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► **To cite this version:**

Eliott Duverger, Alexis Aubry, Rebeca Arista, Eric Levrat. An ontology-based digital thread framework to support early concurrent engineering in the aerospace industry. *Journal of Industrial Information Integration*, 2025, 48, pp.100984. <10.1016/j.jii.2025.100984>. <hal-05348319>

HAL Id: hal-05348319

<https://hal.science/hal-05348319v1>

Submitted on 5 Nov 2025

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Full length article

An ontology-based digital thread framework to support early concurrent engineering in the aerospace industry[☆]

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ARTICLE INFO

Keywords:

Concurrent Engineering
Integrated Product Development
Model-Based Systems Engineering
Ontology-based engineering
Digital thread
Knowledge acquisition

ABSTRACT

The increasing complexity of the aerospace industry has highlighted the need to anticipate issues from the entire lifecycle of aircrafts. Identified too late, issues originating from the manufacturing or the maintenance phases can have considerable consequences on the overall development costs, time and quality of aircraft development. Concurrent Engineering (CE) is an approach that aims to improve the design process of a system by considering all lifecycle phases from the initial conceptualization. However, this way of working demands a high degree of collaboration and extensive knowledge sharing among the involved stakeholders. The digitization of the industry has provided new opportunities addressing such challenges. Approaches based on Model-Based Systems Engineering (MBSE), Knowledge-Based Engineering (KBE) and Artificial Intelligence (AI) are providing compelling ways to foster cross-domain collaboration while incorporating knowledge supporting design decisions. This paper leverages an ontology-based digital thread framework as a bridge between aircraft and manufacturing engineering activities. With enriched insights and global perspectives, this framework aims to enable early cross-domain trade-offs analysis to support knowledge-driven concurrent and collaborative engineering during the conceptual design phase.

1. Introduction

Historically, the aircraft development was depicted as an “*over the wall*” process [1–3]. With this way of working, aircraft engineers would hand the complete product design to manufacturing engineers over a fictional wall. This wall symbolizes the minimal considerations for the later phases, as the responsibilities of aircraft engineers were limited to this point. This led manufacturers to discover defects and weaknesses late in the design process, necessitating costly design changes (Fig. 1a).

Concurrent Engineering (CE) is an approach addressing this issue and is defined as the “*systematic approach to the integrated and concurrent design of products and their related processes, including manufacturing and support*” [4]. Illustrated by Polacsek et al. [5] in Fig. 1(b), this way of working allows to consider aircraft and manufacturing system design at any level of abstraction and, thus enabling the assessment of manufacturing performances. Consequently driving the development toward a global optimum, CE permits to enhance the overall time, costs, and quality of new aircraft design.

Although researchers addressed this problem for a long time, CE implementation remains significantly challenging in sectors involving

complex systems such as the aerospace industry. The lack of interoperability and knowledge reuse leads to siloed engineering activities impeding the integration of product and manufacturing system design [6]. Thus, the anticipation of issues from future lifecycle phases is hindered by the absence of global perspectives and early impact assessments.

Nevertheless, during the past decade, significant advancements were achieved through the digitization of the industry and the development of data-driven approaches. This paper presents a model oriented framework for early concurrent and collaborative engineering involving complex systems. The central element of this framework is developed in this paper by leveraging an Ontology-Based Engineering methodology, to which the authors propose a novel knowledge acquisition method blending expert-centric and data-driven approaches resulting in the integration of system models and engineering knowledge into an ontology-based digital thread.

The remainder of this paper is structured as the following: Section 2 provides a literature review and Section 3 presents the identified gap analysis. The proposed framework is introduced in Section 4 with a first ontology development proposed in Section 5. Subsequently,

[☆] This article is part of a Special issue entitled: ‘AI4IIP-DT’ published in Journal of Industrial Information Integration.

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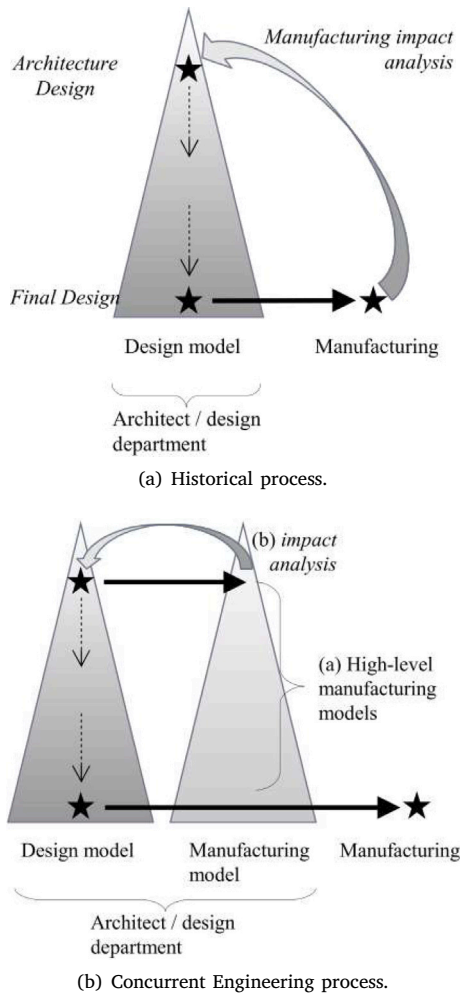


Fig. 1. Concurrent Engineering process according to Polacsek et al. [5].

demonstration of this framework is conducted in Section 6 through a case study. Finally, discussions and outlooks are developed in Section 7 whereas Section 8 concludes this paper.

2. Literature review

This section addresses the challenges of implementing CE during the early design of an aircraft. It presents the opportunities but also the limitations of Model-Based Systems Engineering regarding collaboration between engineers for complex system design. Knowledge-Based Engineering is then examined as a complementary approach to enable interoperability and knowledge sharing toward CE. Finally, the concepts of Digital Thread and Digital Twin are described as the evolution of the previous paragraphs of this review.

2.1. Concurrent engineering for the aerospace industry

Without considering early R&D, the average development time of a commercial aircraft is of 7.5 years between the launch of a new program to the first entry into service [7]. Such long lifecycles involve considerable costs where early design decisions have substantial impact on the rest of the development.

As illustrated in Fig. 2, the design decisions made during the conceptual phase commit 70% of the total lifecycle cost while incurring only 8% [8]. Furthermore, it also shows that the cost for extracting defects

increases tremendously over time. This emphasizes the need to deploy efforts toward developing the right aircraft during the conceptual design phase, while the committed costs are low and the design freedom is high.

Mavris et al. [9] underlined that the aircraft design process must not only address interactions between traditional aerospace disciplines (e.g. aerodynamics, structures, controls, propulsion), but should also account for “life-cycle” disciplines (e.g. economics, reliability, manufacturability, safety, supportability). However, as Bruggeman et al. [10] more recently stated, the integration of the manufacturing system engineering process can be quite challenging during early design stages as limited knowledge is available about the product.

Part of *Product Lifecycle Management (PLM)*, the concepts of CE and *Integrated Product Development (IPD)* laid principles of concurrent work and cross-functional teams, while addressing the business strategy and customer input [11]. With the increasing number of stakeholders, *Collaborative Engineering* has stemmed from Concurrent Engineering, promoting effective communication and multi-disciplinary knowledge sharing among engineers with various cultures, backgrounds, and locations [4]. As these approaches leverage information management processes to share data and automate tasks in order to overcome the traditional disciplinary barriers [12], the industry digitization led to the emergence of new means fostering collaboration during the conceptual design phase.

2.2. MBSE for concurrent engineering

Aircrafts and manufacturing systems are becoming increasingly complex with multi-disciplinary environments. Their development is supported by *Systems Engineering (SE)* that is defined as “a transdisciplinary and integrative approach to enable the successful realization, use, and retirement of engineered systems, using systems principles and concepts, and scientific, technological, and management methods” [13]. From requirement engineering to verification and validation, SE provides standardized engineering processes to collectively address the complexity of modern systems.

During the past decades, most industries have witnessed the combination of SE principles with digital models, introducing *Model-Based Systems Engineering (MBSE)*. Shifting from document-centric to collaborative engineering models, MBSE is defined as the “formalized application of modeling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases” [8].

The rise of MBSE comes with new capabilities incorporating CE and collaboration aspects with the use of digital models. According to Topper and Horner [14], this methodology supports collaboration between various stakeholders through a shared reference, a standardized modeling language and information traceability for complex system design. MBSE has also been identified to transform traditional manufacturing system design into a flexible and collaborative environment for enhanced decision-making toward optimized products and processes [15]. In this sense, MBSE facilitates CE through the modeling of requirements and system architectures while automatically cascading design changes for systematic exploration of the design solution.

