Low-Cost Data Integration Framework for Integration with Simulation-as-a-Service Digital Twins for Make-to-Order Manufacturing SME

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Abstract

Small and medium enterprises (SMEs) face major challenges when implementing Digital Twin (DT) technology due to high infrastructure costs and complex integration requirements. While the development of comprehensive DT models remains an expensive, resource-intensive activity, most issues often lie in the complex integration processes required to connect existing manufacturing systems with simulation environments. This paper presents a novel low-cost data architecture for integrating data from enterprise manufacturing systems (such as MES and WMS) into external simulation-as-a-service platforms, facilitating DT integration while cutting the related costs. The proposed methodology addresses the challenge of connecting different IT systems with simulation services through a data-driven integration approach. Rather than relying on expensive enterprise integration architectures, the solution leverages a simplified framework focusing on intelligent data transformation with minimal pressure on existing infrastructure. The integration strategy centers on comprehensive data modeling that standardizes how products, resources, and materials information are represented across heterogeneous systems for DT consumption, particularly addressing the complexities of make-to-order environments where product-centric information requires flexible approaches. The work has been validated through the implementation in a medium-sized manufacturing company, and it demonstrated simplicity and cost-effectiveness compared to traditional integration approaches. The data architecture successfully transformed production plans, workforce allocation data, and warehouse materials records from native formats into standardized simulation-ready models. By isolating and addressing the integration complexity while utilizing existing simulation-as-a-service providers for the computationally intensive modeling aspects, the proposed methodology significantly reduces the overall burden of DT implementation for SME, supporting the adoption of this technology through a cost-effective integration strategy.

1 Introduction

Manufacturing industries worldwide are experiencing unprecedented transformation through Industry 4.0 technologies, with the Digital Twin (DT) serving as a cornerstone of this evolution.

Within the manufacturing context, the DT is considered a virtual replica of an existing object or system based on a simulation model connected to its physical counterpart [1]. From an information viewpoint, a three layer DT model can be considered, consisting of a physical layer, a data layer, and a model layer [2].

While large enterprises have successfully implemented DT solutions, Small and Medium Enterprises (SMEs) face unique challenges in adoption due to resource constraints, technical complexity, and integration requirements. Worldwide, SMEs constitute 90% of global businesses and provide 50% of employment, which makes the analysis of the solutions they could leverage to adopt DT technology particularly relevant [3].

However, traditional DT implementations require substantial infrastructure investments and technical expertise, as well as complex system integration that typically exceed SME possibilities. This is even more true for SMEs working with a Make-To-Order (MTO) production model, where customization and flexibility are paramount and integration and standardization can become even more difficult.

In fact, DT for companies operating in MTO manufacturing environments demand high flexibility in model configuration and operation. Enabling DT technology requires allowing this flexibility through adaptive system architectures that can accommodate changing requirements and standards.

Within this context, this paper tries to provide a low-cost data architecture for integrating data into external simulation platforms, which copes with the flexibility demanded by MTO processes and offers the simplicity required by SMEs.

The remainder of the paper is organized as follows. Section 2 reviews the existing scientific literature on related topics, while section 3 presents the objectives of this work and the methodology adopted. Section 4 explains the proposed data architecture, section 5 discusses its implementation on a simple case study, and section 6 draws the conclusions.

2 Literature review

Aiming to assess current challenges for both SMEs and for MTO companies, this section reviews relevant results from scientific literature. In fact, SMEs face specific challenges in DT adoption that differ significantly from large enterprise implementations. Previous research has identified nine primary

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barriers, ranging from high investment costs with unclear returns to technical complexity and lack of skilled personnel. Most challenges are also related to the integration with legacy systems, standardization data security concerns [4].

Previous research suggests that financial constraints may represent the most significant barrier for the adoption of DT in SMEs, with traditional DT implementations requiring investments of $500,000-$2 million for enterprise-grade solutions [5], [6] . The financial burden extends beyond initial investment to include ongoing maintenance, upgrades, and specialized personnel requirements that strain SME resources.

2.1 Data management and integration challenges

SMEs face unique challenges in data management, with many companies lacking centralized design repositories or standardized document management systems [7].

Furthermore, the integration of DT technology with existing enterprise information systems presents significant technical challenges, particularly for SMEs operating with legacy equipment and systems. Ensuring interoperability between DT platforms and existing manufacturing Execution Systems (MES), Warehouse Management Systems (WMS), Enterprise Resource Planning (ERP) systems, and other operational technologies require careful planning and often substantial system modifications [8].

