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Virtual Instrumentation for Digital Twin-Based Monitoring of Manufacturing Systems

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Abstract:

Digital Twin implementation in production engineering requires a reliable instrumentation layer between the physical system and its digital representation. This paper proposes a platform-independent, requirement-oriented virtual instrumentation framework for staged Digital Twin-based monitoring. The framework distinguishes three levels of digital representation: Digital Model, Digital Shadow and Digital Twin. For each level, implementation requirements are organized using Ishikawa diagrams adapted as requirement maps. The framework covers modeling, sensing, data acquisition, signal processing, visualization, synchronization and feedback-oriented support. A beam-deflection monitoring setup illustrates the intended measurement and representation chain. National Instruments data-acquisition hardware and LabVIEW software are used as one implementation option, not as limiting components of the framework. The proposed methodology supports systematic planning of monitoring, diagnostics, predictive maintenance and decision-support applications in smart manufacturing.

Keywords: digital twin, virtual instrumentation, digital model, digital shadow, production engineering, data acquisition, real-time monitoring, requirement analysis, decision support

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1. Introduction

In production engineering, the value of a Digital Twin depends on the quality of the link between the physical system and its digital representation. A digital model has limited engineering value when measured inputs are unreliable, delayed or difficult to interpret. For monitoring, diagnostics and maintenance-oriented reasoning, the instrumentation layer is therefore a core implementation component.

The distinction between Digital Model, Digital Shadow and Digital Twin provides a practical implementation scale. Kritzinger [1] define a Digital Model as a digital representation without automatic data exchange, a Digital Shadow as a representation updated by one-way data transfer from the physical domain, and a Digital Twin as a stronger relation between the physical and digital systems. This classification is relevant for manufacturing because it separates static visualization from data-connected monitoring and interaction-oriented digital representation [2], [3], [4].

Current Digital Twin research often focuses on architectures, lifecycle applications or advanced analytics. The instrumentation problem is less explicit: how to build a reliable measurement and synchronization layer between the physical process and the digital representation [5], [6]. In cyber-physical production systems, this link is fundamental because digital services depend on the quality of the data they receive and interpret [7], [8].

Virtual instrumentation addresses this link through sensing, modular acquisition hardware, software-defined signal processing, configurable interfaces and scalable measurement logic. Such flexibility is useful in laboratory development and in production environments with changing monitoring objectives [9], [10]. The same logic can be implemented using modular DAQ devices, industrial I/O modules, PLC-connected measurement systems, edge devices, OPC UA data layers, MATLAB/Simulink, LabVIEW, Python-based tools or other engineering platforms. The proposed framework is therefore platform-independent.

The aim of this paper is to propose a requirement-oriented virtual instrumentation framework for staged Digital Twin-based monitoring in production engineering. The framework uses the Digital Model, Digital Shadow and Digital Twin levels as planning units. Their implementation requirements are organized by Ishikawa diagrams adapted as requirement maps.

A beam-deflection monitoring setup is used only as an illustrative engineering case. It includes a physical object, sensors, data acquisition and digital representation, but the paper does not report quantitative validation, diagnostic indicators or damage analysis. These topics are outside the present scope.

The contribution is methodological. The paper defines the role of virtual instrumentation in the physical-digital data path, structures requirements for the transition from Digital Model to Digital Twin, and discusses implications for monitoring, diagnostics, decision support and modular Digital Twin architectures.

2. Requirement-Oriented Methodology for Staged Digital Twin Implementation

Digital Twin-based monitoring should be treated as a staged implementation task. In production engineering, this helps distinguish whether a system is digitally represented, automatically updated from measured data, or extended towards synchronized interaction and feedback-oriented support. The distinction between Digital Model, Digital Shadow and Digital Twin follows [1], who relate the type of digital representation to the degree of data integrate on between physical and digital domains.

The staged methodology is based on three cumulative levels. The Digital Model represents the physical object through geometry, functional structure and engineering parameters. The Digital Shadow

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extends this representation by automatic data acquisition and one-way data flow from the physical system to the digital domain. The Digital Twin further adds synchronization, interpretation, interaction and a potential feedback or supervisory-control path.