Bruggeman and La Rocca [16] leveraged MBSE with other disciplines to optimize the aircraft and manufacturing system design while guaranteeing compliance with the systems requirements. Li et al. [17] proposed a *Requirement-Functional-Logical-Physical* decomposition to model interdependencies between product features and manufacturing processes, enabling information traceability and impact analysis between domains.

However, as Mas et al. [18] point out, the utilization of these capabilities was historically concentrated on aircraft design only. Manufacturing engineering has only recently begun to employ these tools, leading to an experience gap between the two domains. Consequently, despite initiatives to address this disparity, discrepancies between MBSE

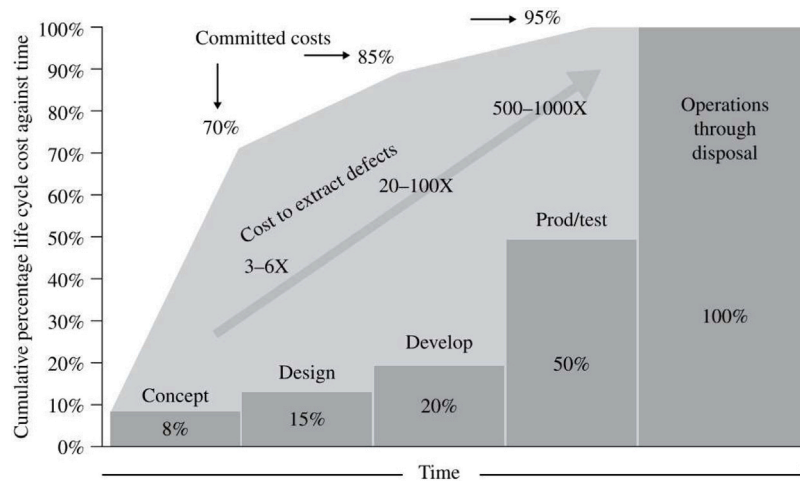


Fig. 2. Committed Lifecycle costs against time [8].

maturity among teams represent a significant obstacle hindering successful CE practices. Furthermore, according to Lu et al. [19], it creates integration issues among architecture models leading to communication, understanding and operational problems between the engineers involved. With concerns toward data integration and linkage maintenance for MBSE in a CE context, the need for a more flexible solution has been highlighted [16,17]. Madni and Sievers [20] identified ontologies as a way to enhance MBSE by interfacing between architectures and supporting tradespace evaluations while ensuring semantic consistency.

2.3. Ontologies for concurrent engineering

Ontologies bring key capabilities to support concurrent and collaborative engineering during the conceptual design phase. In one hand, through a common conceptualization, they enable semantic interoperability and shared understanding among various stakeholders. Furthermore, with semantic web technologies they serve as a communication medium in a flexible manner. On the other hand, their knowledge representation and reasoning capabilities provide enriched insights which support design decisions [21].

2.3.1. Ontologies for semantic interoperability

Used as a central part of the MBSE methodology, ontologies play a fundamental role in information exchange across distributed environments and data management. Hu et al. [22] use ontologies as the semantic core of MBSE approaches for the integration of models and engineering activities. In this paper, the authors employ ontologies as a unified language to support complex system design with digital continuity. Similarly, a combination of a model-driven architecture and ontologies has been proposed by Chungoora et al. [23] to improve interoperability and knowledge sharing across product and manufacturing system design.

For complex system modeling, Sanya and Shehab [24] leverages the definition of domain-specific ontologies to access interdisciplinary knowledge while easily managing the complexity. Comparable aspects have been addressed by Dunbar et al. [25], which incorporated semantic web technologies to favor model integration and interoperability. The authors leverage a flexible and tool-agnostic framework to interface with MBSE artifacts. Furthermore, the underlying ontology allows for enriched knowledge sharing descriptive logic reasoning.

2.3.2. Ontologies for knowledge representation

As the conceptual design phase is characterized by a high degree of abstraction with limited knowledge about the system of interest, the capture, modeling, and reuse of knowledge that supports design decisions is key to support early concurrent and collaborative engineering.

Knowledge-Based Engineering (KBE) addresses these aspects and is defined by Azevedo et al. [26] as “the implementation of knowledge management methods and instruments, which support computational systems that make organizational knowledge the centerpiece of engineering design”.

Bruggeman et al. [10] proposed a generic model to capture and organize knowledge for automatic manufacturing consideration during the conceptual design of aircraft structures. This model has helped identifying trends and ranking manufacturing concepts supporting trade-off decisions. Adopting a comparable approach, Szejka et al. [6] employed ontologies and semantic technologies to identify inconsistencies between product and manufacturing system design while ensuring information interoperability. Although they are mostly leveraged to represent declarative knowledge, Sun et al. [27] identified ontologies as a mean to acquire, manage, and transfer tacit knowledge for product design.

The democratization of ontologies over the past years have strengthened knowledge-based methods by providing structured knowledge representation, automated reasoning, and cross-system interoperability. The integration of KBE with ontologies has introduced *Ontology-Based Engineering (OBE)* approaches [28].

2.3.3. Ontology-based engineering methods

Complex system design activities supported by OBE methodologies use ontology models to enhance collaboration through knowledge capture, management, and sharing [29].

Through ontologies, Curran et al. [30] proposed a methodology for early and continuous use of multidisciplinary knowledge leading to more accurate estimation of manufacturing consequences. Mas et al. [18] defined an OBE methodology leveraging an agnostic approach for knowledge capture and reuse to support complex manufacturing system design. Named MfM, this methodology was employed at the core of the MBSE environments [22]. In a related context, Arista et al. [31] leveraged MfM to structure and manage ontologies for interoperability and knowledge enrichment. By providing shared conceptualizations, a common understanding and reasoning capabilities, MfM offers a convincing structure to support early concurrent engineering [32].

2.4. Knowledge acquisition methods

While most KBE approaches consider human experts for their principal source of knowledge [33,34], the elicitation from human experts remains a notably resource-intensive process, demanding significant efforts in preparation, interaction management, knowledge curation, and subsequent re-formalization. The synergistic progressions of the industrial digital transformation and the advancements in *Artificial Intelligence (AI)* present novel opportunities for knowledge extraction through the analysis of large-scale datasets.

Researchers have leveraged surrogate models to generate aircraft performances as well as supply chain outputs [2,35]. By employing a combination of *Design of Experiments (DoE)* and sensitivity analysis, the authors were able to extract key cross-domain drivers supporting decision-making in the conceptual design phase. Furthermore, the use of *Random Forest (RF)* models has facilitated the extraction of engineering knowledge articulated as *if-then* rules. Adopting a comparable approach, Ali et al. [36] employed *Decision Tree* algorithms to derive manufacturing rules. In this paper, the authors also highlight the need to bridge manual knowledge curation with automatic data-driven knowledge generation. Therefore, approaches for scalable knowledge capture blending human expertise with computational methods as proposed by Li [37] can be leveraged to improve knowledge management practices across various industries.

2.5. Digital Thread and Digital Twin

Within the advancements of industry's digitization, concepts such as *Digital Thread (DT)* and *Digital Twin (DTw)* have emerged as transformative technological enablers. While they are not inherently linked to CE, synergetic capabilities have been identified. On one hand, the Digital Thread is defined as "a linked set of digital artifacts whose consistency is actively managed over the life cycle of a product, process, or system" [38]. By systematically linking digital artifacts across the system lifecycle, the digital thread concept offers a robust platform that facilitates concurrent engineering, leading to enhanced traceability, collaboration, and decision-making during the development process [25,39].

On the other hand, the Digital Twin is defined as "A set of adaptive models that emulate the behavior of a physical system in a virtual system getting real time data to update itself along its life cycle. The digital twin replicates the physical system to predict failures and opportunities for changing, to prescribe real time actions for optimizing and/or mitigating unexpected events observing and evaluating the operating profile system" [40]. During the design phase, as the physical twin does not yet exist, the digital twin focuses on information management and process. Used to simulate manufacturing performances, the digital twin provides precious insights toward cross-domain impact thereby supporting design decisions.

Digital Thread-based modeling approaches have been developed for Digital Twin frameworks in aircraft assembly systems [41]. Used as a DTw backbone, an analytical framework was developed to provide engineering analysis capabilities and support decision-making over the entire product lifecycle [42].

Characterized by semantic modeling, autonomy, real-time reasoning, adaptability, and decision support, the concept of *Cognitive Digital Twin (CDT)* has emerged [43]. CDT capabilities facilitate early concurrent engineering by providing a common understanding, enabling enriched impact assessments and supporting key design decisions. Researchers have employed Cognitive Digital Twins to manage the complexity of multiple interconnected systems with cross-domain knowledge integration through dynamic interrelationship identification and decision-making support [44,45].