Particularly, compatibility issues with legacy system represent a challenge for cost-effective DT implementation, as many manufacturing environments include equipment and systems with limited connectivity, proprietary communication protocols, and incompatible data formats [9]. Retrofitting older equipment with appropriate sensors and communication capabilities can require substantial investments for custom hardware development or extensive system reconfiguration.

2.2 Socio-technical considerations on interoperability

From a technical standpoint, the integration of DT technology requires standardized communication protocols, including TCP/IP/Ethernet standards, uniform data formats like JSON, and predefined protocols like OPC UA and MTConnect [10]. While this brings general requirements on the data exchanges, current studies are not sufficient where standards are compared with a technical depth that allows to identify and understand vendor-specific or implementation-specific interoperability challenges [11].

Technical aspects are not the only focus as interoperability is not just a technical matter. Looking at the production strategy, MTO manufacturing mostly needs standardization on the data management side, requiring approaches to manage product, resource, and material representations across heterogeneous systems [9]. This exacerbates the interoperability challenges as it brings to light the socio-technical considerations of the manufacturing management system, thus leading to specific requirements regarding data utilization.

Indeed, the side of the end-user of applications is a key driver. This is generally valid for digital analytics capabilities, so it is relevant for DT modelling. Therefore, data utilization should be enabled explicitly by interoperability, especially dealing with the several information source types. Therefore, non-interoperability leads to barriers and risks degrading the quality of the resulting analyses [11].

Data quality and consistency represent additional challenges, as DTs require high-quality, real-time data to provide accurate insights and predictions. SMEs often struggle with data duplication and inconsistent data formats across different systems and may lack the data management infrastructure necessary to support DT applications, requiring additional investment in data collection and management systems. However, simplified data architectures that focus on essential data transformation can reduce these requirements [12].

Last but not least, on the data utilization side, computational resource constraints may typically create limitations for DT implementations that require real-time processing capabilities [13].

2.3 Managerial perspective on DT implementation in SMEs

Coherently with the socio-technical issues on interoperability, managerial perspective on DT implementation in SMEs is then required. Several aspects can be remarked.

Organizational resistance to change shall be firstly considered, as a critical non-technical barrier, with employees hesitant to adopt new technologies requiring new skills and processes. Yasin et al. presented a practical six-step roadmap for DT integration in SMEs, addressing the specific challenge of limited technical expertise in SMEs by using off-the-shelf components to achieve bi-directional communication between physical systems and DT [14].

Additionally, the lack of standardized evaluation metrics for DT implementations is another concern. This makes it difficult for SME decision-makers to assess potential returns on investment and compare different implementation strategies. To overcome this challenge, the selection of appropriate demonstration use cases represents a critical success factor for cost-effective DT adoption, with well-defined, measurable problems that can demonstrate clear value [15].

Eventually, it is worth pointing out that the landscape is rapidly changing, thus requiring adaptability to the technological and methodological changes. Lightweight DT architectures can nowadays reduce implementation costs while maintaining operational effectiveness [16]. Furthermore, even in larger corporations, research findings emphasize that successful DT projects require incremental rather than disruptive change, with balanced progression of technology, people, and process factors [17]. In the end, it is notable that successful low-cost DT implementations typically follow successive development steps that go from data collection to optimization and control functionalities [18].

3 Research design

The existing scientific literature demonstrates different implementation patterns between SMEs and large enterprises.

SMEs focus on cost-effective solutions with shorter implementation timelines, while large enterprises invest in comprehensive, integrated systems with longer development cycles. SMEs prioritize cloud-based solutions and SaaS models, rather than custom-built proprietary systems.

The overarching goal of this work is to help reduce the cost barriers which currently prevent SMEs from widely adopting DT. As discussed above, aside from designing and developing DT models, companies incur significant expenses for connecting and integrating these models within existing IT systems.

This work aims to propose a data architecture to allow easing the burden of connecting enterprise manufacturing systems to DT, especially in high variability, MTO contexts, where heterogeneous and unstructured data further hinders the development of DTs. To this end, an effective data model helps reconducting the available information to a standardized description, more suitable for DT simulation.

