Flexible Multi-Aspect Model Integration for Cyber-Physical Production Systems Engineering

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Abstract. *Background.* Consistent cross-disciplinary engineering data models have become increasingly important for engineers and project managers to validate system designs or implement new features in existing systems. However, discipline-specific designs (mechanical, electrical, automation engineering etc.) in isolated data models and proprietary software tools often create information silos. Similar to information systems, the challenges in Cyber-Physical Production System (CPPS) are a high amount of heterogeneous data that needs to be analysed and accessible for stakeholders and systems. *Aim.* The goal of the *Flexible Multi-aspect Model Integration* project is to support the integration of local engineering views and artefacts using the definition of common concepts across different disciplines. Therefore, the thesis project will provide capabilities to integrate and validate multi-aspect models more efficiently to increase the data quality. *Method.* The project will follow Design Science methodology to design and evaluate i) a method for collecting and defining common concepts across engineering disciplines, ii) a modularised software system design that enables flexible model integration processes in a CPPS context, and iii) an exemplary model integration process that supports data integration needs in the planning, operation, and analytics phase. The model integration processes are evaluated with real-world uses cases from industry. *Conclusion.* The information systems community will gain insight into the requirements in engineering and a method for agreeing on an inter-disciplinary common understanding from this research.

Keywords: Industry 4.0 · Multi-Aspect Information System · Multi-Disciplinary Engineering

1 Introduction

Cyber-Physical Production Systems (CPPSs), a foundation for addressing the Industry 4.0 vision [25] of flexible production, are complex systems that require cross-disciplinary engineering views, such as mechanical, electrical or automation engineering [1]. These disciplines share common engineering object or system parts, on which each discipline has a specific view, including specialised data models and property naming.

Information System Engineering (ISE) for CPPS use cases, like digital shadows, require techniques for (i) automated aggregation and reduction of data, (ii) data analysis methods, (iii) data accessibility to stakeholder and systems and (iv) feedback for decision support and system controlling [14]. Therefore, the integration and harmonisation of all this data is an essential task in CPPS engineering to increase to overall data quality [28].

To enable these CPPS aspects the discipline-specific views, local data sources and stakeholder concerns need to be successful integrated in a combined model for further validation and verification of the system design [26]. A major concern for building such a combined interdisciplinary model is the interoperability of software systems as a critical factor for increasing productivity and reducing costs in the automation of production and manufacturing systems [5, 27].

The real-world use case from our industry partner *data exchange towards production system simulation* [4], illustrates a typical data exchange and model integration process and key discipline-specific views and is depicted in Figure 1:

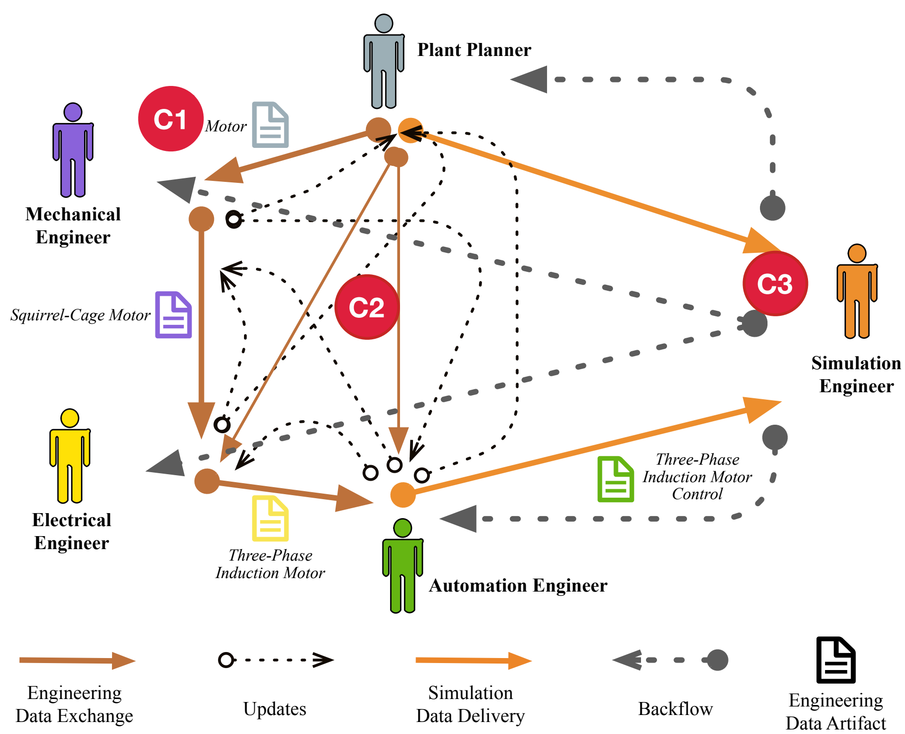

Fig. 1: Data Exchange Towards Production System Simulation Use Case and Challenges.