3. Gap analysis

The considerable consequences of unexpected design changes has highlighted the necessity to integrate aircraft and manufacturing engineering during the conceptual design phase. However, this task has been hindered by interoperability problems and a lack of knowledge sharing.

As synthesized in Table 1, MBSE approaches have brought key capabilities to support CE for aircrafts and manufacturing system design. Through standardized engineering processes, information traceability, and multidisciplinary views, digital models allow to manage the high complexity of such systems of interest. Nevertheless, discrepancies in the modeling maturity across domains, as well as cumbersome interfaces with other digital tools, are causing interoperability issues hindering proper collaboration between engineers.

On one hand, ontologies support the integration and interoperability of MBSE models. While serving as a communication medium, they provide a common understanding with a tool agnostic flexible structure. Used as a shared reference, they also provide the means to coordinate between teams thereby enabling product and manufacturing engineers. On the other hand, their knowledge representation and reasoning capabilities allow to incorporate KBE approaches which centralize system information and design rules to assess cross-domain impact.

Whereas the definition of methods to capture, model, and reuse knowledge is key to support design decisions, traditional knowledge acquisition remains a resource intensive process. The industry digitization and advancements in AI have provided new opportunities to blend human expertise with automatic data-driven practices.

Acting as a link between MBSE architectures and the rest of the digital environment along the aircraft lifecycle, ontologies are identified as robust foundations for a digital thread answering interoperability concerns while providing the knowledge needed to conduct early impact assessments.

4. Ontology-based digital thread framework

The previous section have identified MBSE as a key methodology for the development of complex systems such as aircrafts and their manufacturing systems. The standardized engineering processes coupled with a model-centric decomposition allows for multi-disciplinary views, information traceability, and complexity management in a single source of truth. While these capabilities are plainly fundamental for CE, it has been observed that MBSE alone does not answer completely the collaboration issues between product and manufacturing engineers during the conceptual design phase. Interoperability issues, lack of knowledge sharing and high-effort cross-domain links were identified as major concerns hindering the development aircrafts and their manufacturing systems [6,17,22].

Through a shared conceptualization, flexible queries, knowledge representation and reasoning capabilities, ontology-based approaches present compelling ways to enrich MBSE methodology to support early concurrent and collaborative engineering.

Thus, this paper develops and implements a framework introduced by Duverger et al. [46] to integrate cross-domain design activities while incorporating semantic and engineering knowledge, supporting decision-making during the conceptual design phase.

4.1. Framework description

The proposed framework shown in Fig. 3 is composed of 6 modules:

1. Values & Drivers catalog

The Values & Drivers catalog addresses business and customer needs to develop the right product by considering the whole lifecycle scope. Via the definition of a common catalog of values

Table 1
Gap matrix.

	Strength	Limitations
MBSE	Standardized engineering processes, Information traceability, Multi-disciplinary views, and Complexity management	Modeling maturity discrepancies and interoperability issues
Ontologies	Syntactic and semantic interoperability, Knowledge representation, Reasoning capabilities	Not sufficient for complex systems engineering
Expert-centric knowledge acquisition	Specialized knowledge	Resource intensive and subjective elicitation
Data-driven knowledge acquisition	Robust and scalable knowledge	Sensible to data quantity and quality

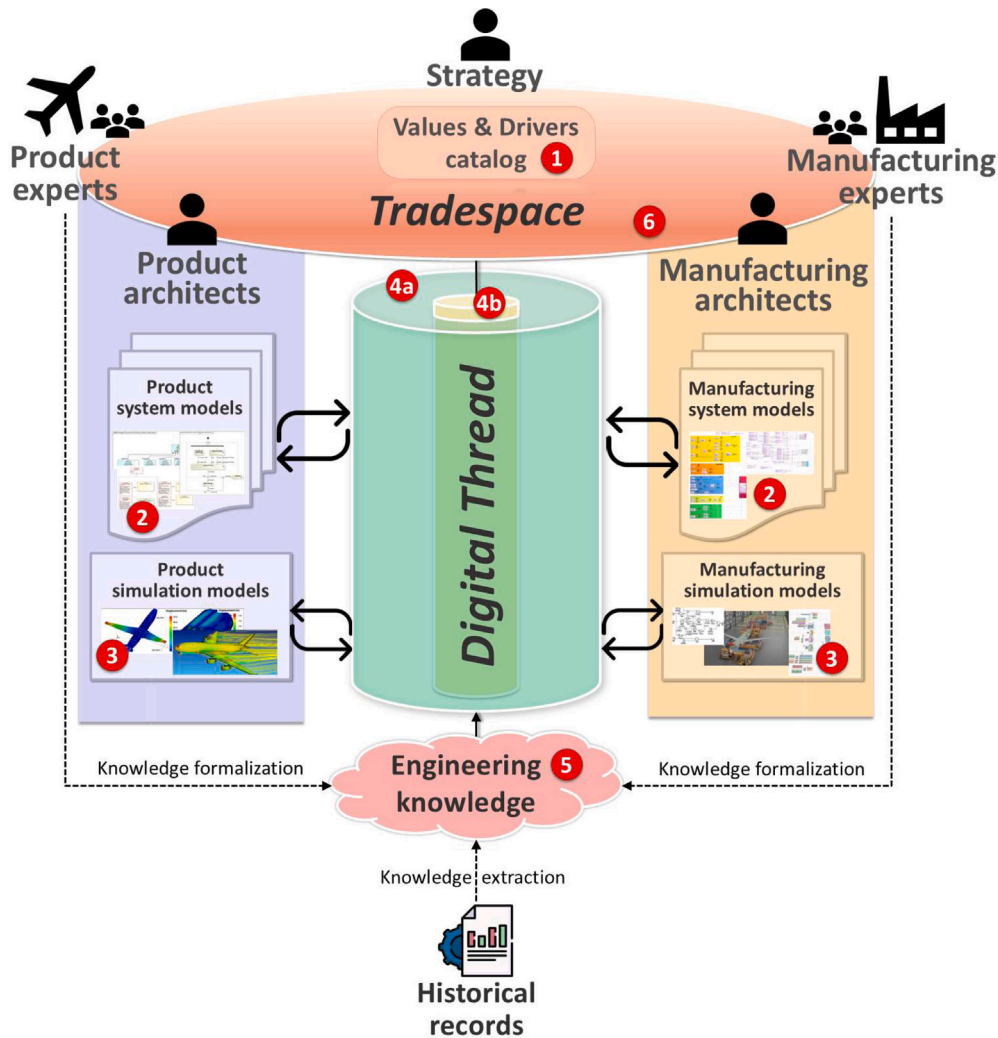


Fig. 3. Ontology-based digital thread framework.

and drivers, this module aims to orient the development of each system toward converging tracks from the initial stage of development. Strategy stakeholders define a hierarchy among these values and drivers from which top level program requirements will be cascaded.

2. System models

During the design phase, aircraft and manufacturing engineers use the MBSE methodology to model their requirements and system architectures. The standardized engineering processes realized with modeling languages such as SysML allow for a structured approach for complex system development. By using the *Requirement-Functional-Logical-Physical (RFLP)* decomposition, as recommended by Li et al. [17], engineers from product and manufacturing domains can collaborate on their system of interest

with multi-disciplinary views connected to the design requirements. Thus, these digital system models permit to efficiently manage the complexity while cascading design changes through information traceability. With the use of SE principles and RFLP modeling, both physical and functional integrations are supported and allow the manufacturing requirements verification to be considered during the aircraft design.

3. Simulation models

Basic tools or complex multi-physics simulation softwares draw upon data derived from MBSE architectures to generate additional information. From aircraft aerodynamic studies to manufacturing flow simulations, their results are used to verify requirement compliance and rank various system concepts. Thus, engineers can explore the design solution space while achieving

early optimization up to a certain degree. Later in the lifecycle, these models can be employed as part of *Multi-Disciplinary Analysis and Optimization (MDAO)* and *Design of Experiments (DoE)* activities for more in-depth optimizations. The data exchange pipeline providing the inputs from the MBSE environment and propagating the simulation outputs is ensured by the core of this framework: the digital thread.

4. Digital thread

This digital thread is one of the main contribution of this paper. Interfacing with all the other modules, it is composed of a knowledge base (4a) that serve as a communication medium between product and manufacturing engineers enabling information traceability. Acting as a single source of truth, tailored graph queries answer the diverse stakeholders concerns regardless of the required data format. Furthermore, the ontological core (4b) of this digital thread provides a shared conceptualization enabling semantic interoperability and a common understanding between the different domains, formalisms and degrees of abstraction. Moreover, the knowledge representation and reasoning capabilities provided by ontologies allow to enrich this digital thread with insights supporting cross-domain design decisions and trade-offs.

