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### ► **To cite this version:**

Eliott Duverger, Rebeca Arista, Alexis Aubry, Eric Levrat. An ontology-based engineering methodology to support early concurrent engineering. 11th IFAC Conference on Manufacturing Modelling, Management and Control, MIM 2025, Jun 2025, Trondheim, Norway. pp.2838 - 2843, <10.1016/j.ifacol.2025.09.477>. <hal-05279682>

**HAL Id: hal-05279682**

**<https://hal.science/hal-05279682v1>**

Submitted on 18 Oct 2025

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# An ontology-based engineering methodology to support early concurrent engineering

Elliott Duverger<sup>\*,\*\*</sup> Rebeca Arista<sup>\*\*</sup> Alexis Aubry<sup>\*</sup>  
Eric Levrat<sup>\*</sup>

<sup>\*</sup> *Université de Lorraine, CNRS, CRAN, F-54000 Nancy, France*  
(e-mail: [elliott.duverger@univ-lorraine.fr](mailto:elliott.duverger@univ-lorraine.fr), [alexis.aubry@univ-lorraine.fr](mailto:alexis.aubry@univ-lorraine.fr),  
[eric.levrat@univ-lorraine.fr](mailto:eric.levrat@univ-lorraine.fr))

<sup>\*\*</sup> *Airbus SAS, Blagnac 31700, France*  
(e-mail: [rebeca.arista@airbus.com](mailto:rebeca.arista@airbus.com))

**Abstract:** The increasing complexity of the aerospace industry has highlighted the necessity to fathom the entire product lifecycle. From initial conceptualization, engineers are meant to consider the production, maintenance, and decommissioning phases of an aircraft. By identifying how design decisions made in the conceptual phase impact the other systems involved, overall development time, costs, and quality can be significantly improved. Over the past decades, digital models have been employed in the design of complex systems, the management of data integration, and the formalization of domain knowledge. This paper examines the application of an ontology-based engineering methodology to support early concurrent engineering driven by knowledge.

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**Keywords:** Concurrent engineering, Model-Based Systems Engineering, Ontology-Based Engineering, Knowledge acquisition

## 1. INTRODUCTION

For several decades, the aerospace industry has aspired to develop aircrafts and their manufacturing systems altogether as soon as possible. This approach is intended to enhance the development, time, costs, and quality through global perspectives and early impact assessments. Concurrent engineering is an approach addressing this issue and is defined as “*a systematic approach to the integrated and concurrent design of products and their related processes, including manufacturing and support.*” (Wognum and Trienekens, 2015). This paper builds upon this principle and focuses on concurrent engineering between product and manufacturing domains to address the identified objectives within the aerospace industry.

Concurrent engineering has the potential to be significantly beneficial. However, its implementation at conceptual phase demands a considerable degree of collaboration between engineers and the integration of knowledge across domains. Furthermore, the complexity of aircrafts and manufacturing systems, combined with the inherently high level of abstraction of early design, pose a significant challenge in identifying influential cross-domain parameters. The advent of digital transformation has facilitated the integration of model-based and knowledge-based methods, thereby enhancing engineering collaboration for complex system development. Moreover, the maturity in some machine learning techniques has opened new perspectives for knowledge mining.

This paper proposes to apply a combination of such methods to support early knowledge-driven concurrent

engineering. The remainder is structured as follows: *Section 2* presents contributions related to model-based and knowledge-based approaches supporting concurrent engineering. *Section 3* summarizes the research gap. *Section 4* presents a methodology to support early concurrent engineering and proposes an extension for knowledge acquisition. *Section 5* illustrates a generic implementation for early concurrent engineering. Finally, *Section 6* holds discussions while *Section 7* concludes this work and presents perspectives.

## 2. RELATED WORK

### 2.1 MBSE and Ontologies for Concurrent engineering

Model-Based Systems Engineering (MBSE) has been used to address system complexity and information traceability. Li et al. (2020) has leveraged a decomposition of Requirements, Functional, Logical, and Physical models to manage interdependencies between product and manufacturing artifacts. The use of *Systems Engineering* principles with models facilitates complex system design while supporting collaboration between product and manufacturing engineers via a standardized modeling language, multidisciplinary views and information traceability. Nevertheless, considering the large scale of aerospace complex systems, the authors mention the need for a more flexible solution addressing data integration issues in an extended enterprise environment.