In the design of the envision data model, the focus is directed towards the identification of the most relevant information required to effectively simulate the production process within the DT. To achieve this, the data model must both fit existing systems and leverage new DT platforms. Coherency with existing standards is required not just to make the proposed approach effective by ensuring compatibility with existing systems. Moreover, the viability of the proposed approach is ensured by the development of DT leveraging open-source or cloud-based solutions to further lessen the costs.

The research methodology adopted in this work is loosely based on a design science approach, focusing on the development and validation of a practical artifact to address identified problems in DT adoption among SMEs.

4 Data architecture

The framework discussed within this work is based on three key elements, which are also depicted in Figure 1:

- Existing legacy enterprise information systems, recognized as data sources.
- A cost-effective DT solution. Potential alternatives are discussed in section 5.1.
- A network of connectors, presented in section 5.3, capable of transforming and transferring the information to the DT as required, based on the data model discussed in section 5.2

Besides the connection to existing enterprise information systems, the data architecture can capture data from different sources such as simple databases or even tabular files, whenever MES or WMS are not in place.

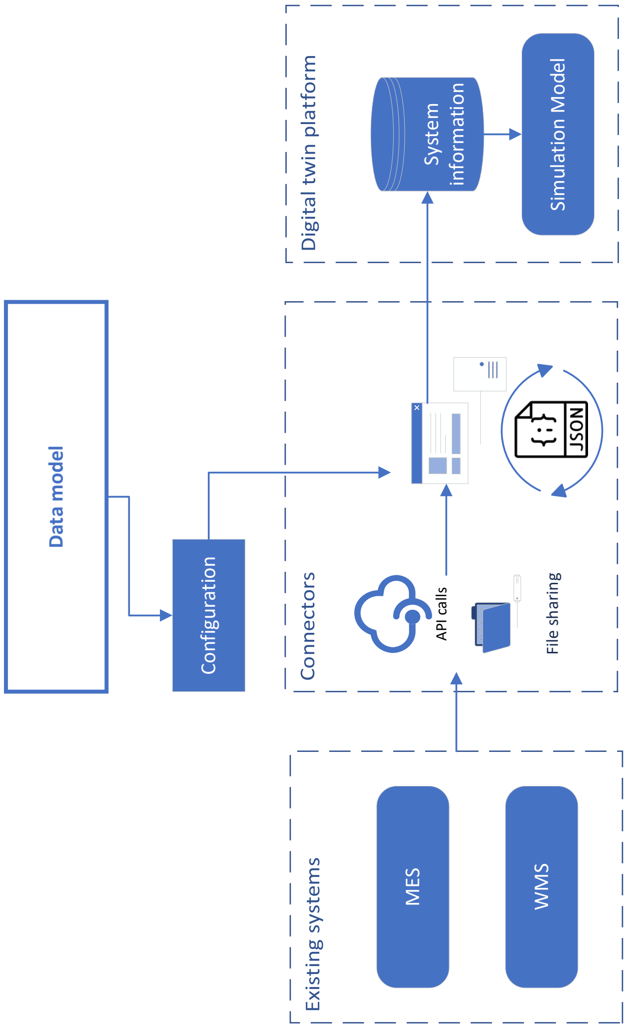

Figure 1 System components

4.1 Simulation model development

Although this paper does not directly address DT model development, this section discusses a range of different technical solutions that could support cost reduction.

- Using open-source solutions, especially for pilot projects, could be an effective way to demonstrate the benefits of the technology without incurring in the costs associated with the software licenses [19], [20].
- Conversely, buying a customized, stand-alone model, comes at a more relevant investment cost but allows to deliver a solution overcoming potential skill gaps, as it involves externally sourcing the capabilities required for model development[10].
- Leveraging a cloud-based solution, cutting initial investment and infrastructure costs. In fact, cloud-based DT platforms represent a paradigm shift toward accessible implementation models. Modeling and Simulation as a Service (MSaaS) architectures enable SMEs to access sophisticated DT capabilities through subscription-based models, dramatically reducing capital expenditure requirements [21].

The adoption of the proposed data architecture requires the simulation model underlying the DT to work with a resource-based mechanisms, which is typical of the DES models and well represents and handles production operations. The model simply works by matching the requirements of each task to the available resources and parts or materials, thus authorizing the execution of each task only if the whole set of requirements is satisfied.

4.2 Data modelling

The proposed data model serves as blueprint for implementing the connection of DT with enterprise information systems in MTO companies. The data model focuses on representing the resources required for the production processes, especially dealing with the different families that are relevant for simulation within the DT. Also, the data model is designed to fit the main elements of the IEC 62264 standard for manufacturing control. The UML class diagram representing the data model is show in Figure 2.