5. Engineering knowledge

As this research addresses early CE, this module contains cross-domain knowledge supporting design decision and trade-off analysis during the conceptual design phase. Despite significant efforts toward robust methods development a gap remains for structured knowledge capture within KBE/OBE approaches. The use of Big Data and AI approaches is envisioned to be integrated to more traditional knowledge acquisition techniques [29,34,37]. Another contribution of this paper is novel a method blending expert-centric and data-driven knowledge to benefit from human intuition and the robustness of large datasets.

6. Tradespace

Incorporating the outputs of modeling and simulation activities, the trade-space module (6) allows multi-attribute exploration for concurrent design. Oriented by the Values and Drivers catalog, MBSE architectures, simulation results, and additional engineering knowledge, the stakeholders are able to conduct trade-off analysis converging toward global optimum architectures.

Fostering syntactic, semantic, and organizational interoperability [47], this framework aims to facilitates cross-functional collaboration by centralizing system information and design rules thereby supporting CE in short iteration loops. The creation of the digital thread, consists mostly of ontology development that rely on organizational and domain-specific knowledge. The development of ontologies allows for design information and knowledge to be shared and maintained with minimal efforts in a collaborative way. This study leverages the OBE methodology named MfM to develop this digital thread for several reasons. Firstly, MfM is used as a central part of MBSE approaches. As this study is grounded on MBSE for aircraft and manufacturing system design, MfM's compatibility with MBSE environments is conceived to support the integration of MBSE artifacts while interfacing with the rest of digital tools and services. Secondly, this method has demonstrated its business value through numerous industrial implementations. Furthermore, this research has benefited from a proximity with the research group developing MfM. This proximity has led to rich working sessions and the elaboration of an extension proposal for knowledge acquisition.

4.2. MfM methodology

The *Models for Manufacturing (MfM)* is an OBE methodology developed to support complex manufacturing system design. By structuring the management of ontologies, MfM helps to capture functions, behaviors and semantics of the systems of interest. Used at the center of MBSE

approaches, this methodology provides a shared conceptualization and knowledge representation capabilities that support engineering activities [18]. As illustrated in Fig. 4, MfM is based on a 3-Layers Model (3LM) with each layer independent for modularity and maintainability aspects. The *Data layer* gathers everything that store data, the *Service Layer* comprises the software services, and the *Ontology layer* incorporates the knowledge of the organization. The core of MfM is the *Ontology layer* where the knowledge is collected, stored, managed and reused through four models: *Scope*, *Data*, *Behavior*, and *Semantic*.

MfM implementation is composed of two steps: the ontology development and the ontology instantiation. During the ontology development, expert's knowledge and historical records are exploited from the data layer to capture functions, behaviors and semantics of the systems of interest. Through iterative modeling sessions with engineers, architects, and domain experts, the four ontological models are elaborated.

The *Scope model* defines the limits of the ontology to facilitate understanding and agreement between the stakeholders. Kept as simple as possible, it identifies key concepts and functions which are respectively described in the *Data model* and the *Behavior model*.

The *Data model* develops the conceptualization with taxonomic structure, relationship, and attribute definition. This central representation is agnostic to any tool or language.

The *Behavior model* represents how the concepts interact with each other. Defining simulation requirements or activities from the *Scope model*, it specifies rules, procedures, and constraints.

Finally, the *Semantic model* ensures the seamless interfaces between the other layers. Providing consistency in the connection between models and tools, it enables interoperability between the diverse information formats.

Morales-Palma et al. [48] have proposed meta-models for common specifications regarding MfM implementation. With this defined formalism, the elaboration of the ontological layer is supported by a modeling structure easily human-readable while remaining concise and ensuring information longevity. The correspondence between the proposed ontology-based digital thread framework and MfM is synthesized in Table 2.

The development of the *Scope*, *Data*, *Behavior* and *Semantic* models forming the ontological core of the digital thread (4b) is detailed in Section 5. Subsequently, the populated knowledge base (4a) containing the instances, their interfaces, and engineering rules will be developed in Section 6 through a case study.

4.3. Hybrid knowledge acquisition method

This paragraph proposes an original approach to enrich the current knowledge acquisition process within OBE. Blending expert-centric and data-driven approaches, it leverages human expertise to drive data-mining approaches which benefit from the robustness and scalability of large databases. As illustrated in Fig. 5, the notion of cross-domain knowledge pattern is at the core of this approach.

First, expert-centric formalization delineates patterns of knowledge, identifying key concepts and properties for early cross-domain impact analysis. These patterns are then used at the foundation of data-driven studies which, conducted on large industrial databases, enable the extraction of explicit engineering rules.

Designed to formalize engineering rules and constraints, this method address the development of the *Behavior model* of the ontology layer. Functioning in a complementary manner to more traditional methods, it can be regarded as an enrichment of MfM.

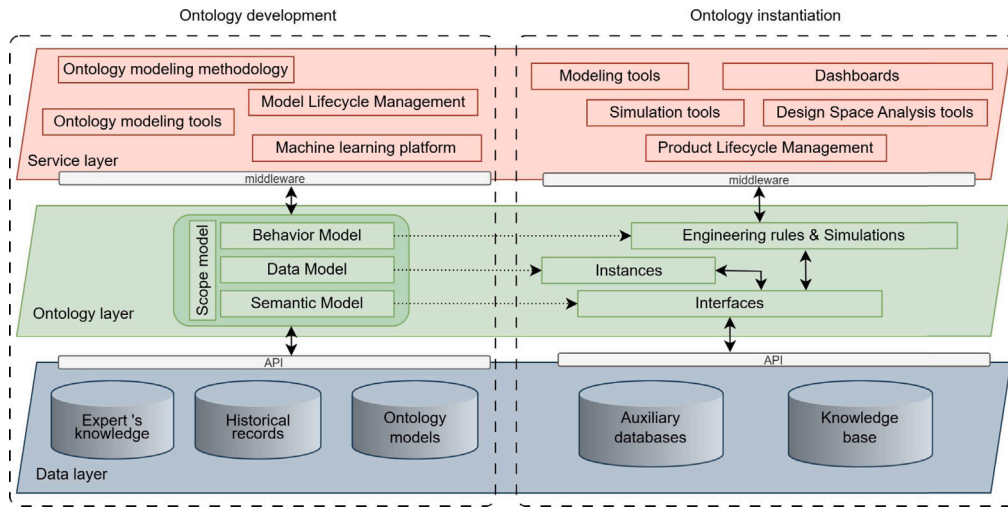


Fig. 4. 3LM framework adapted from [29].

Table 2

Correspondence between the proposed framework and MfM.

Framework module	MfM development	MfM instantiation
Values and Drivers catalog (1)	∅	Auxiliary databases
System models (2)	∅	Instances, Modeling tools, auxiliary databases
Simulation models (3)	∅	Simulation tools, simulations, auxiliary databases, and knowledge base
Ontological core (4b)	Scope, Data, Semantic, and Behavior models	∅
Knowledge base (4a)	∅	Instances, interfaces, engineering rules and simulations
Engineering knowledge (5)	Expert's knowledge and historical records	∅
Tradespace (6)	∅	Dashboards and design space analysis tool

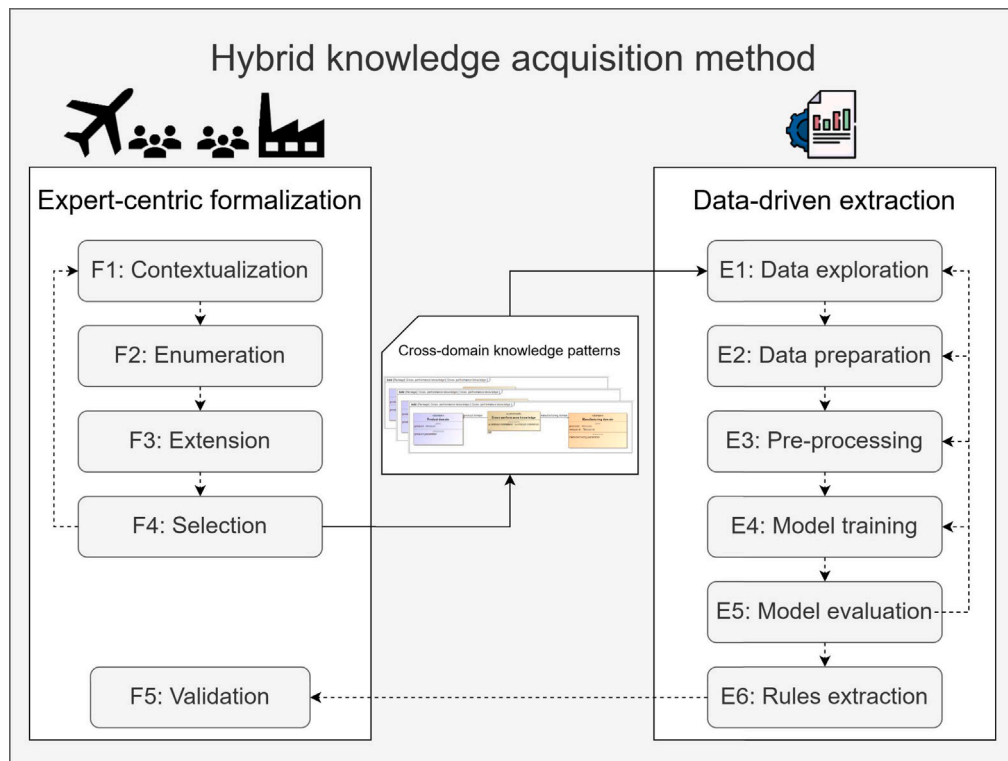


Fig. 5. Hybrid knowledge acquisition method.