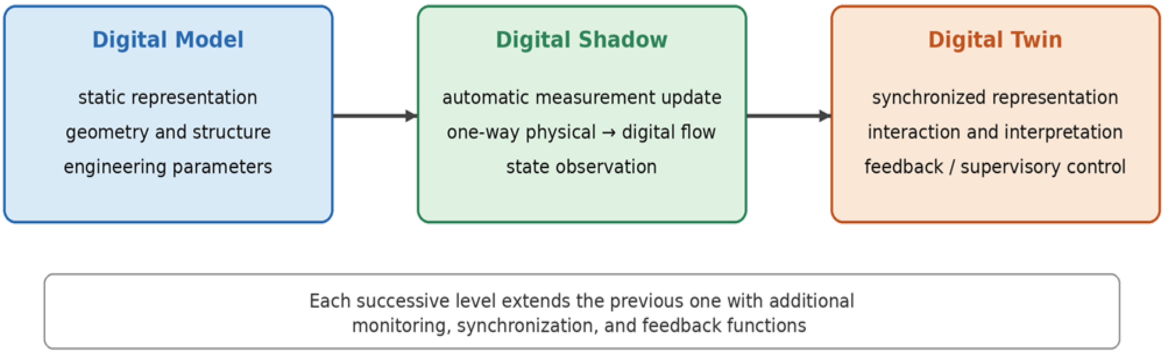

Fig. 1. Progressive implementation path from Digital Model to Digital Twin

Figure 1 summarizes this logic. Each level preserves the requirements of the previous level and adds new functions. The Digital Model requires a coherent object description. The Digital Shadow requires a reliable measurement and data-acquisition layer. The Digital Twin requires synchronization and a mechanism for interpretation, decision-making or supervisory action.

Ishikawa diagrams are used as requirement maps. In their traditional use, they represent cause-and-effect relations in quality management. Here, the effect at the head of each diagram is not a defect, but the successful implementation of a digital-representation level. The branches define engineering requirement groups for the corresponding level. This adapts the original cause-and-effect approach to requirement analysis and implementation planning [11].

At the Digital Model level, the requirements concern geometry, structure, parameters, software representation, purpose and output. The model defines the object, dimensions, support conditions, functional elements, loading or operating conditions and evaluation points. It may support documentation, explanation, training or preliminary simulation. It is not automatically updated from the physical object.

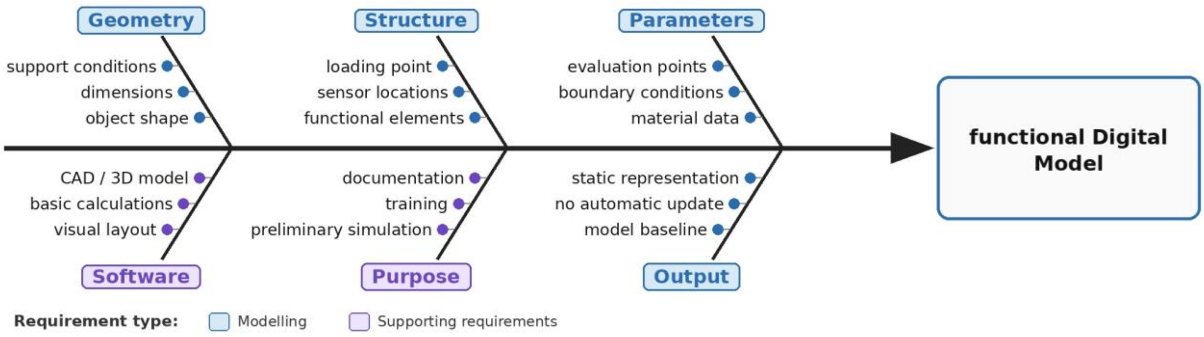

Fig. 2. Requirement-oriented Ishikawa diagram for the Digital Model level. Blue labels denote core Digital Model requirements; purple labels denote supporting requirements

The Digital Shadow level adds automatic acquisition of operating data. Its requirements include the inherited model basis, sensors, data-acquisition or industrial I/O hardware, calibration, communication and output variables. The key difference from the Digital Model is a reliable data path from the physical object to the digital domain. The Digital Shadow therefore forms an observation layer for production monitoring.

