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École doctorale IAEM Lorraine

Model-Based SoI and Manufacturing systems Co-Engineering Framework, for early concurrent architecture tradeoff

THÈSE

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par

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Mis en page avec la classe thesul.

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Résumé de la thèse

Au fil des décennies, les produits d'ingénierie ont subi une augmentation substantielle et continue de leur complexité. Ils sont passés de simples assemblages mécaniques à des systèmes de systèmes (Systems of Systems - SoS) intégrant logiciels, réseaux de communication, composants électroniques et opérateurs humains. Cette complexité n'est donc pas seulement introduite par la taille des composants, mais aussi par la multiplication de leurs interdépendances qui créent des comportements émergents, non linéaires, avec de fortes incertitudes. Ces systèmes sont donc particulièrement difficiles à concevoir, analyser et contrôler selon les méthodes d'ingénierie traditionnelles, d'autant plus lorsqu'ils présentent une hétérogénéité technologique.

Face à cette complexité, l'Ingénierie des Systèmes (Systems Engineering - SE) propose des approches formelles telles que la traçabilité des exigences, le raisonnement architectural, l'analyse de compromis, ainsi que la vérification et validation continue au cours du cycle de vie. Ces activités ont pour but de faciliter la conception de systèmes complexes tout en préservant une cohérence parmi des système hétérogènes et interdépendants.

Dans ce contexte, les systèmes aérospatiaux, et les avions spécifiquement, constituent un exemple de système technique complexe. Un avion présente les caractéristiques déterminantes de la complexité telles qu'énoncées dans la théorie de l'Ingénierie des Systèmes : des sous-systèmes étroitement couplés, des exigences rigoureuses en matière de sécurité et de fiabilité, des contraintes réglementaires strictes et des comportements émergents significatifs. Les performances de vol, les marges de sécurité et la robustesse opérationnelle, par exemple, résultent des interactions entre l'aérodynamique, les commandes de vol, la propulsion, l'avionique et les opérateurs humains, plutôt que d'un seul sous-système.

Par ailleurs, le long cycle de vie des avions accentue encore davantage les défis liés à la complexité. L'ingénierie de systèmes complexes souligne que les décisions prises en début de cycle de vie sont cruciales car les choix architecturaux influencent fortement les phases en aval, notamment la production, l'exploitation, la maintenance et le retrait. Dans le domaine de l'aéronautique, où les cycles de vie des produits s'étendent souvent sur plusieurs décennies, la capacité à anticiper et à gérer les conséquences à long terme est essentielle. C'est dans cette optique que les technologies issues de l'Industrie 4.0 offrent des opportunités innovantes, non seulement pour la conception du produit (l'avion), mais également pour son système de production.

Au travers de la transformation numérique, l'industrie 4.0 adresse un nouveau paradigme intégrant des systèmes cyber-physiques (Cyber-Physical Systems - CPS), l'internet des objets (Internet of Things - IoT), la science des données ainsi que l'intelligence artificielle au sein des activités de conception et des systèmes conçus. Ce paradigme ne se contente pas d'apporter de nouveaux outils, il transforme fondamentalement l'architecture des systèmes, les interactions et les dynamiques de cycle de vie.

Néanmoins, cette transformation introduit également des couches supplémentaires de complexité, avec leurs lots de défis. Les ingénieurs doivent dorénavant faire face à de la complexité fonctionnelle, comportementale et structurelle avec une explosion de nouvelles technologies

hétérogènes.

La rapide et constante évolution des diverses technologies impliquées contraste avec les long cycle de développement et de certification, compliquant d'autant plus les capacités d'anticipation d'impact au travers des cycles de vie. Ainsi, la transformation numérique agit comme une réponse, mais aussi comme un amplificateur de complexité. D'un côté, elle permet de nouvelles capacités, mais de l'autre, elle intensifie les défis rencontrés par les ingénieurs. Comprendre cette dualité est fondamental pour analyser comment la transformation numérique change non seulement les systèmes produits et leur système de production, mais aussi les approches d'ingénierie elles-mêmes.