4.3.1. Expert-centric formalization

Through the iterative modeling sessions promoted by MfM for knowledge acquisition, experts from aircraft and manufacturing domains are asked to identify a list of patterns describing cross-domain

impact. This list aims to be completed, corrected, and strengthened along the iterations. As illustrated in the left part of Fig. 5, the typical session consists in four distinct steps. *Contextualization (F1)* is performed to present the research objectives to the experts. This

step is supported by the *Scope model* which helps to have a common understanding about the addressed issue between experts with diverse backgrounds and points of view. Then, each pattern from the list is discussed to be refined, validated, or refuted through *Enumeration (F2)*. Afterward, for *Extension (F3)*, new patterns can be added to the list if the experts identify new kinds of cross-domain impacts. Finally, *Selection (F4)* concludes the session by asking the experts to select one pattern which seems the more relevant to support early concurrent and collaborative engineering. Each selected pattern aims to be the input of a data-driven study.

4.3.2. Data-driven extraction

Data-driven studies aims to derive explicit engineering rules from a cross-domain knowledge pattern. In this regard, these studies employ conventional data science techniques on large industrial databases with the aim of executing interpretable machine learning models [35,36]. The interpretability of such models allows to extract explicit *if-then* rules from their inner structure. As illustrated in the right part of Fig. 5, the data-driven extraction is composed of six steps.

Data exploration (E1) consists in a rigorous investigation across the data sources of the organization to find the pattern's concepts and parameters. As knowledge patterns link concepts from product and manufacturing domains, the information is often stored in heterogeneous formats. Thus, transformation and joining processes may be needed for the *Data Preparation (E2)* into a homogeneous input dataset.

Once this preparation is done, conventional *Pre-processing (E3)* techniques are applied to facilitate the learning process while avoiding undesired biases [49]. Some of the most common pre-processing techniques are data cleaning, outlier management, dataset balancing, value normalization and feature encoding. The next step is the *Model training (E4)*. As expressed above, the core of this approach relies on the interpretability of machine learning models such as *Decision Tree* or *Random Forest*. The processed dataset is then used for a Grid Search training which explores the performances of the models over predefined sets of hyper-parameters values. Subsequently, a *Model evaluation (E5)* is conducted on the model with the hyper-parameters exhibiting the best performances through a data subset which was not used during the training. Different metrics can be employed depending on whether the knowledge pattern involves a classification or a regression task. The training process is considered successful if the metrics satisfy a predefined threshold. If the model evaluation does not satisfy the expected threshold, either additional iterations are conducted on the previous steps, or the learning process is considered unattainable with the available data.

Finally, the *Rules extraction (E6)* is performed with algorithms corresponding to the machine learning model [35,36,50]. The explicit rules are ultimately validated by the experts (*F5*) and integrated in the *Behavior model*.

By combining human expertise with the learning scalability of AI techniques, this knowledge acquisition method provides complementary means to integrate cross-domain engineering knowledge within this framework to support early concurrent and collaborative engineering.

As described in Table 3, the proposed framework and method can be compared to similar approaches with the addressed design phase, the knowledge acquisition techniques, its knowledge representation, and how systems are modeled and integrated.

5. Co-architecture ontology development

This section implements MfM for the development of the digital thread's ontological core (*4b*) to answer the identified concerns of co-architecture within the aerospace industry. While this ontology aims to be developed and specialized in specific use-case contexts, it provides a common basis for diverse applications of the proposed framework. This research has benefited from a close collaboration

with partners from Airbus Commercial Aircrafts, which allowed us to organize iterative modeling sessions with experts from aircraft and manufacturing domains. The models presented in this section result from these sessions.

5.1. Scope model

The formalization of stakeholders, activities and deliverables permits a common comprehension of the co-architecture process. As illustrated in Fig. 6, the *Scope model* encompasses the activities involved for conducting the co-architecture between aircraft and manufacturing system design.

Top-level requirements, and technology bricks from each domain are the first inputs of this model. Describing the AS-IS capabilities, the technology bricks are assembled to generate a list of aircraft concepts. Cross-domain knowledge supports this step by managing dependencies and conflicts between bricks thereby reducing the number of concepts to explore while ensuring their validity.

Concepts from this list are then provided to product engineers for the development of their associated architectures. First product breakdown structures are given to the manufacturing engineers, who, supported by cross-domain knowledge, define their own architectures and share constraints with the product teams.

Finally, trade-off studies are performed between the diverse architectures. Enhanced by cross-domain knowledge for early impact assessment, iteration loops are performed, until both product and manufacturing architectures are satisfying the requirements.

5.2. Data model

The *Data model* is agnostic to any tool, framework, or methodology. As illustrated in Fig. 7, aircraft and manufacturing architectures are described following the *Product Process Resource (PPR)* decomposition promoted by A.F. et al. [51]. The PPR structure is widely adopted across industry and provides a high modularity capability for the representation of product and manufacturing system.

Instantiated in use-case contexts, this model shall be specialized by adding classes and properties in a modular manner while still following the BFO/IOF-Core structure [24,32].

5.3. Semantic model

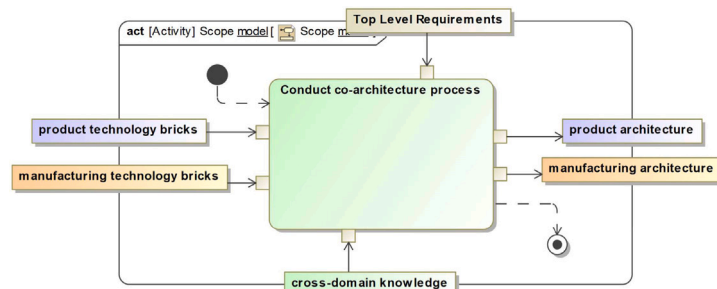
The *Semantic model* is the primary interface between MBSE artifacts and the digital thread. Therefore, this model is highly specialized according to the use-case application and the corresponding *Data model*. However, the *Requirement-Functional-Logical-Physical* decomposition [17] chosen as a MBSE reference has permitted to elaborate a first generic model. As illustrated in Fig. 8, *Product* elements refer to *Physical* artifacts from the product MBSE architecture while *Process* and *Resource* elements correspond respectively to *Functional* and *Physical* artifacts from the manufacturing MBSE architecture.

5.4. Behavior model

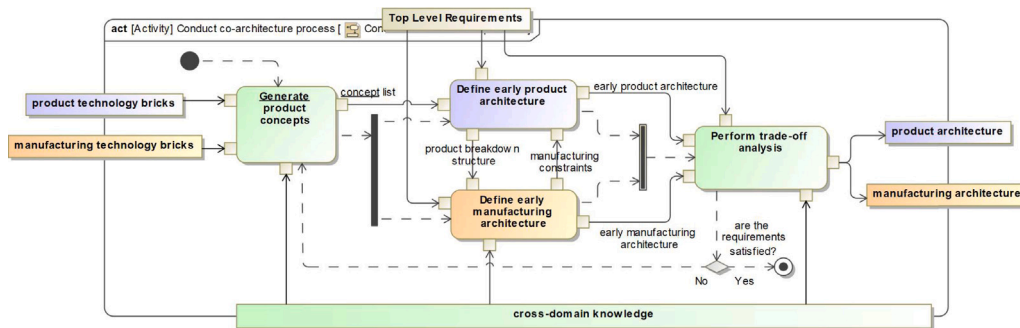
This research has leveraged the expert-centric knowledge formalization protocol described in Section 4.3.1 to establish generic knowledge patterns. Acting as components of the *Behavior model*, they specify rules and constraints that support impact assessment during the conceptual design phase. Some of the resulting patterns are shown in Fig. 9. While remaining at a high degree of abstraction, by linking concepts from the *Data model*, these patterns allows to delineate additional relationships between aircraft and manufacturing MBSE architectures.