Works such as Madni and Sievers (2018) have identified ontologies as an important part of the MBSE methodology. The close collaboration between engineers from different

domains require semantic interoperability and the knowledge sharing capabilities which are provided by ontologies. A combination of model-driven architecture and ontologies has been proposed by Chungoora et al. (2013) to improve knowledge sharing across product design and manufacturing. Sanya and Shehab (2015) developed a framework that promotes the use of modular ontologies for complex system modeling. The author have linked ontologies from product, process and resource domains to enhance collaboration capability and to provide interdisciplinary knowledge. On a more technical side, Dunbar et al. (2023) propose ontologies to support reusability and interoperability between domains by developing concepts such as digital threads. The authors highlight the need for a top-level ontology driving co-development principles across domains. Similar architectures have been proposed with ontologies at the core of engineering activities (Duverger et al., 2024; Wu et al., 2021). These architectures link MBSE artifacts to various tools in a flexible and agnostic manner, acting as a shared reference for improved communication, understanding, and coordination.

## 2.2 Knowledge-based and Ontology-based engineering

The high level of abstraction inherent in early design phase can prevent manufacturing architects from performing impact analysis. The capture, modeling, and reuse of knowledge that supports design decisions at this stage is key for early concurrent engineering. Knowledge-Based Engineering (KBE) leverages *“the implementation of knowledge management methods and instruments, which support computational systems that make organizational knowledge the centerpiece of engineering design”* (Azevedo et al., 2020). Knowledge-based engineering promotes knowledge capture and reuse to enable cross-functional collaboration by centralizing system information and design rules. KBE systems thus support concurrent engineering by efficiently propagating design changes across components and systems from various domains.

Curran et al. (2010) proposed a methodology for early and continuous use of multidisciplinary knowledge leading to more accurate estimates of manufacturing consequences. Bruggeman et al. (2024) introduced a generic model to capture and organize knowledge for automatic production consideration during the conceptual design of aircraft structures. This model has helped identifying trends and ranking manufacturing concepts supporting trade-off decisions.

Although exhibiting encouraging capabilities, these methodologies frequently lack reusability and adoption. Kuegler et al. (2023) suggest that knowledge management limitations and a lack of clear terminology may impede the development of Knowledge-Based Engineering.

In that regard, KBE methodologies centered on ontologies introduce Ontology-Based Engineering (OBE) to provide explicit specifications of shared conceptualizations for knowledge representations and reasoning. OBE approaches support complex system design by allowing to model and represent a particular domain in terms of axiomatic definitions and taxonomic structures, thereby incorporating additional knowledge within the engineering process.

Since almost a decade, an OBE methodology has been developed and reused within the aerospace industry: Models

for Manufacturing (Mas et al., 2018; Zheng et al., 2022; Arista et al., 2023).

## 3. GAP AND NEEDS SUMMARY

The digital transformation has helped engineers to address system complexity while enabling integration, traceability, and management of information, thereby assisting the development of new aircrafts and manufacturing systems. MBSE and ontologies have been considered as means to improve collaboration between domains. However, the engineering knowledge necessary to implement early concurrent engineering remains to be addressed in terms of acquisition, formalization, and usage.

On the other hand, Knowledge-Based Engineering addresses cross-system collaboration via early impact analysis. The shared conceptualizations, knowledge representations and reasoning capabilities of Ontology-Based Engineering methodologies facilitate early concurrent engineering of complex systems.

By merging these two approaches, this paper builds upon the Digital Thread framework proposed in a previous work (Duverger et al., 2024), and leverages the application of the MfM methodology to develop the involved models. Furthermore, a novel knowledge acquisition method is proposed to extend MfM by combining human-centric and data-driven knowledge supporting cross-system impact analysis during the early design phase.