The task class describes the activities and that executed within the manufacturing plant (e.g., machining, assembling or testing), which are thus required to be simulated in the DT. Task needs to show information on the time needed to be completed and the resources and the materials required to perform the task itself. The task is also associated with a product or anyway a physical item that is realized. In order to allow the synchronization of the DT with the physical system, especially.

The key difference requiring a clear separation between the pooled resources and the parts is that the latter get consumed and removed from the model as the task starts, besides the fact that these are usually managed within different information systems (i.e., WMS).

Three classes are defined as pooled resources:

- Fixed resources, which are typically associated with a clear physical sense that is reflected in the model by means of static components such are workstations and machines. The information related to the required fixed resources influences the routing of the parts within the plant.
- Tools, which represent other resources which may be requested for and released flexibly within the model.
- Human resources represent people involved in production operations, which can be further refined to accommodate information such as specialized skills or shift schedules.

The first step includes the task view provided by the MES. The data model supports hierarchy and precedence among tasks. Precedence is required to sequence the operations related to a product and thus to respect technological constraints. The hierarchy allows to retrieve and aggregate information regarding the required resources from parent or child tasks.

The integration of WMS data permits to share the information on the materials available within the warehouse and to allow the match between required and available materials.

The so-called resource pool includes data on the production resources available within the scope of the DT. Further enhancements allow to integrate dynamic information about resource availability, tool usage, and personnel schedules directly into the DT.

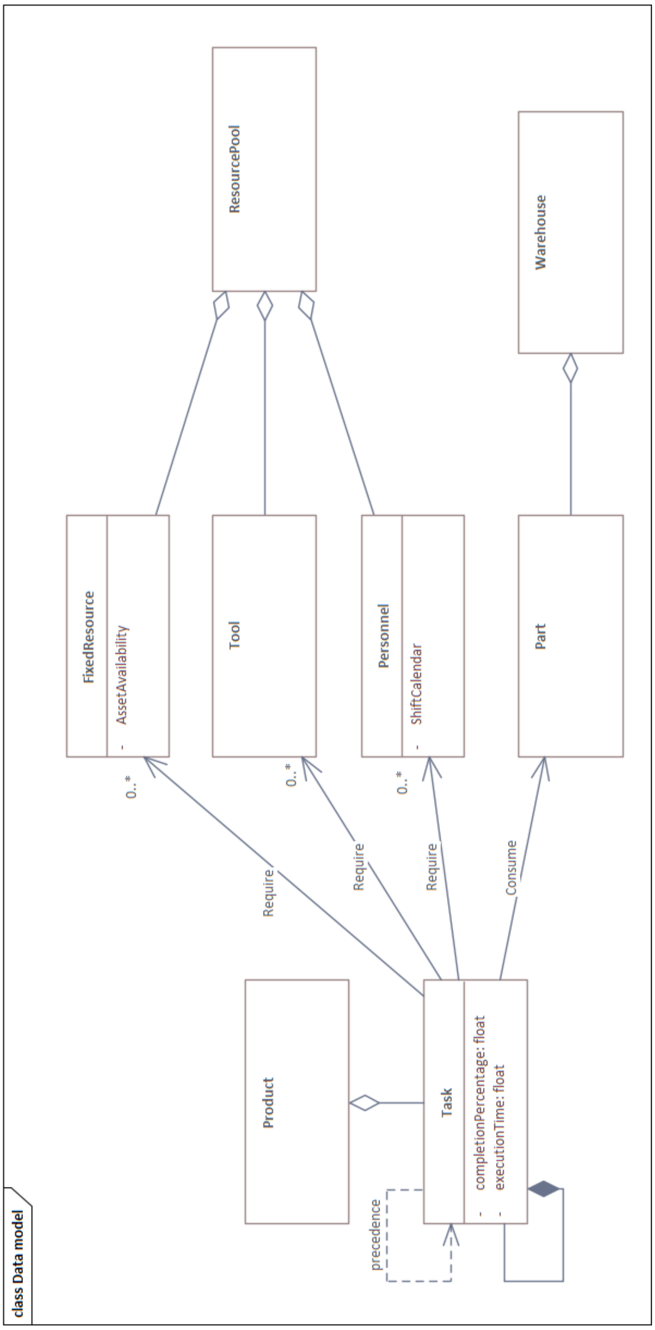

Figure 2 Data model

4.3 Data connectors

The connectors are the software implementation of the data model presented in section 5.2, and the working core of the whole data architecture. They consist of different pieces of software containing the functions which process the available data. The connectors must implement a range of different functionalities, including:

- Retrieving information from enterprise data sources through appropriate interfaces, which depend on the existing systems, but typically do not require any change to them.
- Convert retrieved data into a format which is suitable for DT simulations, leveraging the data model.
- Storing or publishing the data onto the DT platform, either directly loading them within the model, or saving them into a data storage available to the DT.