The *plant planner* designs the initial CPPS functions and structure. Subsequently, the *mechanical engineer* builds up the system tree based on the basic plan with mechanical functions, system parts, properties, and location of parts. Next, the *electrical engineer* adds electrical components with interfaces to the mechanical parts and views (electrical system parameters, such as voltage or energy supply). Finally, the *automation engineer* adds control code that automates the previous engineered parts. At a later stage, the simulation expert integrates the engineering artefacts from basic, mechanical, electrical and automation engineering to design the simulation model.

Ideally, these tasks would be completed sequentially. Yet, engineers design in parallel regularly triggering follow-up changes across disciplines due to increased competition and complex dependencies between hard- and software. Hence, they need to synchronise engineering artefacts during the engineering phase. These data are often synchronised and integrated manually or with poor tool support that takes additional effort and tends to be error-prone, inducing avoidable project risks.

Challenges to Data Integration in CPPS Engineering. Information systems and computer-assisted engineering aim at supporting model integration processes to achieve a common view on engineering objects and accessing the combined model. However, we have identified the following challenges (depicted in Figure 1) from the industrial use case and literature [11, 16, 17].

C1 Information loss due to artefact-based data exchange. Data exchange in a multi-disciplinary environment is usually based on artefact-based transactions across several workgroups [3]. The use of proprietary or hierarchy limited file formats, such as PDF, spreadsheets or drawings, can lead to information loss [17]. The reasons can be the unclear syntax of engineering data or difficulties with traceability of file updates leading to diverging work versions. As a result, inconsistencies and difficulties with data integration often arise.

C2 High effort of repetitive tasks and configuration of domain data. Data integration in a multi-disciplinary process often requires repetitive tasks that are usually performed manually or require high configuration effort [11]. This is because the engineering data exchange is not regarded as a value-creating business process, and thus data providers send their data in discipline-specific formats and structures. Often data structures change during the project, bearing the effort for data extraction and integration on data consumers [3].

C3 Insufficient common understanding of system boundaries. From the engineers perspective, foreign views and data formats from other disciplines are, in general, not visible [16]. However, the general heterogeneity of existing interfaces and system boundaries, views and process complicates the design of common understanding (cf. Figure 2) and thus also error detection [26].

Aim. The proposed doctoral thesis aims to address the factors that lead to low data quality within industrial information systems. Low data quality and the aforementioned issues with data integration hinder the system transformation towards more complex use cases, such as digital twin, big data or adaptive

CPPS architectures. We aim at proposing an information system design that will improve the data exchange and integration in Multi-Disciplinary Engineering (MDE) (see Figure 2).

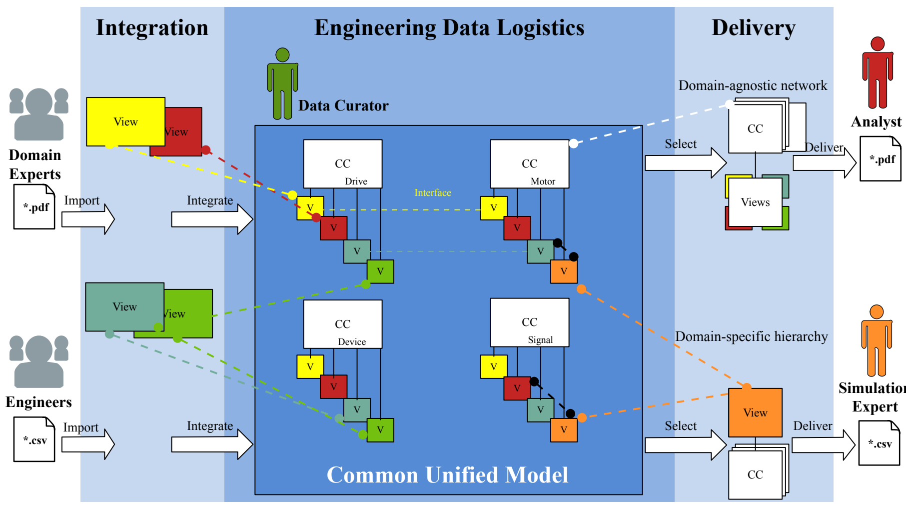

Fig. 2: Data Integration Information System Design for MDE.