La complexité croissante des systèmes et l'adoption progressive de l'industrie 4.0 ont profondément transformé l'Ingénierie des Systèmes avec ses méthodologies et ses processus. Alors que les approches traditionnelles centrées sur les documents peinent à gérer des volumes considérables d'informations diverses en constante évolution au sein de systèmes hautement interconnectés, des approches basées sur les modèles ont émergé pour répondre à ces nouveaux défis. L'Ingénierie des Systèmes Basée sur les Modèles (Model-Based Systems Engineering - MBSE) place les modèles numériques au centre des activités d'ingénierie en promouvant des principes d'abstraction, de consistance et de traçabilité de l'information pour adresser la complexité des systèmes et l'intégration de leur cycle de vie dans une vision à long terme.

Cette thèse se situe au sein d'une chaire industrielle nommée ACTE MBSE. Elle étudie les opportunités innovantes permises par l'Ingénierie des Systèmes Basée sur les Modèles sur la base de quatre piliers : *Actionnable* (utilité pragmatique et déploiement réel), *Collaborative* (casser les fonctionnements en silos), *Trustworthy* (intégrité et fiabilité des modèles et des données face aux certifications) et *Executable* (modèles actifs permettant des simulations).

Ces travaux de recherche répondent à un problème structurel majeur dans le développement des avions commerciaux : la conception séquentielle du produit et de son système de production, entraînant des découvertes tardives de défauts ou de difficultés de production. Celles-ci nécessitent alors des révisions de conception lourdes et coûteuses, causant d'importants retards. Pour un avion dont la durée de vie peut atteindre 50 ans, ces défauts initiaux ont des répercussions considérables en sachant que les décisions prises lors de la phase conceptuelle définissent jusqu'à 70% des coûts totaux du cycle de vie, alors qu'elles ne représentent que 8% des dépenses réelles à ce stade.

Ce phénomène a historiquement été décrit comme une mentalité de type *"over the wall"*. Les ingénieurs concepteurs de l'avion finalisaient la conception du produit avant de la transmettre aux ingénieurs de production, avec une considération minimale pour les phases ultérieures du cycle de vie. Aujourd'hui, la conception de l'avion et celle de son système de production se sont éloignées de cette logique séquentielle. Des défis majeurs font toutefois encore obstacle à leur intégration complète au sein d'une ingénierie dite concourante ou collaborative.

Ces travaux de recherche se sont appuyés sur leur proximité avec l'industrie afin de mettre en place une série d'entretiens auprès d'un large panel d'acteurs d'Airbus (ingénieurs produit, ingénieurs de production, architectes, experts en IA et outils numériques). Ces entretiens ont permis de d'identifier trois obstacles structurels à la mise en œuvre d'une telle ingénierie :

- Résistance culturelle : Les anciennes méthodes de travail laissent une forte empreinte dans les échanges et les rapports de force. L'approche en silos perdure malgré l'introduction de nouvelles directives collaboratives.
- Déficit de maturité en Ingénierie des Systèmes : Le déploiement rapide du MBSE et des outils numériques a créé un décalage technique. Les ingénieurs de production étant moins

familiarisés avec ces méthodes que leurs homologues du produit, des écarts de maturité dans les méthodes, processus et outils freinent l'intégration numérique et la collaboration entre les domaines.

- Faible capitalisation de la connaissance : Des décennies de données de conception et de décisions sont stockées, mais la logique et les motivations derrière chacun de ces choix sont rarement documentées avec un but de capitalisation, rendant leur réutilisation difficile.