In the conversion process, the connectors should implement relevant functions to process MES data. Aiming to specifically support MTO companies, the data model supports a project-oriented representation of production activities, including hierarchical and semi-structured.

The products and the tasks associated with it follow a set of dependencies, meaning that the initiation or completion of one task may be contingent on another. These constraints require a highly coordinated workflow, as certain assembly stages cannot progress until prerequisite tasks are fulfilled, adding another dimension of scheduling complexity. As the constraints model is designed to accommodate project management practice, the precedence relationships may go beyond the traditional Finish-to-Start constraints, where a subsequent activity can only begin once the preceding activity has been completed, and supports also Finish-to-Finish, Start-to-Start, and Start-to -Finish constraints.

5 Implementation

5.1 System details

The implementation of the proposed data architecture was conducted in the facilities of a MTO company assembling machine tools for metal cutting in Northern Italy. The production system is composed of a set of fixed position workplaces where all the assembly operations required to manufacture a machine are performed, including testing activities. The company operates with relatively low volumes, realizing products which are highly customized based on customers' needs, making it an ideal testbed for evaluating the effectiveness of the proposed low-cost DT integration approach.

The different skills required and available within the operators' pool have been grouped into four categories, including mechanical, electrical, painting and testing qualifications. Each operation is associated with a set of required parts according to the bill of materials.

5.2 Data architecture implementation

The implementation requires three main steps to enable the synchronization of the DT with the information provided by MES and WMS:

- Identification of the data sources and the relevant information to be provided to the simulation model.
- Configuration of the connector transforming raw data into a format compliant with the standardized data model.
- Conversion from the data model format to the one required by the DT platform.


```json
{
  "taskId": "T004-A",
  "productId": "MACH-2025-07",
  "taskType": "assembly",
  "duration": 480,
  "precedents": ["T001-PREP"],
  "requiredResources": {
    "fixedResources": ["WS-05"],
    "humanResources": ["MECH"],
    "materials": ["C-A-001", "F-M8"]
  }
}
```


Figure 3 JSON schema

The information related to the products realized and to the assembly tasks requires merging data sources including both structured project data, providing precedence relations, and tabular data, containing information about the people assigned to these tasks. Inventory data can be extracted from WMS with a tabular format in a CSV file.

The proposed data architecture relies on a two-stage conversion pipeline designed to bridge heterogeneous enterprise data sources with DT native data structures. The first stage consists in the conversion of the raw data acquired into a dictionary-like, JSON formatting, as shown in Figure 3. This representation is fully compliant with the data model and enables successive data elaboration. Within the following step, the connectors convert the data into the XML format required by the simulation software.

The data architecture uses a configurable approach by defining field mappings, value transformations, and data structures adaptations, separating transformation logic from code implementation. This enables the configurability of the whole data architecture, granting the possibility to implement it in different domains. The conversion pipeline addresses three fundamental data integration challenges: format heterogeneity across source systems, semantic mapping between domain-specific terminologies, and structural transformation from hierarchical project data to simulation-ready flat representations. Key and value mapping configurations define transformations between source field names and target schema requirements. The system supports three levels of mapping rules, including direct, exact match substitution, regular expression-based pattern matching with template substitution, and default fallback behaviors.

The task flattening module implements a depth-first traversal algorithm that converts hierarchical structures into flat task lists. This conversion implements task identification algorithms that distinguish between parent tasks, which serve organizational purposes, and child tasks, which represent executable operations. Only child tasks are retained in the flattened output as these will be simulated within the DT. The inheritance mechanism ensures that children tasks receive complete specifications of resource requirements accumulating personnel assignments and material requirements from all parent nodes.

Predefined data injection capabilities enable the configuration system to insert default values for required simulation parameters that may not exist in source data. This feature addresses the common integration challenge where simulation platforms require complete data models while source systems may contain partial information.