Table 3
Comparative table with existing frameworks.

Artifact	Curran et al. [30] Methodology	Tang et al. [2] Framework	Dunbar et al. [25] Framework	This paper Framework & method
Design phase	All design phases	Conceptual	All design phases	Conceptual
Knowledge acquisition	Various human-centered techniques	DoE, surrogate modeling, and sensitivity analysis	Not mentioned	Modeling session with experts and hybrid method
Knowledge representation	Ontologies	Surrogate models and Feature importance	Ontologies	Ontologies
System modeling	Not mentioned	CAD and Physic-based modeling	MBSE	MBSE
Integration	Ontologies	Third-party tools	Ontology-based digital thread	Ontology-based digital thread



(a) Scope model - black box view.



(b) Scope model - white box view.

Fig. 6. Scope model.

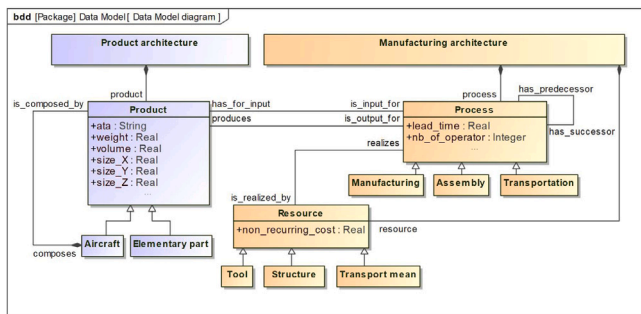


Fig. 7. Data model.

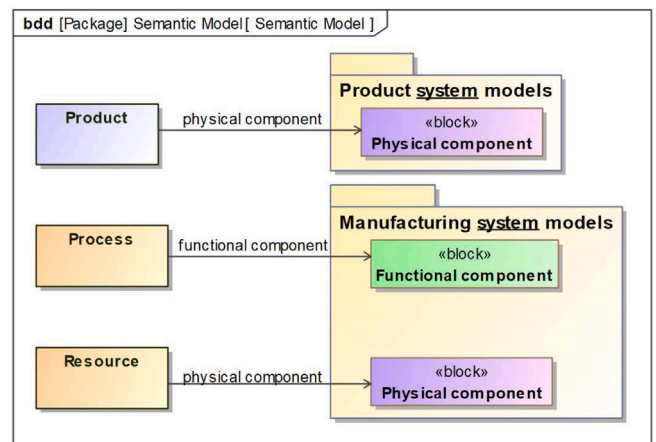


Fig. 8. Semantic model.

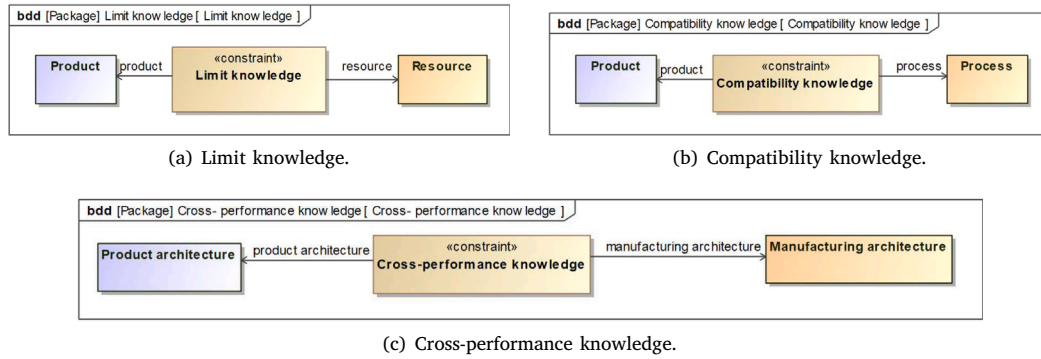


Fig. 9. Generic cross-domain knowledge patterns.

6. Case study

As previously cited, this research has benefited from a close collaboration with industrial partners. Included in an innovation project involving a new generation of aircrafts using hydrogen fuel, this section aims to demonstrate the added value of the contributions detailed in Sections 4 & 5 through a case study.

6.1. Problem statement

In the context of this project, architects from product and manufacturing domains have issues to iterate through a co-architecture process. Indeed, problems of interoperability between the MBSE environment and simulation models hinder manufacturing impact analysis. A heavy custom solution has been previously implemented to extract the required information from the MBSE architectures. However, this solution demanded high efforts at each iteration while being difficult to maintain. Furthermore, when this difficult process was achieved, manufacturing architects were faced with another challenge: the workload estimation.

The workload is the amount of work-time required to achieve a manufacturing process. Workload estimation is one of the initial steps of the manufacturing performance analysis. From a process sequence and the associated workloads, manufacturing engineers define product lines and allocate the workforce. After balancing the lines, early architectures can be evaluated.

From a first workload estimation, the rest of the manufacturing performances can be cascaded with various tools. However, this task remain highly experience-based and can require some exchanges with domain experts. By shortening the time needed to estimate this workload, iteration loops could become closer, allowing faster convergence between product and manufacturing architectures toward a global optimum.

The aim of the following paragraphs is specialize and instantiate the co-architecture ontology to enable early workload estimation through hybrid knowledge acquisition method and to ensure the interoperability of MBSE architectures with the rest of the digital environment.

6.2. MfM instantiation

6.2.1. Data model

In this project, the *Resource* management is not addressed. Only *Product* and *Process* concepts are developed. As illustrated in Fig. 10, a *Product* is characterized by its shape, mass, material, and its *ata*. Products are also used as input and output of *Processes* which are specialized in 4 categories: *Welding*, *Assembly*, *Check or Inspection*, and *Control*. Each process is also defined with properties such as *successor/predecessor* and *workload*.

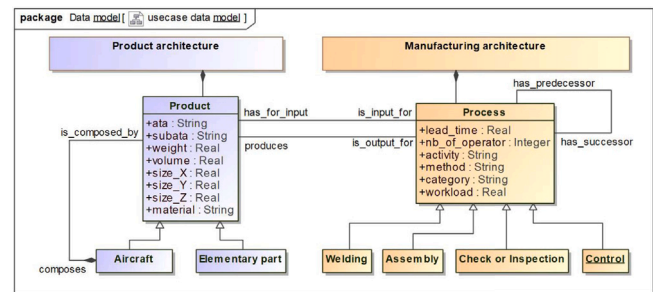


Fig. 10. Data model.

6.3. Behavior model

This paragraph aims to leverage the method for knowledge acquisition outlined in Section 4.3 to extract executable cross-domain knowledge related to workload estimation. Workload estimation is categorized as a cross-performance knowledge (seen in Fig. 9(c)). A new round of the expert-centric formalization has resulted in a detailed specialization illustrated in Fig. 11. This pattern identifies key parameters from product and manufacturing domains (e.g. *weight*, *volume*, *material* and *process category*) to play a significant role in the estimation of the workload.

Oriented by this pattern, the data-driven part of the knowledge acquisition method has been conducted. Through the exploration of industrial databases, product information from past programs was found in legacy datasets and their associated manufacturing information was available in operational databases. These parameters were then linked and transformed into a homogeneous dataset on which pre-processing techniques were performed.

Afterward, a *Random Forest Regressor* model has been iteratively trained and evaluated with the *coefficient of determination* (R^2) and the *Root Mean Squared Error* (*RMSE*) metrics. The combined assessment of a R^2 over 70% and a *RMSE* below 500 min was defined with experts as a successful learning process. It is important to note that the objectives of this project are not to have estimations with a high degree of precision, but to perform quick approximations enabling short iteration loops.

As illustrated in Fig. 12, a validation sample, which has not been used during the training, was employed to compare the measured workload values to their associated predictions. The accuracy of the predictions, represented by the blue dots, can be visualized by their distance to the central red line. With a R^2 of 94% and a *RMSE* of 265 industrial minutes, a concrete trend can be noticed although some outliers remain. This performance has met the metrics requirements, thereby confirming the learning process.

