in Section II. The case study is intended to demonstrate how the proposed model-based and decision-oriented principles can be instantiated in a realistic manufacturing-oriented environment, rather than to provide a full validation of the methodology. In this context, the case study represents a concrete realization of the framework depicted in Fig. 1.

The experimental setting is the Smart Mini Factory (SMF) Laboratory, located at the NOI Techpark in Bolzano (Italy) within the Faculty of Engineering of the Free University of Bozen-Bolzano [8]. The SMF operates as a Learning Factory tailored to Industry 4.0 and Industry 5.0 and is widely used for applied research, hands-on teaching, and collaborative activities with small and medium-sized enterprises (SMEs). The laboratory is designed as a flexible and reconfigurable environment for studying advanced manufacturing technologies, including automation, robotics, mechatronics, human-machine collaboration, DTs, and simulation-based planning. As a multipurpose platform, the SMF bridges academia, industry, and student learning by providing a testbed in which researchers, students, and company representatives collaborate on innovation-driven applications. Its focus on SME-relevant production scenarios related to digital modeling and decision support remains closely aligned with industrial needs and makes the SMF a suitable environment for applying VLF concepts based on the proposed methodology.

Following the abstraction and modeling principles defined in Section II, a digital model of the SMF laboratory has been developed using the industrialPhysics (iPhysics) simulation platform. The initial version of the model focuses on the structural representation of the laboratory, including workstations, robotic cells, assembly areas, and collaborative spaces, thus corresponding to the static modeling stage described in Section II-B. This digital representation provides the basis for subsequent model enrichment steps aimed at introducing dynamic behavior and decision-oriented analysis capabilities.

Figure 2 displays an overview of the digital SMF model developed in iPhysics with a three-dimensional perspective which is meant to enhance interpretability and contextual understanding of the laboratory environment. The developed DM serves as foundation for the Virtual Learning Factory used in the remainder of the case study. The following section illustrates the preliminary results of evolving the digital model of the SMF laboratory towards a control-oriented DT.

### B. *Evolution into a control-oriented Digital Twin*

Starting from the static digital model, the evolution toward a control-oriented DT is achieved through the progressive integration of kinematic, dynamic, and synchronization capabilities into the simulated VLF of the SMF laboratory.

In line with the staged model enrichment strategy discussed in Section II-B, this evolution aims to describe the transformation of the digital representation from a descriptive virtual model into an active environment for decision-oriented experimentation, monitoring, and analysis of manufacturing system behavior. From a technical standpoint, the target DT can be framed as a state-driven simulation model, where the system is represented through a state vector $\mathbf{x}(t)$, a set of configurable parameters $\boldsymbol{\theta}$, and observable outputs $\mathbf{y}(t)$ relevant for decision support, i.e.,

$$\dot{\mathbf{x}}(t) = f\big(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}\big), \qquad \mathbf{y}(t) = g\big(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}\big), \quad (1)$$

where $\mathbf{u}(t)$ represents inputs such as motion commands, scheduling decisions, or controller signals. In this sense, control orientation does not imply closed-loop control deployment, but rather the explicit structuring of the DT around interpretable states and outputs (e.g., joint positions, resource modes, cycle times, utilization), enabling systematic what-if analysis and sensitivity studies with respect to $\boldsymbol{\theta}$. In the SMF case study, the state vector $\mathbf{x}(t)$ includes variables such as shuttle positions, robot joint states, workstation occupancy, and resource execution modes, while $\boldsymbol{\theta}$ includes configurable process parameters such as transport speeds, sequencing rules, and synchronization delays. The outputs