## 4. MfM METHODOLOGY APPLIED TO EARLY CONCURRENT ENGINEERING

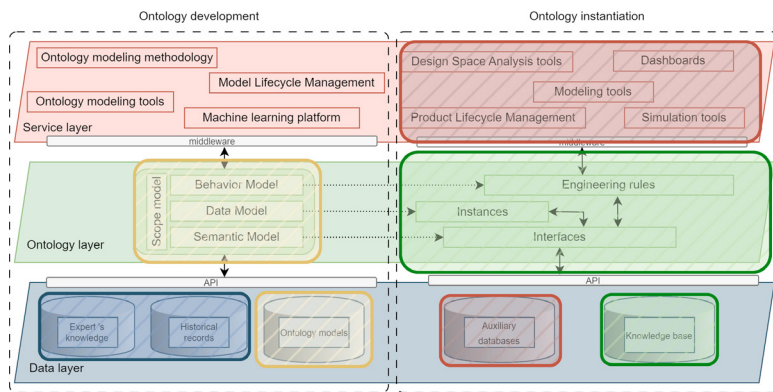
### 4.1 MfM introduction

Models for Manufacturing (MfM) is an OBE methodology allowing to capture functions, behaviors, and semantics of complex manufacturing systems. It helps to define and manage ontologies, capturing implicit and tacit knowledge from domain experts, as well as explicit domain knowledge from databases. This crucial part of the conceptualization process, merging human-centric and data-driven knowledge, enables intelligent design tools to reach their full potential within complex system design processes (Mas et al., 2018).

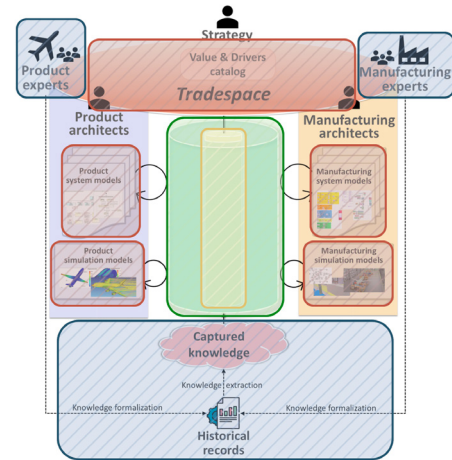
MfM was initially developed to support the development of complex manufacturing systems within the aerospace industry. As an OBE methodology positioned at the core of an MBSE environment, MfM is sufficiently generic and flexible to be applied to other complex system domains.

As illustrated in Figure 1a, the MfM methodology is based on a 3-Layer Model (3LM) framework decomposed in *Service*, *Ontology*, and *Data* layers. 3LM is designed to allow interoperability among the layers while ensuring their independence.

The *Service* layer incorporates the tools and softwares used by any stakeholder for modeling, simulation, analytics or visualization activities. On the other side, the *Data* layer is defined as the aggregation of all information that is stored, in use, or archived in databases or on the cloud. At the core of 3LM, the *Ontology* layer represents the organizational knowledge, which is collected, stored, managed, and used. The *Ontology* layer is built on 4 models:



(a) 3LM framework (Mas et al., 2024)



(b) Digital Thread framework (Duverger et al., 2024)

Fig. 1. Correspondence between 3LM and Digital Thread frameworks

The *Scope* model defines limits for the ontology's application. The *Data* model describes the concepts and relationships involved in the designated scope while the *Behavior* model reflects the manner in which they interact. Finally, the *Semantic* model ensures interoperability between the other layers in operational use cases and their associated tools.

Morales-Palma et al. (2022) has proposed meta-models for common specifications regarding MfM. The defined formalism is intended to facilitate the elaboration of the four ontological models. Thus, MfM allow to overcome one of the main issues hindering the development of KBE systems by providing a modeling structure easily human-readable while remaining concise and ensuring information longevity.

#### 4.2 Hybrid knowledge acquisition

Most OBE approaches consider experts as their main source for knowledge capture. As Kuegler et al. (2023) mention, “the shift to a more model-based and data-driven engineering knowledge management provides new opportunities for the application of AI techniques considering knowledge acquisition”. The close proximity of this research to the industry makes a large amount of real-world data accessible. Consequently, there is an opportunity to study more data-oriented approaches than classic KBE methodologies. It is important to keep in mind that the integration of AI techniques do not replace traditional methods. Instead, it serves as a complementary toolbox, extending conventional capabilities to address data analysis challenges in a modern industrial context. The method presented in the following section leverages a combination of human-centric and data-driven approaches to extract complex cross-domain knowledge relevant in early development phase.