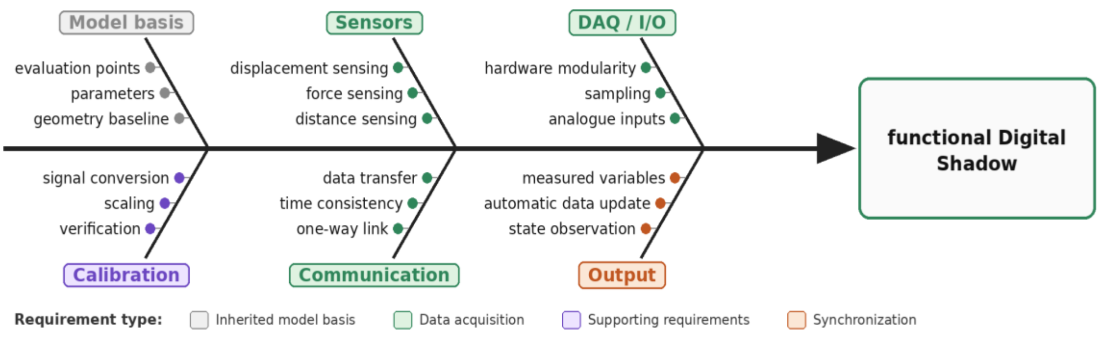

Fig. 3. Requirement-oriented Ishikawa diagram for the Digital Shadow level. Grey labels denote inherited requirements; green labels denote acquisition requirements; purple labels denote supporting requirements; orange labels denote synchronization output.

The Digital Twin level goes beyond one-way data updating. In the proposed methodology, feedback is a defining requirement of this level. It does not necessarily imply fully autonomous closed-loop control. In production engineering, feedback may also mean supervisory action, parameter adjustment, decision support or operator-mediated intervention. The digital representation is no longer used only for observation, but becomes part of an interaction-oriented engineering support system.

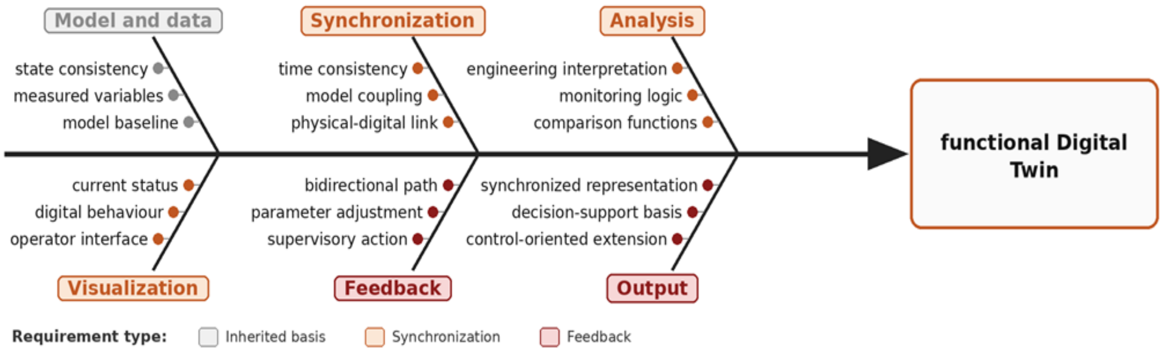

Fig. 4. Requirement-oriented Ishikawa diagram for the Digital Twin level. Grey labels denote inherited requirements; orange labels denote synchronization requirements; red labels denote feedback functions

The three requirement maps are cumulative. Requirements from the Digital Model remain relevant for the Digital Shadow, and both remain relevant for the Digital Twin. This prevents the Digital Twin from being reduced to a graphical interface or isolated software platform. A functional Digital Twin-based monitoring system requires a coherent model, reliable measurement, interpretable data flow, synchronization and feedback-oriented support. This requirement logic provides the basis for the framework presented in the next section.

3. Platform-Independent Virtual Instrumentation Framework

Based on the staged methodology, the proposed framework treats virtual instrumentation as the connecting layer between the physical system and its digital representation. It provides the environment for acquiring signals, converting them into engineering variables, managing data flow, supporting visualization and maintaining the physical-digital link. Virtual instrumentation is therefore understood as an enabling layer for Digital Twin-based monitoring, not as a specific software product. This interpretation is consistent with the general concept of virtual instrumentation based on modular hardware and software-based signal processing, visualization and control logic [9], [10].