Cette proximité avec l'industrie a permis de mieux appréhender les difficultés concrètes des concepteurs d'avions. Croiser ces divers points de vue a affiné la compréhension des problématiques industrielles et de leurs causes profondes. Aujourd'hui, l'enjeu ne réside plus dans une ingénierie séquentielle au sens de la mentalité *"over-the-wall"*, mais plutôt dans une ingénierie désynchronisée où la temporalité des collaborations inter-domaines est centrale. Concrètement, lorsque le système de production est enfin intégré aux réflexions de conception, les décisions d'architecture critiques sont déjà arrêtées, souvent au détriment des exigences de production.

Ce fonctionnement ne relève pas d'une mauvaise volonté des ingénieurs, mais découle d'une résistance culturelle, d'un manque d'intégration numérique et d'une faible capitalisation des connaissances, autant de freins à la collaboration inter-domaine et à la synchronisation des phases de conception.

Afin de cadrer les contributions de cette recherche, cette thèse définit l'Ingénierie Concourante et Collaborative (Collaborative and Concurrent Engineering - CCE) comme l'approche privilégiée pour répondre aux problématiques identifiées. La CCE s'appuie sur les travaux issus de la littérature en ingénierie concourante et en ingénierie collaborative. Elle combine, d'une part, une approche systématique intégrant simultanément la conception du produit et de ses processus associés (production, support) et, d'autre part, un fonctionnement reposant sur le travail en parallèle, le partage d'objectifs et la mutualisation des ressources.

L'application de l'Ingénierie Concourante et Collaborative en phase amont de conception s'avère toutefois complexe. L'abstraction élevée des informations, la multiplicité des hypothèses et des alternatives, ainsi que la rareté des retours d'expérience formalisés génèrent de longs cycles d'itération et obligent les ingénieurs à s'en remettre principalement à la connaissance tacite de certains experts métier. Cependant, les nouvelles technologies engendrées par la transformation numérique offrent d'intéressantes opportunités pouvant répondre à ces problématiques.

Le MBSE est la clé de voûte de cette transformation. En remplaçant les documents par des modèles dynamiques (souvent via le langage SysML), le MBSE permet la traçabilité des exigences, la modélisation des architectures, la simulation de certains comportements, et la cascade automatique des modifications. Par ailleurs, l'Ingénierie Numérique (Digital Engineering - DE) a vu émerger le concept de Fil Numérique (Digital Thread) servant de cadre analytique reliant des sources de données disparates et des modèles tout au long du cycle de vie.

L'intégration du MBSE au sein d'un fil numérique est essentielle pour faciliter la conception de systèmes complexes, tout en garantissant la traçabilité de l'information à chaque étape du cycle de vie. Toutefois, ces opportunités s'accompagnent de défis majeurs : l'interopérabilité entre les environnements MBSE et le reste de l'écosystème digital reste fragilisée par la gestion manuelle des liens, les disparités de maturité MBSE entre les domaines ainsi que l'utilisation de cadres de modélisation hautement personnalisés.

L'interopérabilité est classée en quatre niveaux : technique, syntaxique, sémantique et organisationnelle. Si les outils actuels gèrent l'interopérabilité technique, des barrières syntaxiques, sémantiques et organisationnelles demeurent, provoquant des ruptures de la continuité numérique et des désynchronisations des processus de travail.

Pour résoudre ces défis d'interopérabilité, cette thèse met en avant les Technologies du Web Sémantique (Semantic Web Technologies - SWT) et les ontologies. Une ontologie est une description formelle de la connaissance, définissant un ensemble de concepts et de relations dans un domaine précis. Ces approches permettent d'assurer des échanges d'information entre des sources de données structurées différemment tout en transmettant sens partagé.

En outre, les ontologies possèdent des capacités de raisonnement de Logique de Description (Description Logic - DL) via des moteurs d'inférence.

Ces capacités d'interopérabilité et de représentation de la connaissance ont donné naissance à l'Ingénierie Basée sur les Ontologies (Ontology-Based Engineering - OBE) qui est une branche appartenant au champ de l'ingénierie basée sur la connaissance (Knowledge-Based Engineering - KBE).