The proposed method consists of knowledge pattern formalization via semi-structured interviews with experts to drive knowledge mining studies. The idea is to capitalize on human experience to identify the type of knowledge that is suitable for the given context, and use data-driven techniques to capture it as explicit engineering rules.

#### Knowledge pattern formalization

In the industry, a tremendous amount of available data is created without any knowledge sharing intent and is stored in heterogeneous formats. The application of data mining techniques to such targets may not yield satisfying results. The knowledge of domain experts is precious to understand such data variety and may be used to identify various kinds of impact from one system to another. The objectives of this first step are to formalize knowledge patterns that shall be used to drive data-oriented approaches. Product and manufacturing architects usually have a good intuition about these types of knowledge even if they need help formalizing them.

Following with the guidelines elaborated by Schreiber (2000), individual semi-structured interviews were selected as the method for knowledge elicitation. The individual aspect of these meetings addresses issues related to expert availability while avoiding conflicting views. The targeted audience for these sessions are experts and architects from aircraft and manufacturing domains. A first list of knowledge patterns is advised to be initially drafted, thereby serving as the basis for upcoming discussions. This cross-domain knowledge pattern list shall be updated in accordance with each interview results. The session process steps are defined as follows:

##### Step 1: Contextualization

A simple contextualization of the research scope is performed to introduce a clear definition of the session objectives to the expert.

##### Step 2: Enumeration

Serving a basis for discussion, the list of current knowledge patterns is perused. For each pattern, the expert can:

- Recognize the pattern as valid.
- Propose some modifications to the pattern.
- Refute the pattern.
- Have no opinion or expertise on the matter.

##### Step 3: Extension

Once all the patterns have been discussed, the experts are asked to complete the list with other patterns that they can think of.

#### Step 4: Conclusion

To conclude, the experts are asked to select the pattern the most useful to support early concurrent engineering in their opinion. This conclusion often allows to identify concrete parameters, drivers and data sources which are precious for the data-driven part.

#### Step 5: Verification

The results of each interview must be verified before updating the pattern list. Firstly, the elaborated patterns should all be cross-domain by linking aircraft and manufacturing elements. Secondly, the elements or parameters involved should be compatible with the level of abstraction of early decision making.

#### Data-driven knowledge extraction

Once cross-domain knowledge patterns are considered sufficiently mature, data-driven studies can be conducted to extract their explicit design rules. In this regard, a generic process using conventional data science techniques is proposed in the following steps:

##### Step 1: Data exploration

This step involves the identification, comprehension and selection of relevant data associated with the chosen knowledge pattern. The consultation of experts or architects may reduce the time spent in exploration by orienting towards specific tools or data sources.

##### Step 2: Join and transform

The identified data sources must be linked in a way that results in a clean dataset which is properly structured with all essential parameters. Frequently, transformations must be executed to integrate data from disparate sources that are stored in heterogeneous formats.

##### Step 3: Pre-processing

A collection of various pre-processing techniques exists in the data science community. The most commonly used are the following:

- **Data cleaning:** Detecting errors or missing values in the dataset. Anomalies may be simply removed or replaced by a “neutral” value.
- **Outliers management:** The two main techniques to handle outliers are Z-score and IQR. The former is suited to normally distributed data whereas the later applies for other type of data distribution.
- **Dataset balancing:** Controlling the value distribution of a dataset is advised to avoid biases. The two most common techniques are the under-sampling and the over-sampling depending on the dataset size.
- **Categorical features encoding:** In order to be understood by the model, the categorical data, usually stored in string format, have to be encoded into machine interpretable numbers.
- **Value normalization:** To smooth value gaps between various parameters, discrete values can be normalized between 0 and 1.

#### Step 4: Choose, Train and Fine-tune the model

Dasari et al. (2019) and Bénard et al. (2021) presented methods to extract IF-THEN rules from the inner structure of RandomForest models. This interpretability capability is the core of this approach as it enables the integration of data-driven knowledge within ontological environment (Kim and Ahmed, 2018).

#### Step 5: Trained model evaluation

The performances of models are evaluated using metrics which depend on the model nature and the study context. The model is considered adequately trained when it satisfies all metrics within an acceptable threshold.