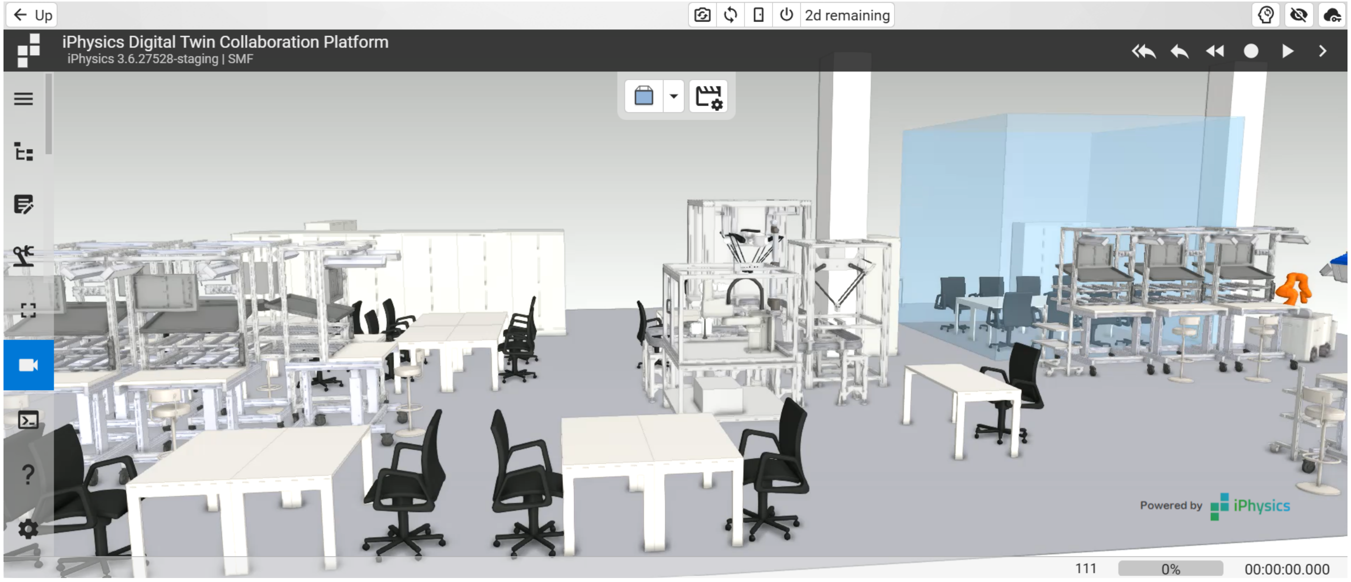


Fig. 2. Digital model of the Smart Mini Factory (SMF) Laboratory developed in the iPhysics platform (detailed view)

$\mathbf{y}(t)$ are associated with monitoring and decision-support indicators including cycle times, and resource utilization.

As a first step, some selected SMF subsystems have been enriched with explicit kinematic and dynamic behavior. In particular, for a small transfer line and the robotic manipulators operating along the simulation has been enabled to represent motion constraints, joint configurations, and time-dependent interactions between robots and transport units. This enrichment allows the DT to capture execution-related phenomena, such as sequencing dependencies, which cannot be analyzed using static layout models alone. As a result, the DT supports simulation-based reasoning on execution logic and resource interaction under different operating conditions.

Beyond kinematic and dynamic modeling, a subset of manufacturing equipment has been connected to the simulation environment via a communication protocol, enabling bidirectional exchange of state information between the physical system and the virtual model. For these components, the DT is synchronized with the real system in a quasi real-time manner, such that the virtual representation reflects ongoing operations, execution progress, and current system states. Conceptually, this corresponds to a digital shadowing in which measured signals $\mathbf{z}(t)$ update the virtual state, e.g.,

$$\mathbf{x}(t_k^+) = \mathbf{x}(t_k^-) + \mathbf{K}\big(\mathbf{z}(t_k) - \mathbf{h}(\mathbf{x}(t_k^-))\big), \qquad (2)$$

where $t_k$ denotes discrete synchronization instants (consistent with the discrete-time simulation cycle), $\mathbf{h}(\cdot)$ maps model states to measurable quantities and $\mathbf{K}$ denotes an update gain that captures how strongly the DT is corrected using real observations. Within the current implementation, the measured signals $\mathbf{z}(t)$ include the status information of the robot and the transfer-line exchanged between the physical equipment and the environment of iPhysics. The update mechanism therefore allows the DT to progressively align simulated and observed execution states during operation.

In practice, this hybrid configuration represents an intermediate stage between offline simulation and a fully live DT, in which synchronized assets provide data-driven state updates while the remaining equipment is still statically simulated. At the current stage, synchronization capabilities are available only for selected resources; consequently, the DT should be interpreted as a partially connected system rather than a fully integrated one. Nevertheless, this configuration already enables control-oriented observation, since the virtual model exposes interpretable system states, execution status, and resource utilization in a form suitable for monitoring and decision support. Moreover, the coexistence of synchronized and simulated components makes explicit which parts of $\mathbf{x}(t)$ are data-driven and which rely on model-based prediction, supporting transparent analysis and experimentation.