The framework is platform-independent. It may use modular data-acquisition devices, industrial I/O systems, PLC-connected acquisition modules, edge devices or other measurement hardware. The software layer may use LabVIEW, MATLAB/Simulink, Python-based tools, OPC UA middleware, SCADA systems or dedicated industrial platforms. Hardware and software selection should follow the monitored object, sampling rate, signal type, communication infrastructure, visualization needs and expected level of interaction.

The framework contains six functional layers: physical object, sensing, signal conditioning and calibration, data acquisition or industrial I/O, processing and visualization, and feedback or decision support. These layers do not define a fixed technological architecture. They define the minimum functional structure required for staged Digital Twin implementation. At the Digital Model level, the framework supports modeling and parameter organization. At the Digital Shadow level, it enables automatic measurement update. At the Digital Twin level, it supports synchronization, interpretation and feedback-oriented functions.

Table 1. Main characteristics of successive digital-representation levels

Level	Main function	Key implementation elements	Engineering value
Digital Model	Static digital representation	Geometry, structure, parameters	Documentation, explanation, preliminary analysis
Digital Shadow	Automatic measurement update	Sensors, calibration, DAQ/I/O, data conversion, one-way transfer	Real-time monitoring and data availability
Digital Twin	Synchronized representation and feedback-oriented support	Integrated model, visualization, interaction, feedback path	Monitoring context, supervisory action, decision basis

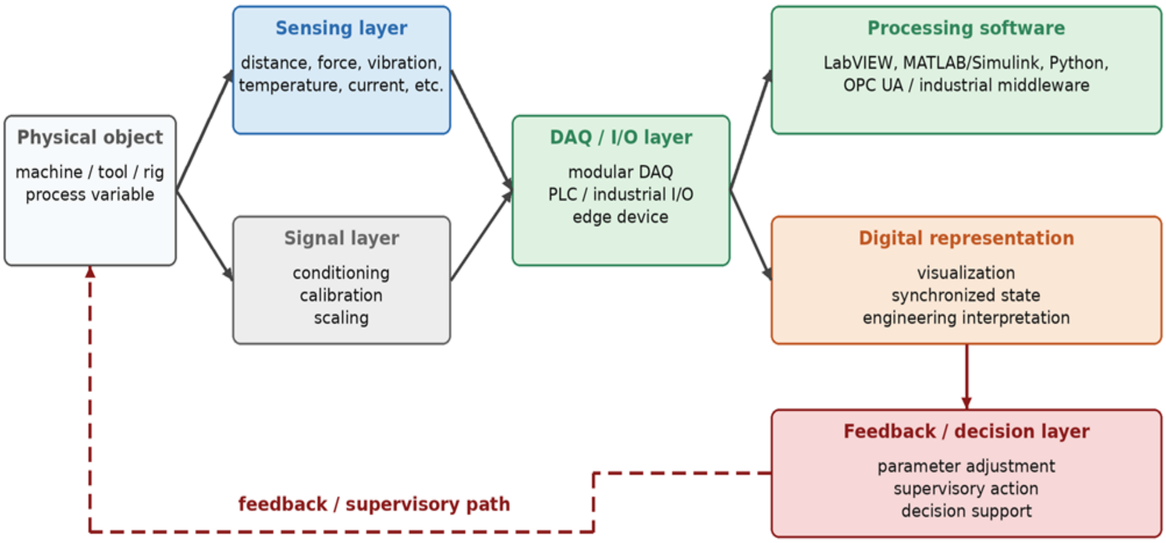

Fig. 5. Platform-independent virtual instrumentation framework

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Figure 5 shows the general framework structure. Sensors capture relevant process or state variables from the physical object. Signals are conditioned, calibrated and transferred through the acquisition layer into the processing environment. Engineering variables are then linked with a digital representation and used for visualization, interpretation and further processing. At the Digital Twin level, a feedback or decision-support layer may be added. In this methodology, this layer may represent supervisory action, operator-mediated intervention, parameter adjustment or decision-support output, not necessarily autonomous closed-loop control.

In the laboratory context, the framework was illustrated by a beam-deflection monitoring setup with distance, force and inductive displacement sensing. Measurement signals were acquired and processed using selected virtual-instrumentation tools. National Instruments data-acquisition hardware and LabVIEW software represented one possible implementation path. They are not mandatory components of the framework.