#### Step 6: IF-THEN rules extraction

The application of the approaches previously cited results in the extraction of explicit design rules. The degree of confidence of each rule can be quantified with the model metrics and the number of samples on which the rule is based.

This hybrid method is proposed as an extension to MfM for knowledge acquisition. The results of this method can be integrated within the ontology layer as part of the *Behavior* model. Cross-domain knowledge patterns, acting as links between elements from the *Data* model, are described by their related design rules.

## 5. DIGITAL THREAD DEVELOPMENT WITH MFM

The development of the Digital Thread following the MfM methodology as illustrated in Figure 1 must consider compatibility and reusability capabilities with other industrial ontologies. For this purpose, each model follows the hierarchical principle presented in Figure 2. The Basic Formal Ontology (BFO) lays the foundation as international standard for information technology (ISO/IEC 21838-2:2021). The IOF-core middle ontology, referring to BFO, has been developed as a standardized suite of ontologies to support digital manufacturing industry (Kulvatunyou et al., 2022). Domain ontologies are then reused or developed to address the relevant concepts and relationships between aircraft, manufacturing and MBSE domains during the early design phase.

- **Scope model:** The limits of the ontology are defined by the formalized co-architecture process. The Top Level Requirements and Objectives combined with existing technology bricks and cross-domain knowledge support the early architectures of the aircraft and the manufacturing system. The architecture processes iterate through feedback loops composed of manufacturing constraints and aircraft structure breakdowns.
- **Data model:** The main concepts and properties used to perform early concurrent engineering are defined in this model. Following the PPR (Product Process Resource) decomposition, the *Data* model represents the shared conceptualization agnostic to any tool or modeling framework.
- **Behavior model:** Impact relationships that certain concepts have on others are characterized as cross-domain knowledge patterns which are formalized with