The long-term objective of this evolution is the realization of a fully functioning VLF operating as a live and online DT of the Smart Mini Factory. In such a setting, experiments could be observed remotely, system behavior monitored continuously, and interactions between resources analyzed across the entire laboratory. This would enable the VLF to support not only simulation-based experimentation, but also remote supervision, collaborative analysis with external and international partners, and decision-oriented assessment of ongoing manufacturing scenarios.

A fully live VLF can also deliver tangible outcomes for SMEs and for manufacturing innovation management. By providing remote access to a shared DT-based experimentation environment, SMEs can prototype and evaluate alternative process configurations, automation options, and operational strategies with reduced disruption, lower risk, and limited upfront investment. At the same time, the VLF supports learning-by-experimentation: operators, engineers, and students can observe system states and KPIs, compare what-if scenarios, and develop skills in interpreting cause–

effect relationships between decisions, configurations, and performance. In this sense, the DT acts as a boundary object between technical and managerial perspectives, enabling structured experimentation cycles that can inform manufacturing innovation management activities such as technology adoption, reconfiguration planning, and continuous improvement in SME-relevant contexts.

### C. Sensitivity analysis for decision-oriented experimentation

One of the key capabilities enabled by the proposed control-oriented DT framework is the possibility to perform parameter-based sensitivity analyses within the VLF environment. In this context, configurable operational parameters belong to the parameter set $\boldsymbol{\theta}$ introduced in Eq. (1) and can be systematically varied to evaluate their influence on manufacturing system behavior. As an example, let $\omega$ represent an operational speed parameter associated with the transfer-line subsystem. Given an output indicator $T_c$, such as the execution or cycle time of a transport operation, the local sensitivity of the DT response with respect to $\omega$ can be expressed as:

$$S_\omega = \frac{\Delta T_c / T_c}{\Delta \omega / \omega}. \tag{3}$$

This formulation illustrates how the DT can support what-if reasoning and parameter-oriented experimentation without requiring modifications to the physical system. By varying $\omega$ within the simulation environment, users can evaluate how transport dynamics influence execution timing, resource coordination, workstation occupancy, and synchronization behavior across the VLF.

Although the implementation presented in this paper is still work in progress, this example highlights how the proposed framework can evolve toward more systematic simulation-based decision support functionalities. In particular, sensitivity analyses may support manufacturing innovation management activities by identifying parameters with a strong influence on system behavior before physical deployment.

## IV. CONCLUSIONS AND OUTLOOK

This paper presented a model-based integration framework for the design of VLFs aimed at supporting manufacturing innovation through simulation and decision-oriented analysis. Rather than focusing on a specific DT implementation or proposing a new DT modeling paradigm, the contribution emphasized general design principles for structuring virtual factory models as experimentation and decision-support environments. The framework highlights the progressive evolution from static digital representations toward dynamic and control-oriented DTs, enabling systematic what-if analysis and behavior-oriented reasoning.

The applicability of the proposed approach was illustrated through a case study based on the Smart Mini Factory laboratory, where a digital model was developed and progressively enriched with kinematic, dynamic, and partial synchronization capabilities. Preliminary results show how control-oriented DTs can be incrementally realized by combining simulation-based modeling with selected quasi real-time data integration, while maintaining a clear separation between methodological principles and implementation-specific constraints. This staged evolution supports both learning through experimentation and decision-oriented observation, without requiring full system connectivity from the outset.

The work also highlights current limitations and open challenges. At present, synchronization between the physical system and the virtual model is available only for a subset of resources, resulting in a partially connected DT. Furthermore, the what-if analysis presented in this paper is preliminary and intended to demonstrate the decision-support potential of the framework rather than to provide exhaustive validation. Extending synchronization to additional equipment, increasing the number of analyzed scenarios, and ensuring scalable integration remain important topics for further investigation.

Future work will focus on advancing the VLF toward a fully live and online laboratory DT, allowing continuous monitoring, remote experimentation, and collaborative analysis between distributed stakeholders. Additional research directions include the systematic validation of model accuracy under real operating conditions, the integration of performance and sustainability indicators, and the exploration of how control-oriented DTs can support manufacturing innovation management processes in SME environments.

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