The multi-aspect information system consists of three parts: (1) *Data integration* will handle the import, transformation and integration to *Common Concepts (CCs)* of engineering artefacts coming from data providers, such as engineers or domain experts. (2) *Engineering data logistics* will handle the common unified model. The *data curator* will be responsible for the management of discipline-specific concepts, their relations to CCs and semantic links between engineering views. (3) *Data delivery* will handle specific data consumer requests. Data consumers will be able to request data deliveries (a) in their domain-specific hierarchy (e.g., a simulation view) or (b) as domain-agnostic networks (e.g., for analysis tasks across several engineering views) [2]. New views, data integration and data delivery workflows will be efficiently added by configuration.

The advantage of this information system design will be the flexible adaption to different application environments and delivery needs. This will improve the work process of multi-disciplinary environments and facilitate more efficient data provision that will likely lead to better data quality for consumers.

2 Related Work

The *challenges to data integration* (cf. Section 1) lead to an error-prone and inefficient knowledge creation and quality assurance in information system engineering in Industry 4.0, and can lead to information loss or silos.

System modelling in CPPS engineering is challenging due to discipline-specific views, tools, languages and legacy system environments [23]. For the Industry 4.0 vision, domain-specific modelling languages are a crucial part to facilitate model-driven engineering for complex data-driven use cases [30]. Several initiatives, such as the Reference Architecture Model for Industry 4.0 (RAMI 4.0) and new standards and technologies, such as AutomationML (AML), Systems Modeling Language (SysML) or OPC Unified Architecture (OPC UA), aim at alleviating these limitations [9]. A notable approach for enterprise integration in the manufacturing domain is the Computer Integrated Manufacturing Open System Architecture (CIMOSA) framework, especially object capability profiles and collaboration view to organise collaborative organisation networks [13]. On the one hand, these solution designs have made fundamental contribution to the conceptual key elements and abstraction layers of interoperability. However the translation to the applied field is still challenging due to the lack of standardisation. Missing system interface and boundary object [22] information are impediments to consistent data integration. On the other hand, semantic web technologies, like ontologies, seem promising as a solution approach for describing and managing such integration knowledge, but their construction is still highly complex and lacks adequate tool support [11].

Inconsistency management and consistency checking in systems engineering is crucial to organise collaborative organisation networks. Egyed et al. [6] use Object Constraint Language (OCL) expressions to maintain consistent dependencies across engineering objects and views in UML/SysML multi-models. Kattner et al. [12] investigate inconsistency management in heterogeneous engineering models and propose an approach to identify model dependencies. Both approaches require precise data and process knowledge of the organisation and information system, which is often not well defined in Multi-Disciplinary Engineering Environment (MDEE).

The thesis will explore methods that build on the strengths of these modelling and inconsistency management approaches and mitigate the impact of their shortcomings on the data exchange process.

Engineering data logistics [4] in Multi-Disciplinary Engineering is a socio-technical system ensuring that engineers receive the required data at the right amount, quality, and point in time. The system realises an interdisciplinary round-trip data exchange, transformation, integration, and selection [3]. A major concern for information modelling in an industrial context is the lack of adequate multi-view modelling processes [7]. Relevant groundwork is established by the research around Multi-perspective Enterprise Modeling (MEMO) both from the requirements and the meta-modelling perspective [8].

Open challenges mentioned in this context are the lack of use case scenarios and the need for an adaptable architecture to cover enterprise model evolution. Tunjic *et al.* [24] proposed the Single Underlying Model (SUM), as a method to synchronise multiple model views, which is automatically populated with data from single views, based on previously defined mappings.

In this work, we build on the SUM concept and engineering data logistics to enable a common unified model with processes for distributed data integration and model evolution.

3 Research Questions

To address the *challenges to data integration* introduced in Section 1, we raise the following research questions (RQs).

RQ1: What are requirements and capabilities to enable multi-view model integration towards a common model view? RQ1 investigates the multi-view capabilities needed to integrate different viewpoints in CPPS engineering. We will elicit requirements from relevant industrial use cases for integrating heterogeneous views. We will also explore different data integration approaches and methods to find common attributes and concepts among different system contexts. We will elicit these capabilities from literature and industrial use cases.