Les approches traditionnelles du KBE (Knowledge-Based Engineering), comme les méthodologies MOKA ou CommonKADS, sont centrées sur des experts humains comme source de connaissance. Leur défi majeur est l'acquisition de cette connaissance. Pour ce faire, elles nécessitent de longues interviews afin d'extraire la connaissance tacite ou implicite des experts, ce qui est extrêmement chronophage. D'autant plus, les experts peuvent avoir des points de vue divergents, rendant difficile l'agrégation de connaissance dans un tout homogène.

Face au volume massif de données générées par l'ingénierie numérique (historiques de production, temps de cycle, rapports d'erreurs), plusieurs contributions scientifiques de la littérature plaident pour une méthode d'acquisition hybride. Elles combinent la formalisation classique auprès des experts avec une extraction orientée par les données en exploitant l'Intelligence Artificielle et des modèles interprétables d'apprentissage automatique (Machine Learning - ML). Cela permet de découvrir automatiquement des règles de conception complexes liant l'architecture du produit aux contraintes de production.

L'application de méthodologies d'Ingénierie Basée sur les Ontologies peut donc répondre aux problèmes d'interopérabilité tout en permettant la mise en œuvre d'approches de capitalisation de la connaissance. Parmi les différentes méthodologies présentes dans la littérature, ces travaux de recherche ont sélectionné la méthodologie intitulée Models for Manufacturing (MfM) pour sa proximité avec les environnements MBSE ainsi que pour ses nombreux cas d'utilisation industriels. Par ailleurs, l'utilisation de méthodologies établies permet de répondre aux problématiques récurrentes de l'Ingénierie basée sur la Connaissance en terme d'adoption et de réutilisation.

En s'appuyant sur les concepts cités ci-dessus, cette thèse développe un cadre de *"Fil Numérique Basé sur les Ontologies"* pour répondre aux problématiques de l'Ingénierie Concourante et Collaborative pendant les phases amont de la conception.

En premier lieu, ce cadre définit un catalogue de valeurs et de vecteurs qui servent de boussole commune pour le développement des différents systèmes d'intérêt. Ce catalogue permet d'abord d'initier les activités de conception sur des rails convergents, puis sert ensuite de référentiel d'arbitrage lors des activités de compromis.

Le cadre intègre aussi les modèles MBSE de l'avion et de son système de production. Ces modèles servent de fondation aux activités d'ingénierie dans un environnement collaboratif avec des vues multi-disciplinaires, une granularité ajustable de l'information, un langage structuré, la traçabilité de l'information ainsi que la propagation automatique des changements.

Au-delà de ces activités centrales d'ingénierie, les phases amont de conception nécessitent également certaines capacités de simulation complémentaires. Ces modèles allant de simple outils mathématiques à des simulations physiques poussées, permettent des analyses préliminaires sur les différentes hypothèses d'architecture.

Les échanges d'information et l'interopérabilité entre les différents éléments de ce cadre sont

assurés par l'élément central : le Fil Numérique Basée sur les Ontologies. Les modèles ontologiques de ce fil numérique représentent une connaissance partagée, agnostique à un domaine ou un outil spécifique. Cette structuration de la connaissance répond aux exigences d'interopérabilité au sein d'un écosystème numérique hétérogène. Fondé sur les technologies du web sémantique, ce fil numérique sert de vecteur de communication pour assurer la continuité numérique et l'interopérabilité syntaxique. De plus, la structuration des connaissances via des ontologies permet d'atteindre une compréhension partagée, garantissant l'interopérabilité sémantique. Constituant ainsi un socle commun pour la coordination inter-domaine, ce fil numérique favorise également l'interopérabilité organisationnelle.

La connaissance nécessaire aux analyses d'impact est un autre élément de ce cadre. Formalisée avec des experts, extraite par des méthodes basées sur la donnée ou au travers d'approches hybrides, cette connaissance est intégrée dans les modèles ontologiques du fil digital. Les capacités de raisonnement automatisé offertes par les ontologies sont ensuite exploitées pour mener les études relatives aux décisions de conception critiques et de leurs répercussions au travers des phases du cycle de vie.