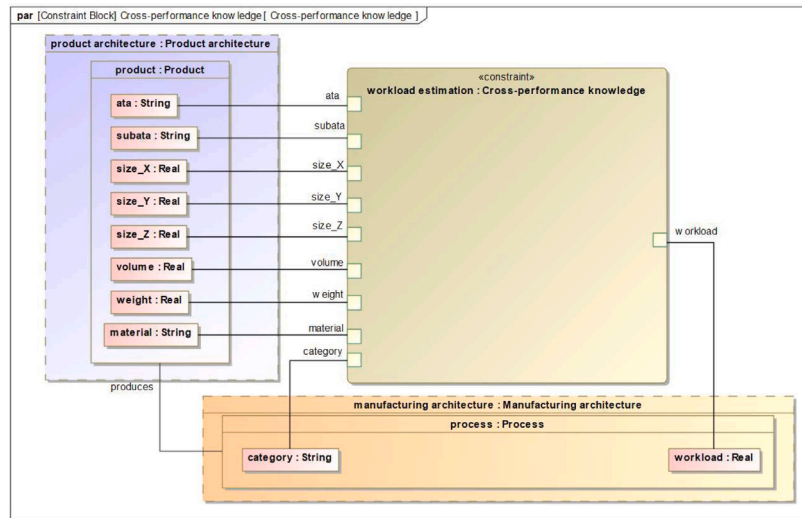


Fig. 11. Workload estimation as behavior model component.

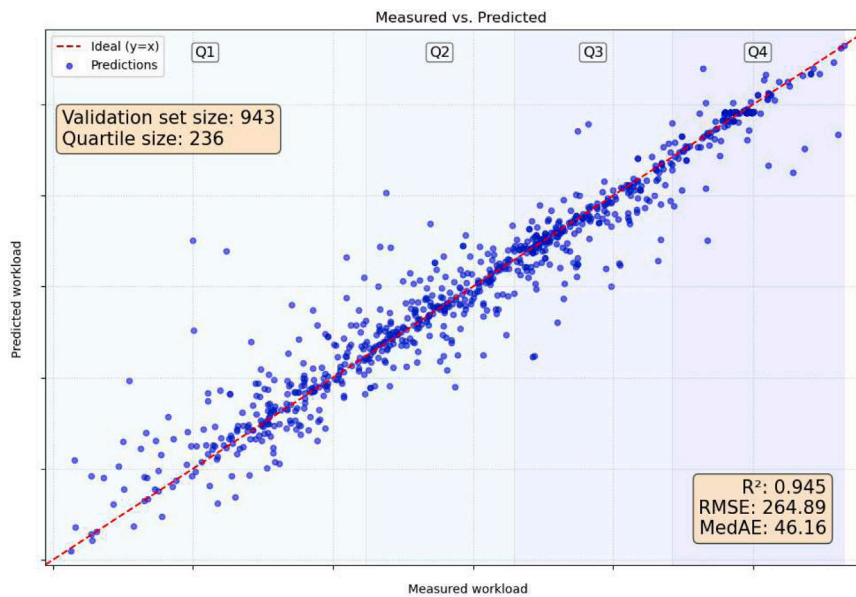


Fig. 12. Random Forest Regressor evaluation.

Table 4
Most occurring extracted rules.

nb occurrence	Rule body	Rule head
222	IF volume ≤ 703 566 965 mm ³	THEN workload = 343.06 IM
212	IF size_Z ≤ 2600.76 mm	THEN workload = 555.65 IM
188	IF volume > 703 566 965 mm ³	THEN workload = 958.6 IM
162	IF size_Z > 2600.76 mm	THEN workload = 2548.17 IM
135	IF category = “assembly”	THEN workload = 1571.49 IM
124	IF ata = “21”	THEN workload = 121.3 IM
115	IF weight ≤ 4154.8 g	THEN workload = 385.22 IM
107	IF size_Y > 891.84 mm	THEN workload = 956.86 IM

Finally, the SIRUS algorithm proposed by Bénard et al. [50] has been executed on the trained *Random Forest Regressor*, deriving *if-then* rules from its inner structure while preserving the model’s accuracy. Attention has to be paid that these rules should not be considered individually. The complete ruleset has to be used for each prediction by averaging the results of each rule with its weight. A subset of the resulting rules are listed in Table 4.

After validation with industrial experts, the workload estimation knowledge pattern has been instantiated with the ruleset. Incorporated into the *Behavior model* (see Fig. 13), this knowledge becomes accessible to any stakeholder, providing a mechanism for instantaneous cross-domain impact assessments in an MBSE environment.

6.3.1. Semantic model

The *Semantic model* ensures the seamless interface between the *Data model* and the MBSE environment. Product and manufacturing architectures were developed in SysML using a RFLP decomposition. Due to confidentiality aspects, the MBSE models cannot be shared. However, illustrative models from Fig. 14 have been drafted for illustrative purposes. Specialized from the generic *Semantic model* in Fig. 8, its instantiation focuses on the physical layer from the product architecture and the functional layer of the manufacturing architecture.

All elements from the *Data model* are mapped to their related MBSE artifacts through the *Semantic model* as illustrated in Fig. 15. Concepts are mapped with *scope* and *type* information while their properties rely on *Opaque Behaviors* to derive the right information. *Opaque Behaviors*

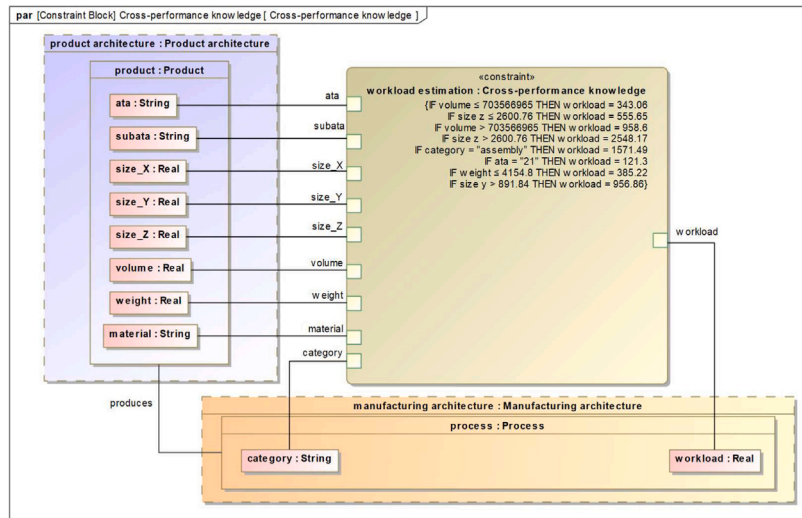
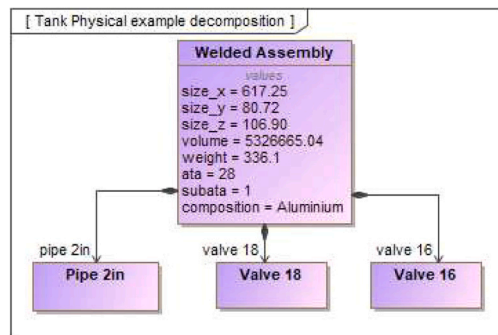
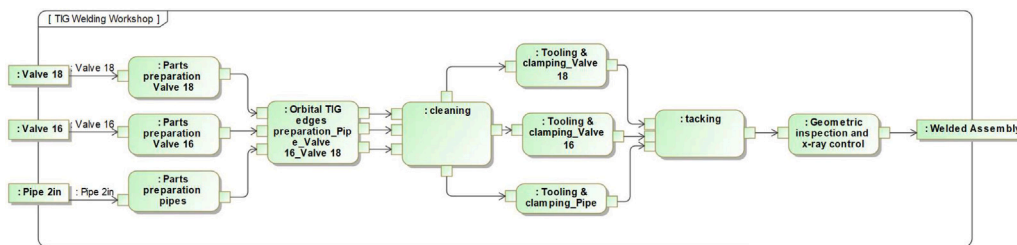


Fig. 13. Extracted rules formalized in the behavior model.



(a) Illustrative product model - Physical layer.



(b) Illustrative manufacturing model - Functional layer.

Fig. 14. System models.

can range from simple value retrieval to more complex navigation through the MBSE framework.

It should be noted that in case of multiple MBSE projects by different teams with heterogeneous tools, frameworks or formalisms, additional semantic models would be required to map all the involved artifacts.

6.4. Results

The MfM instantiation results in both architectures and their interdependencies instantiated in the *Data model*. This instantiation has been performed through the interfaces defined by the *Semantic model*. Using an internal plugin developed in Cameo Systems Modeler named MBSELab [52], the instantiated *Data model* is automatically exported in an OWL file that is uploaded on a Neo4J server as shown in Fig. 16.

Integrating MBSE artifacts across domains in a tool-agnostic manner, this knowledge graph then becomes a communication medium within the rest of the digital environment. The shared conceptualization of overlying ontology ensures semantic interoperability with the rest of the digital environment through flexible queries.

Although the workload estimation ruleset has been integrated in the *Behavior model* for enriched cross-domain impact assessment within MBSE environment, such ruleset could be incorporated in the knowledge base with Semantic Web Rule Language (SWRL) or other semantic web approaches [53].

