Model-Based Interoperability: A Framework for Evaluating Emerging Trends

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1 Introduction

Informed and agile decision-making at various stages of the value chain for complex systems relies on contextualized data that is up-to-date, reliable, and available in near-real time. Digital continuity plays a crucial role in this decision-making within organizations, as it ensures the convergence of data and the creation of shared contexts necessary for dynamic integration and analysis.

In the context of Industry 4.0, digital continuity becomes central to addressing interoperability challenges that arise from the diversity of interconnected subsystems, the need for autonomous and dynamically reconfigurable systems, and the demand for near-real-time responsiveness to changing conditions. These challenges underscore the need for an interoperability mechanism that integrates multiple systems seamlessly and minimizes manual intervention. Building on this foundation, model-driven interoperability provides a systematic approach to resolving these challenges by defining flexible mapping mechanisms for system integration.

According to (Brilhault et al., 2023), such mechanism should be (1) dynamic (plug & unplug) to adapt to system and standard changes, (2) automatic (plug & play & unplug) to reduce the time and effort required for connections, and (3) scalable (plug & live update streaming & play & unplug) to integrate ongoing system modifications and real-time updates. This leads to a model-based interoperability process as depicted in the figure 1;

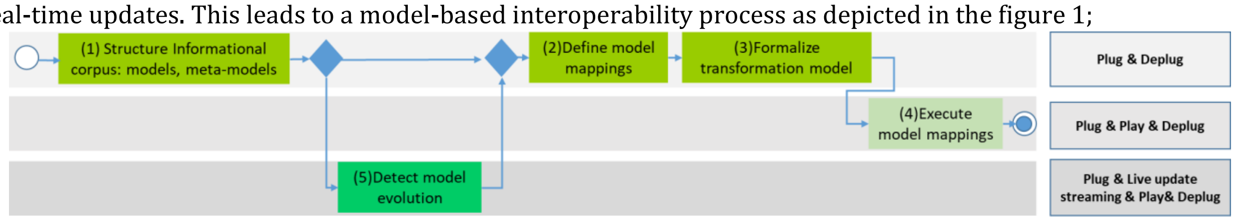

Figure 1: Model-based interoperabilty steps

Several approaches have been developed to address all these stages; however, they have shown limitations in their ability to respond quickly and flexibly to interoperability requirements while minimizing manual interventions. New directions rely on facilitators such as artificial intelligence, generative AI, and predictive models to create architectures that can evolve and adapt continuously. This article proposes a comparative framework to evaluate these advanced model-driven interoperability approaches, highlighting their contributions to digital continuity and their potential to shape the next generation of interconnected systems

2 Methods

This study seeks to offer a thorough review of existing approaches to model-based interoperability, while also proposing a comparative framework to assess these approaches in light of emerging challenges in digital continuity. The comparative analysis will be conducted at each stage of the process outlined in Figure 1, with a primary focus on identifying key methods and defining the comparison criteria.

Starting from the observation that informational corpus convey explicit knowledge in structured, semi-structured, or unstructured forms, as well as implicit knowledge, it is essential to “structure informational corpus” and specifically the minimum necessary knowledge (Lezoche et al, 2012) to ensure interoperability, allowing different systems to work together seamlessly despite their inherent differences. Achieving this involves addressing technical, semantic, and organizational challenges, with various methodologies and frameworks proposed to organize the knowledge required for interoperability, ensuring that models serve as the primary carriers of information throughout the development process. These models can take the form of knowledge graphs, ontologies, or data models. Their definition can be achieved through various approaches and depends on the

nature of the data; it can range from manual structuring to AI-facilitated structuring and the use of large language models (LLMs). The comparison framework will take into account the effort (complexity and time) required to determine the scope of the necessary data, the effort of elicitation, and the effort of structuring.
Regarding the "Define model mappings" step, (Brilhault et al., 2023) proposed a comparison framework based on the input data (number and level of modeling) across models, metamodels, and the presence or absence of prior alignment (Zhao et al, 2020). Approaches ranging from descriptive to machine learning-based were evaluated based on their execution or training time and their accuracy.
“Generating model mappings” necessitates the automatic creation of relationships between various models, and leveraging automated tools and algorithms can significantly enhance the efficiency of this process. Specific model transformation tools, such as ATL and QVT, automatically facilitate this generation. In contrast, other methods require the definition of specific generation algorithms. The framework necessary to compare these approaches is based on the time taken for generation and updates.
“Executing model mappings” involves facilitating interoperability in a way that provides all the necessary components. Various frameworks (Ibrahimet al, 2010) exist to ensure this execution when needed within service-oriented architecture (SOA), Enterprise Service Bus (ESB), APIs, and more. These frameworks streamline communication and data exchange between services, allowing them to work together effectively (Wimmer et al, 2007). By ensuring that services can accurately understand and process information, these frameworks ultimately enhance system integration and performance. The comparison framework is mainly based on those criteria: ease of Implementation, scalability, performance (time) and user-friendliness.
“Detecting model evolution” is crucial for maintaining the accuracy and relevance of models in dynamic environments; it allows tracking changes in models over time. Different strategies could occurs among Change Tracking Mechanisms, Diff algorithms, change impact analysis, learning approches,…By employing these strategies, organizations can effectively monitor and manage model evolution, ensuring models remain relevant and effective. The comparison framework is based on the effectiveness, the ease of implementation, the scalability, the level of automation and accuracy.
In the literature, several datasets will also be presented to illustrate and validate the effectiveness of various approaches. An additional level of comparison will involve defining these datasets and characterizing them in relation to the approaches defined later, according to the established comparison frameworks. This analysis will rely on the comparison framework proposed by (Pinquié et al.,2022), which specifies the level of exploitability of the datasets and the availability of the data and algorithms used.

3 Conclusion

A comprehensive literature review has provided a structured overview of the phases involved in ensuring model-driven interoperability. Each phase of the process has been defined, highlighting its specific role in addressing interoperability challenges. Furthermore, key criteria for comparing approaches within each phase—such as execution time, accuracy, scalability, and ease of implementation—have been outlined to guide the evaluation.

This initial work emphasizes the "define model mapping" phase, where the criteria for comparison have been identified and the potential of reinforcement learning and other AI-driven models to enhance this step is explored. While the review has identified promising directions, the actual comparison of approaches remains to be conducted in future work. This next step will also require selecting relevant datasets to validate and benchmark the methodologies.

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