Le dernier élément du cadre proposé par cette thèse est l'espace de compromis. Alimenté par le fil digital avec les informations des architectures MBSE, les résultats des modèles de simulation et les connaissances enrichies d'analyse d'impact, cet espace de compromis est le support pour les études entre les différentes alternatives. Cet espace, accessible à toutes les partie prenantes, permet d'effectuer les décisions de conception critiques de la manière la plus éclairée possible en utilisant le catalogue de valeurs et de vecteurs comme référentiel d'arbitrage.

Cette thèse s'articule aussi autour de l'élaboration des modèles ontologiques constituant le fil numérique. Au travers de la méthodologie MfM, des modèles Périmètres, Données, Comportementaux et Sémantiques ont été proposés pour faciliter la co-architecture de l'avion et de son système de production. Ces modèles ont été développés en SysML au sein de l'environnement MBSE pour la proximité engendrée avec les architectures des systèmes d'intérêt.

Le modèle *Périmètre* définit les activités d'ingénierie nécessaires pendant les phases amont de conception. Ce modèle a notamment permis de faire émerger des activités de co-architecture, n'appartenant ni à l'ingénierie de l'avion, ni à l'ingénierie du système de production. Ces activités collaboratives globales ont pour but d'orienter les architecture vers des choix de conception équilibrés entre les systèmes d'intérêt.

Le modèle *Donnée* est la structuration taxonomique des concepts utilisés. En utilisant la décomposition Produit-Processus-Ressource (PPR), ce modèle permet de formaliser, non seulement les classes et les propriétés associées au différents domaines, mais surtout les liens inter-domaines. Ce modèle a mis en exergue la notion de contraintes *"cross-domaine"* établissant un pont supplémentaire entre le produit et le système de production.

Pour ces travaux de recherche, le modèle *Comportemental* décrit plus en détail les différentes contraintes cross-domaines. Au travers de la traçabilité de l'information établie par le MBSE, ces contraintes permettent l'identification de leviers d'action concrets entre certains attributs des architectures de l'avion et du système de production. De plus, l'élaboration de ce modèle comportemental a joué un rôle central dans le développement d'une méthode hybride d'acquisition de la connaissance.

En effet, cette thèse propose, de manière complémentaire à MfM, une méthode d'acquisition de connaissance cross-domaine en deux phases. La première phase formalise des patrons de connaissance via des sessions de modélisation collaborative avec des experts. La deuxième phase utilise les patrons de connaissances, identifiant des attributs clé dans les relations d'impact inter-domaines, pour diriger des études basées sur les données, et notamment des modèles

d'apprentissage automatique interprétables. Cette deuxième phase se conclut avec l'extraction de règles d'impact explicites qui sont intégrées dans l'ontologie, permettant des analyses exécutables via les capacités de raisonnement.

Enfin, le modèle Sémantique sert de lien dynamique entre les architectures MBSE et l'ontologie. L'établissement de ces liens et leur maintenance sont facilités par l'environnement MBSE avec ses capacités de collaboration et de traçabilité de l'information. Ce modèle est ensuite utilisé pour l'instanciation des architectures MBSE dans une base de connaissance externe, structurée par le modèle *Donnée*.

L'ensemble des contributions de ces travaux est ensuite appliqué à une étude de cas en situation réelle concernant la co-conception d'un réservoir de nouvelle génération basé sur l'hydrogène. L'analyse des problématiques rencontrées lors de ce projet correspond aux verrous industriels et scientifiques identifiés au début de cette thèse. Il en ressort notamment deux difficultés majeures, sources de longs cycles d'itération : d'un côté, les enjeux d'interopérabilité entre architectures MBSE et modèles de simulation, et de l'autre, la lourdeur d'une évaluation de la charge de travail fondée sur la seule expertise métier.