Platform-agnostic connectors were developed using Python scripts with API interfaces to enable data transformation and transfer. This ensures the possibility to use this data architecture across heterogeneous information systems. The configuration files are implemented with declarative transformation language expressed through YAML structured documents, which allows domain experts to specify complex data transformations without direct code modification. The code related to this work is fully available online on GitHub® platform[1].

5.3 Digital Twin implementation

The DT, implemented in Tecnomatix® Plant Simulation, is represented in Figure 4. At model startup, the software loads the production tasks from the MES, mirrors the materials availability provided from the WMS, and instantiates the pools of resources. Although Tecnomatix® Plant Simulation is not a low-cost solution *per se*, the DES model can be provided as a stand-alone solution, since the proposed data-driven approach allows for complete flexibility in accommodating different production processes. This approach does not require embedding process logic within the model itself but instead infer it from the input data.

During the execution, the model controls resources and parts availability and starts operations as scheduled. Before starting an operation, the DT verifies the constraints related to fixed resource availability precedence. It governs the maximum number of operations that can be processed simultaneously within a given facility while ensuring that task execution follows predefined dependencies.

Moreover, DT manages resource allocation by enforcing constraints related to operators' skills, parts, and tools. Before executing an operation, the system verifies:

- Operators' availability: ensuring that a worker with the required skill set is present and not assigned to other tasks.
- Part inventory: confirming that the necessary components are available in stock before the operation begins.
- Tool accessibility: checking that tools are available and not assigned to other tasks.

Although input and output of the system leverage the core Plant Simulation® *source* and *drain* components, the flows within the system (i.e., from one station to another) are not modelled, as they fully rely on the data provided to the DT. In fact, the model does not require the configuration of any routing, as this is solely based on the task information provided. The remainder of model components include workers and warehouses, which are used to represent system capacity and components availability.

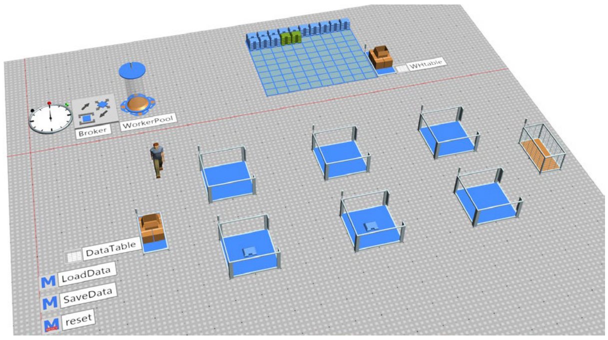

Figure 4 DT simulation model

6 Conclusions

This paper presents a novel low-cost data architecture for DT integration specifically designed to address the implementation barriers faced by SMEs in manufacturing MTO environments. The proposed methodology successfully demonstrates that DT technologies can be made accessible at a low cost by simplifying data integration rather than opting for comprehensive system replacement.

The key contribution of this work lies in the development of a practical framework that separates the complex integration challenges from the modeling aspects of DT implementation. By leveraging existing enterprise systems as data sources and connecting them to cost-effective simulation-as-a-service platforms through standardized connectors, the proposed approach reduces implementation costs by up to 95% compared to traditional enterprise integration solutions. The methodology specifically addresses the needs of make-to-order manufacturing environments through flexible data models that accommodate product customization and variable production requirements.

This research contributes to the democratization of the implementation of DT by providing evidence that these technologies can be made accessible to organizations beyond large enterprises with substantial technological resources. The economic and technical viability demonstrated through this work supports the broader goal of enabling digital transformation across the full spectrum of manufacturing organizations, potentially accelerating the adoption of Industry 4.0 technologies and improving global manufacturing competitiveness.

The implications for practice are significant, as this work provides a practical solution which facilitates the adoption of DT in SMEs, which has been validated through a real-world

[1] https://github.com/Industry40Lab/DTconnector

implementation. Manufacturing organizations can leverage the proposed data architecture as cost-effective integration strategy allowing to implement DT capabilities within budget, and possibly also time and skills constraints.

Future research directions should focus on extending the proposed framework to explore automated connector generation to further reduce implementation complexity. The integration of artificial intelligence or process mining capabilities and the development of industry-specific templates could enhance the value for different manufacturing sectors. Moreover, the proposed data architecture only deals with the synchronization of the DT using the data available in enterprise information systems. In fact, it overlooks the solutions which would be required to close the loop by returning DT outputs to the physical counterpart.

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