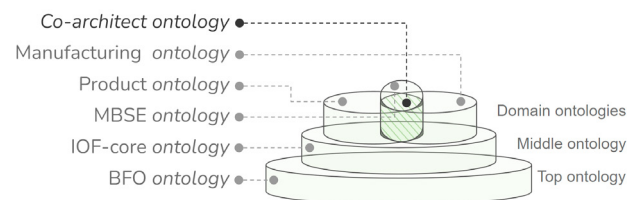


Fig. 2. Ontology hierarchy

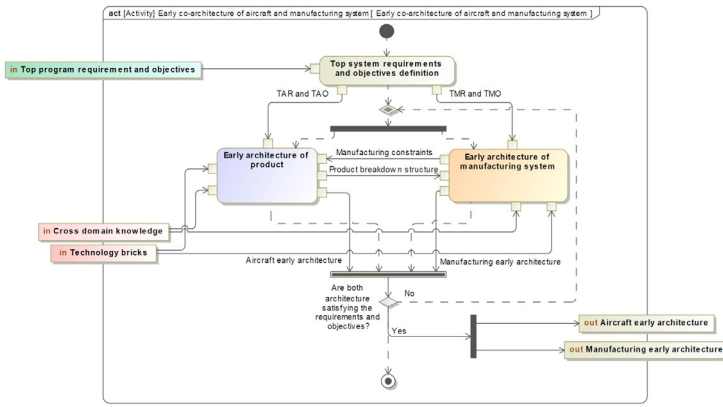


Fig. 3. Co-architect scope model

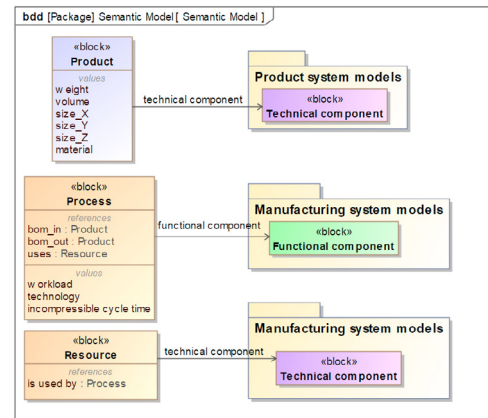


Fig. 6. Co-architect semantic model

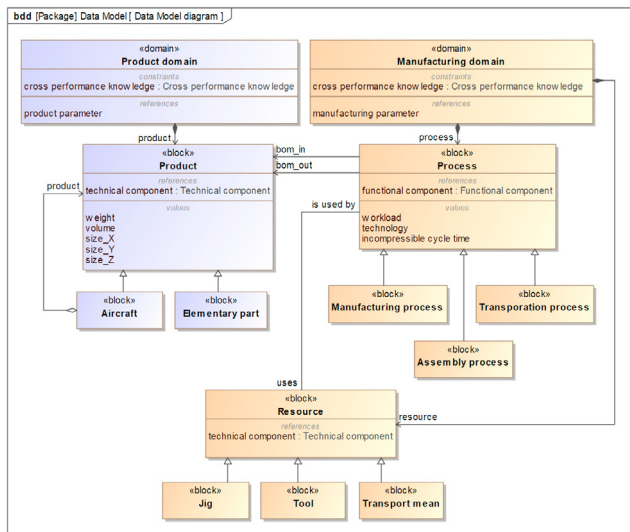


Fig. 4. Co-architect data model

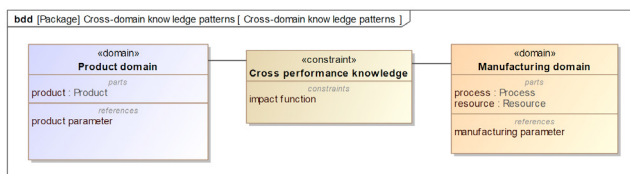


Fig. 5. Co-architect behavior model

experts. These patterns are subsequently described by the design rules extracted with data-driven techniques in IF-THEN format. Thus, the *Behavioral* model provides executable knowledge supporting instantaneous cross-domain impact assessments.

- **Semantic model:** Links between the MBSE meta-model and the *Data* model elements are defined in the *Semantic* model. The interoperability between MBSE formalism and the ontology layer allows instantiation of both architectures within the digital thread. Efforts have been focused to enable the communication between MBSE and the ontology layer but the semantic model can be declined into tailored modules to exchange with any other digital tool from the service layer.

It is important to note that the presented models remain at a high level of abstraction and must undergo further development and refinement to align with specific use-case applications.

### 6. DISCUSSION

The use of MfM methodology allows to link Aircraft and Manufacturing MBSE artifacts by formalizing cross-domain dependencies. Moreover, the extension proposal for knowledge acquisition leverages a combination of expert-centric and data-driven techniques to integrate explicit engineering rules in the *Behavior* model. Thus, quick cross-domain impact assessments can be executed within the ontology layer.

In addition, the combination of the extracted IF-THEN with *Top Level Requirements and Objectives* can generate manufacturing constraints over the aircraft. Therefore, this approach enables bi-directional cross-domain impacts during the earliest design stage.

Although knowledge modeling in the form of patterns can support maintainability activities, there are still unaddressed considerations for knowledge management. Procedures must be developed to deal with conflicting rules or technological breakthroughs invalidating old rules. The ability to manage and maintain knowledge is essential to the effective implementation of this framework throughout the entire development lifecycle. Future works will focus on a detailed application of these methods and frameworks to a real-life use case.

### 7. CONCLUSION

Concurrent engineering between aircraft and manufacturing domains during early design phase necessitates a high degree of collaboration and knowledge sharing. The use of Ontology-Based Engineering methods as central part of Model-Based Systems Engineering activities represents a structured approach to complex system design with knowledge sharing capabilities.

The development of a digital thread based on ontologies and following the MfM methodology offers compelling ways to support early concurrent engineering. An approach for knowledge acquisition merging expert-centric and data-driven techniques has been proposed as an extension of MfM. This method aims to complements the

knowledge palette available to architects for early collaboration with high levels of abstraction. Thus, ontologies do not only serve as a communication medium providing a common understanding and the means to coordinate, they also provide global perspectives enabling early cross-impact analysis.

The 3-Layer Model framework offers a structured approach to integrate shared conceptualization, engineering knowledge, and semantic interfaces. The resulting flexible interconnections and executable knowledge capabilities between cross-domain MBSE artifacts, as well as any other digital tools, present promising opportunities to facilitate early knowledge-driven concurrent engineering for the aerospace industry.

#### ACKNOWLEDGEMENTS

This research was performed in the context of a partnership between Airbus and the University of Lorraine.

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