Les modèles ontologiques composant le cœur du fil numérique sont spécialisés pour correspondre au contexte spécifique du cas d'étude. Le modèle *Périmètre* n'a pas nécessité de spécialisation, dans la mesure où il décrivait avec suffisamment de précision les activités de co-architecture du projet.

Le modèle *Donnée* a été spécialisé pour formaliser les attributs spécifiques au cas d'étude. Le projet se déroulant en phase amont d'analyse des risques, la gestion des ressources n'était pas intégrée. Afin d'éviter une complexité inutile, le modèle spécialisé adopte une décomposition Produit-Processus plutôt que le schéma PPR du modèle générique.

Un travail conséquent a été alloué à la spécialisation du modèle *Comportemental* en utilisant la méthode hybride d'acquisition de la connaissance. L'estimation de la charge de travail ayant été identifiée dès le début du cas d'étude comme le principal défi pour la capitalisation de connaissance, ce modèle a formalisé un patron de connaissance spécifique via des sessions de modélisation menée avec des experts. Ce modèle, qui fait office de passerelle entre des attributs clés du modèle *Donnée*, établit un lien d'impact inter-domaine permettant aux ingénieurs d'identifier des leviers d'action. En outre, ce patron de connaissances a orienté des travaux d'apprentissage automatique interprétable. Appliqués à de grands volumes de données, ceux-ci ont permis d'extraire deux ensembles de règles d'impact explicites. Le premier, facilement appréhendable par l'humain, permet des analyses d'impact manuelles avec un haut degré de granularité. Le second, plus volumineux mais plus précis, s'intègre au moteur d'inférence de l'ontologie pour une exploitation semi-automatique des connaissances.

Enfin le modèle *Sémantique* établit les correspondances dynamiques entre les architectures MBSE et la structure ontologique du modèle *Donnée*. Grâce à ces liens, les architectures du produit et de son système de production ont été instanciées au sein d'un graphe de connaissances Neo4j sous un format agnostique. Accessible à l'ensemble des parties prenantes, ce graphe supporte des requêtes flexibles en lecture et en écriture afin de répondre à n'importe quel besoin ou format spécifique de modèle de simulation. Intégrant les modèles MBSE, l'ontologie, les résultats de simulation, et la connaissance acquise par la méthode hybride, ce graphe de connaissance constitue le fil numérique issue du cadre proposé.

En prolongeant les travaux menés en Ingénierie Basée sur les Ontologies, ces recherches répondent aux verrous caractérisant les phases amont de l'Ingénierie Concourante et Collaborative.

S'appuyant sur l'architecture d'un fil numérique, une méthode hybride d'extraction de con-

naissances et des modèles ontologiques consolidant les liens inter-domaines, les contributions de cette thèse ont été éprouvées sur un cas d'étude industriel réel, confirmant ainsi leur pertinence.

A travers l'intégration de l'Ingénierie des Systèmes Basée sur les Modèles comme méthodologie fondatrice, le cadre, les méthodes et les modèles proposés ont démontré avec succès leurs dimensions *Actionnable*, *Collaborative*, *Trustworthy* et *Executable*.

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Acronyms

AI Artificial Intelligence. 2, 34, 36, 44, 51

AST Authoritative Source of Truth. 26

BFO Basic Formal Ontology. 29, 50

CAD Computer Aided Design. 24

CCE Collaborative and Concurrent Engineering. 19–22, 25–29, 31–39, 41, 44, 45, 48, 50, 51, 53, 55, 57, 77, 79, 84, 85, 88–91