The contribution is methodological rather than vendor-specific. The framework does not evaluate a particular hardware or software platform. It organizes the functional requirements needed to move from a Digital Model to a Digital Shadow and then towards a Digital Twin. A Digital Shadow can later be extended by synchronization, analytical functions, interaction logic or supervisory feedback. This staged logic follows the broader idea of configurable technical-system monitoring through virtual instrumentation [12].

4. Methodological Discussion and Implications

The proposed framework is an implementation-planning methodology, not a universal Digital Twin architecture or a validated diagnostic system. Its value lies in defining the requirements needed to move from static representation to data-connected and interaction-oriented monitoring. This distinction is relevant because Digital Twin terminology is often applied to visualization or isolated measurement systems that do not yet provide synchronization, interpretation or feedback-oriented support.

For production monitoring, the framework structures the route from measured signal to engineering information. Sensing and acquisition provide data, but their usefulness depends on calibration, conversion, synchronization and context. A Digital Shadow can therefore be useful before a full Digital Twin is implemented, because it establishes the data basis for monitoring, trend evaluation and diagnostic reasoning. This view is consistent with smart-manufacturing concepts in which data availability, integration and interpretation are prerequisites for decision support [13].

The methodology supports gradual deployment. An enterprise may first create a Digital Model for documentation or training, extend it to a Digital Shadow by automatic data acquisition, and later add Digital Twin functions such as synchronization, analytical interpretation, supervisory feedback or decision support. This sequence reflects practical constraints related to integration complexity, data quality, organizational readiness and industrial transfer of digital methods [14].

Feedback is treated as a defining requirement of the Digital Twin level, but not only as autonomous closed-loop control. In production engineering, it may be implemented as operator-mediated intervention, parameter adjustment, maintenance recommendation, supervisory action or decision-support output. This preserves the active role of the digital representation without reducing Digital Twins to control systems alone. The importance of autonomy and feedback-oriented functionality in future manufacturing has been emphasized by [15].

The framework can also be interpreted from a modular perspective. The Digital Model concentrates structural and computational knowledge. The Digital Shadow acts as an observation unit for data acquisition and state monitoring. The Digital Twin integrates observation, interpretation, interaction and

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feedback-oriented support. This interpretation is compatible with holonic manufacturing principles, where autonomous but cooperative units support adaptability and reconfigurability [16], [17].

The holonic perspective is not a claim that the laboratory example is a holonic manufacturing system. It is a conceptual extension for future distributed Digital Twin environments, where modeling, sensing, analysis and supervisory decision-support functions may operate as cooperating units with separate responsibilities.

The limitations follow from the methodological scope. The paper does not provide quantitative validation of a specific Digital Twin, compare hardware or software platforms, or evaluate diagnostic accuracy or control performance. These aspects require dedicated experimental studies.

5. Conclusions

This paper presented a platform-independent, requirement-oriented virtual instrumentation framework for staged Digital Twin-based monitoring in production engineering. The framework separates static digital representation, automatic measurement updating and interaction-oriented monitoring support through the levels of Digital Model, Digital Shadow and Digital Twin.

The main contribution is methodological. Ishikawa diagrams are adapted as requirement maps for successive digital-representation levels. They define conditions required for implementation rather than causes of failure. This provides a planning tool for engineers who need to determine whether a system is digitally represented, data-connected or extended towards synchronization and feedback-oriented support.

The framework clarifies virtual instrumentation as the connecting layer between physical object, sensors, acquisition hardware, signal processing, visualization and digital representation. The methodology is not limited to a specific platform; National Instruments hardware and LabVIEW are used only as one implementation option.

The beam-deflection monitoring setup illustrates the intended measurement and representation chain. It is not used as quantitative validation, diagnostic accuracy assessment or closed-loop control evaluation.

Future work should focus on experimental validation in specific manufacturing and monitoring tasks. Relevant directions include comparison of measured and modeled variables, uncertainty assessment, diagnostic indicators, AI-supported interpretation, feedback-oriented implementation and distributed Digital Twin functions compatible with modular or holonically inspired manufacturing architectures.

Acknowledgments

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