RQ2: What methods can address the multi-aspect model integration in CPPS engineering? This research question aims at developing and evaluating methods for multi-aspect model integration to address the requirements coming from RQ1. First, we will define a method for collecting engineering concepts and for defining common concepts, such as products, production processes, or production resources, which link the discipline-specific engineering views. Second, we will develop a method for designing a data integration pipeline consisting of multi-aspect model integration operations and process flow specification as a foundation for flexibly designing and configuring data transformation capabilities for data integration and delivery (see Figure 2). Third, we will design a method for operating pipelines for data integration and delivery based on DevOps approaches.

RQ3: What information system design can automate multi-aspect model integration in CPPS engineering? RQ3 aims at designing and evaluating a system that automates tasks for flexible multi-aspect model integration based on the methods coming from RQ2. We will develop a system design that will include (a) tool support for common concept definition; (b) a Domain-specific language (DSL) for data integration workflow specification considering approaches such as DevOps and business process modelling; (c) data integration operators that can be flexible orchestrated to data integration pipelines. In this context, we define flexibility as the ease to adapt the system design to different application environments, such as the number of engineering disciplines, data sources and stakeholder perspective. We will conduct a workshop with domain experts to evaluate the flexibility of our approach concerning the effort needed to conduct adaption tasks.

4 Methodology

We follow the *Design Science* approach [10] and the *Engineering Cycle* based on Wieringa [29] to define the research methodology.

In the **problem investigation** phase, we will conduct a domain analysis to investigate what kind of data integration is required to support the CPPS engineering process and data exchange. Specifically, we will focus on the key stakeholders' needs and processes and analyse their data models and existing standards and solutions. Consequently, we will develop a conceptual problem framework as a guiding use case for further system design and evaluation.

In the **treatment design phase** we will derive requirements for data integration needs from the conceptual problem framework. Candidate treatments from model-driven engineering, semantic web, and software engineering will be evaluated and investigated. Formal concepts from model-driven engineering, such as the Meta Object Facility (MOF), will be explored to derive a DSL for object-oriented meta-models. We will research semantic web-based methods on how to construct and combine discipline-specific taxonomies and other structures. Also, linking and integrating these discipline-specific taxonomies to a common model will be a topic of interest. Further, we will explore software engineering design patterns for modularising software system design.

In the **treatment validation phase** we will derive typical use cases for stakeholder goals. Typical aspects include (i) data integration during CPPS engineering, operation, e.g., integration of sensor data, (ii) connection to open interfaces, such as OPCUA, and (iii) query aspects of the CPPS for non-experts in information systems methods to analyse the process or to perform data quality tasks.

In the **treatment implementation phase** we will develop a prototype that realises the identified capabilities.

5 Preliminary results

We will build on recent research of the Christian Doppler Laboratory on *Security and Quality Improvement in the Production System Lifecycle* [3,4,15,18,19,28], resulting from a technical debt analysis [28], which highlighted the gaps between established practices and state of the art.

We have developed an engineering data exchange approach that focuses on the data consumer's needs and requirements [3]. The process is split into data definition and data operation phases separating the exchange model building and the concrete data exchange tasks. These results provide the basis to build an initial prototype for multi-aspect model integration using AML, as a CPPS engineering standard, as modelling language and evaluated it with industry partners [4,15].

To support domain experts in their analysis tasks, we have explored graph-based visualisation methods that support domain experts to review multi-view engineering data [20]. The developed prototype supports features, such as dependency highlighting, easy graph node management and data search capabilities.

We designed and prototypically evaluated an initial approach of a multi-view model transformation pipeline using a common underlying model and automated by a Continuous Integration (CI) server [19].

6 Conclusion

This thesis' aim is to overcome gaps and challenges in engineering data integration by combining semantic and model-based approaches to facilitate a lossless, transparent and comprehensive data exchange and transformation. However, major challenges of these techniques are a steep learning curve, high setup costs, scarce expert knowledge required to gain the expected benefit [11] and limited tool support. Thus, we consider novel approaches, such as low code [21], to provide an accessible way to implement multi-aspect model integration tool support, which is needed to reduce technical debt in CPPS engineering [28]. This research will contribute to the information system community artefacts, knowledge and insights on (a) requirements and capabilities for multi-aspect data integration; (b) method for multi-aspect model integration; and (c) flexible information system design for multi-aspect model integration within the context of CPPS engineering. At the current stage, we would like to ask the advisory committee: (1) How to improve the understandability of the use case and challenges? (2) How to improve the planned results for the research community? (3) What further related work and research initiatives would you recommend? Thank you for your valuable time and advice.

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