By sharing, and maintaining design information and engineering knowledge across systems and throughout various lifecycle phases, this digital thread concept can be considered as a foundational component toward Cognitive Digital Twins.

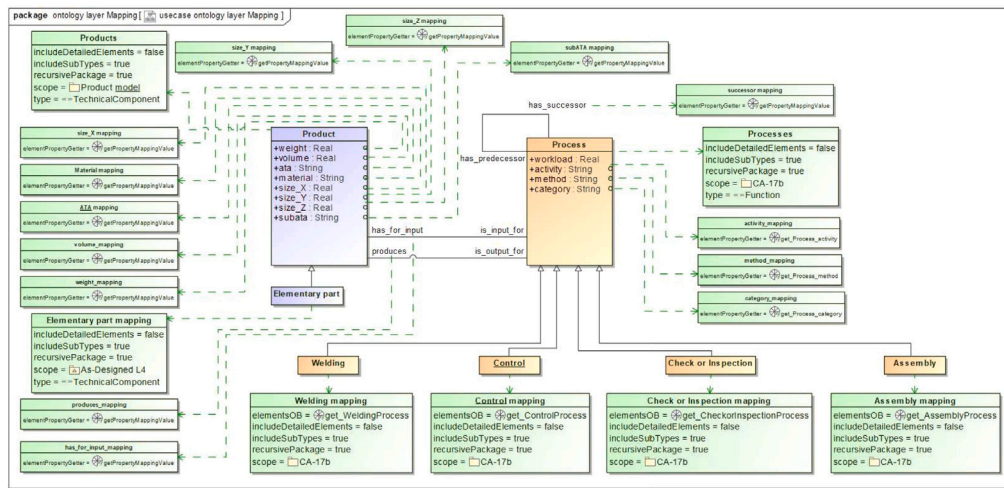


Fig. 15. Semantic model.

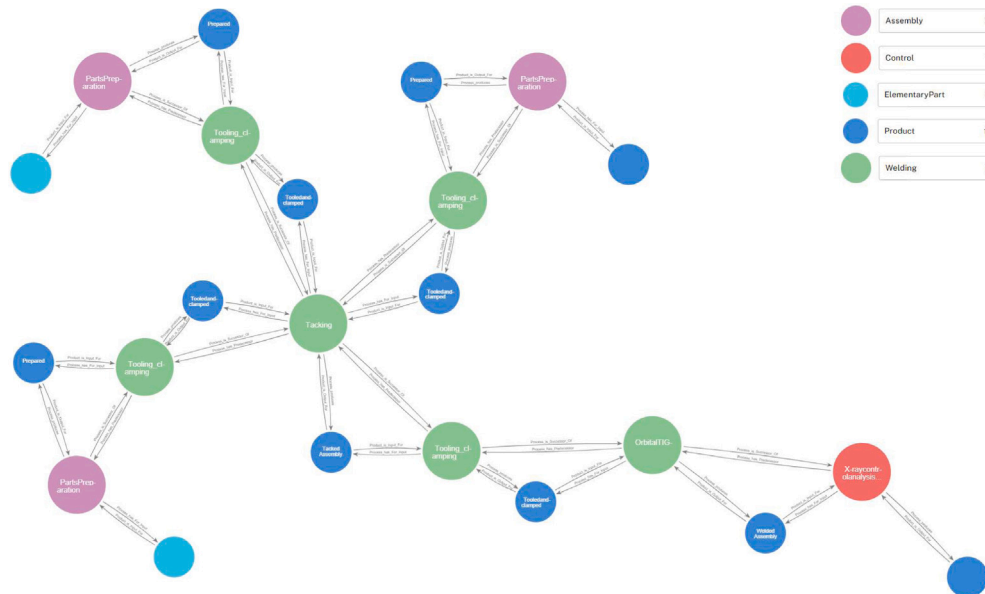


Fig. 16. MBSE architecture extracted in the digital thread.

7. Discussions and outlooks

In this paper, an ontology-based digital thread framework has been proposed to enhance early collaboration between product and manufacturing domains. Implementing the MfM methodology, multiple ontological models were developed, defining the structure of a digital thread supporting the co-architecture process of next-generation aircrafts. While key stakeholders and activities were defined in the *Scope model*, the *Data model* has provided a shared conceptualization by describing tool-agnostic structures and relationships. Acting as a bridge between the MBSE environments and the ontology, the *Semantic model* has ensured interoperability with the rest of the digital environment. Finally, the *Behavior model* has provided explicit knowledge for early impact assessment by leveraging a novel hybrid knowledge acquisition method, blending expert-centric and data-driven practices,

As this research focused on methods, their principles, and their implementations, the scalability of the leveraged approach has not been addressed. The authors believe that concerns about scalability may arise with large MBSE models before they become an issue within the digital thread and semantic web technologies.

The authors emphasize that this framework relies on MBSE modeling. Therefore, inconsistencies across system models could impede its deployment. Future work should address inconsistencies detection and management between MBSE architectures through SWRL or Shapes Constraint Language (SHACL). Nevertheless, the approaches applied in this paper remain relevant for the integration of consistent MBSE models developed by multiple teams employing different modeling tools, languages or frameworks.

Furthermore, while this case study has demonstrated innovative capabilities for model integration, semantic interoperability and knowledge acquisition, considerations about knowledge management still need to be addressed. Clear guidelines for knowledge validation, maintenance, and reuse need to be defined. Future work should tackle the knowledge lifecycle with the evolution of capabilities from product and manufacturing domains.

The approach demonstrated in this paper was based on expert qualitative validation. Nevertheless, it is important to note that the SIRUS algorithm is inherently limiting the tree depth of *Random Forest* models. For knowledge necessitating deeper trees, a similar approach can be employed with *Decision Trees* at the cost of a bigger ruleset. Also, only one cross-domain knowledge pattern has been studied in

this paper. More patterns supporting CE should be considered. It is expected that some of these patterns will not benefit from the data-driven knowledge extraction. Patterns such as *Compatibility knowledge* (see Fig. 9(b)) could be instantiated with expert-centric formalization alone. An interesting perspective nonetheless, is the combination of the extracted rules with manufacturing requirements. Indeed, as the rules are usually directed from the product toward the manufacturing system, they can be reversed using requirements as limits thereby generating manufacturing constraints over the product, prior to initial product breakdown decomposition.

Moreover, future perspectives should integrate the support system design to consider the complete product lifecycle. Additional considerations could also extend the proposed framework toward the preliminary and detailed design phases. In that regard, this framework would serve as a robust foundation for Cognitive Digital Twin development.

Finally, the authors underline that the proposed framework and approaches, despite their development within an aerospace context, are applicable to other industries with minimal adaptation. The structures leveraged such as RFLP and PPR are agnostic to any specific system and could be employed for other complex engineering sectors such as the automotive, naval, or railroad industries.

8. Conclusion

Early concurrent and collaborative engineering between product and manufacturing domains is a key endeavor for aerospace companies. However, this approach requires a high degree of collaboration and knowledge sharing among the involved stakeholders.

This paper presented an ontology-based digital thread framework to integrate cross-domain engineering activities during the conceptual design phase. Combining MBSE and KBE approaches, this framework leveraged standardized engineering processes with multi-disciplinary views and information traceability. Through a flexible communication medium it provides a common conceptualization and engineering knowledge supporting design decisions.

The implementation of an OBE methodology has permitted interoperability between SysML models and the rest of the digital environment by elaborating easily maintainable ontological models collaboratively. Furthermore, the proposed hybrid knowledge acquisition approach has enriched this methodology by leveraging the combination human expertise with the robustness of large datasets. This approach has resulted in the extraction of a ruleset imitating the behavior of a machine learning model. Such knowledge has been incorporated into the ontology to support early cross-domain impact assessment, thus shortening iteration loops for faster convergence toward a global optimum.

By employing ontologies to improve interoperability within engineering activities and by providing additional insights supporting design decision, this ontology-based digital thread framework offers compelling ways to support knowledge-driven concurrent and collaborative engineering during the conceptual design phase.

Although this paper introduced the general idea, future work should address more knowledge patterns while focusing on the framework's deployment over diverse use-cases.

CRedit authorship contribution statement

Elliott Duverger: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alexis Aubry:** Writing – review & editing, Validation, Supervision, Funding acquisition. **Rebeca Arista:** Supervision, Resources, Methodology, Conceptualization. **Eric Levrat:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Elliott Duverger reports financial support was provided by Airbus SAS. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The work presented in this paper results from the ACTE MBSE research project funded by Airbus SAS.

The authors would like to thank all Airbus colleagues for their expertise and time, crucial to this contribution.

Data availability

The data that has been used is confidential.

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