CE Concurrent Engineering. 4, 15, 18, 19, 21

CM Configuration Management. 20, 21, 48

CommonKADS Common Knowledge Acquisition and Design System. 33

CPKT Cross-Project Knowledge Transfer. 79, 80, 82, 87

CPS Cyber-Physical System. 2

DDMS Digital Design, Manufacturing, and Services. 5

DE Digital Engineering. 5, 17, 22, 23, 25, 26, 31, 35–39, 41, 59, 74, 77, 82, 91

DfMA Design for Manufacturing and Assembly. 20

DL Description Logic. 30

DoE Design of Experiments. 34

DSRM Design Science Research Methodology. 12, 13, 17, 39, 41, 55, 59, 79, 82

DT Decision Tree. 34, 63

ERP Enterprise Resource Planning. 26, 62

IM Industrial Minutes. 64

IoT Internet of Things. 2

IPD Integrated Product Development. 19, 21, 42

IPPD Integrated Product-Process Development. 19

KBE Knowledge-Based Engineering. 29–31, 33, 36, 39, 44, 48

KM Knowledge Management. 32

LLM Large Language Models. 89

MBSE Model-Based Systems Engineering. 4, 5, 15, 24–27, 29, 31, 35, 37–39, 41, 46, 48, 55, 57, 59, 73, 83, 85, 86

MDAO Multi-Disciplinary Analysis and Optimization. 24

MfM Models for Manufacturing. 30, 31, 45–48, 52, 55, 57, 60, 77, 85, 86

MOKA Method and tools Oriented to Knowledge-based engineering Application. 33

OBE Ontology-Based Engineering. 30, 31, 36, 39, 41, 44–46, 57, 85–87, 91

OWL Ontology Web Language. 43

PLM Product Lifecycle Management. 19–22, 25, 26

PPR Product-Process-Resource. 50, 55, 57, 86

RAG Retrieval Augmented Generation. 89

RDF Resource Description Framework. 43

RF Random Forest. 34, 62

SE Systems Engineering. 1–5, 10, 17, 19, 24, 26, 37, 41, 43, 57

ShaCL Shapes Constraint Language. 55

SoS System-of-Systems. 3, 4

SWRL Semantic Web Rule Language. 55, 76, 87

SWT Semantic Web Technologies. 23, 26–31, 35, 38, 39, 43, 55, 57

VSM Value Stream Mapping. 60

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Chapter 1

Introduction

Competitive industrial sectors require the delivery of reliable, safe, and cost-effective products within increasingly short development cycles. Meeting these demands has become a fundamental pillar of company growth. Furthermore, products are progressively required to integrate a wide range of functionalities and technologies.

Over the past decades, engineered products have consequently undergone a continuous and substantial increase in complexity, to the extent that they must now be considered as complex systems (Yassine, 2021). This evolution is driven by multiple converging factors, including the rising number of system components, the integration of heterogeneous technologies realizing diverse functions, and the intensification of interactions among components as seen in Figure 1 (INCOSE, 2021).

Modern engineered systems are no longer defined solely by their physical architecture. They increasingly incorporate software, electronics, communication networks, and human operators. Consequently, system complexity arises not only from size, but also from the nature and interdependence of its components.

This complexity generates non-linear behaviors, emergent properties, and higher uncertainties, making the systems increasingly difficult to predict, analyze, and control using traditional engineering methodologies.

A major theoretical shift in engineering has been the recognition of emergent behaviors as a defining feature of complex systems. Emergence refers to system-level properties that cannot be attributed to any single component, arising from interactions between them.

This perspective underpins the discipline of Systems Engineering (SE). SE frameworks explicitly address complexity through practices such as requirements traceability, architectural reasoning, trade-off analysis, and continuous verification and validation throughout the system lifecycle (ISO/IEC/IEEE-15288, 2023). These practices are designed to preserve system coherence despite growing heterogeneity and interdependencies among components.

Within this context, aerospace systems, and aircraft in particular, constitute a paradigmatic example of complex engineered systems. An aircraft exhibits the defining attributes of complexity as articulated in SE theory: tightly coupled subsystems, stringent safety and reliability requirements, strong regulatory constraints, and significant emergent behaviors. Flight performance, safety margins, and operational robustness, for instance, arise from the interactions among aerodynamics, flight control, propulsion, avionics, and human operators, rather than from any single subsystem.

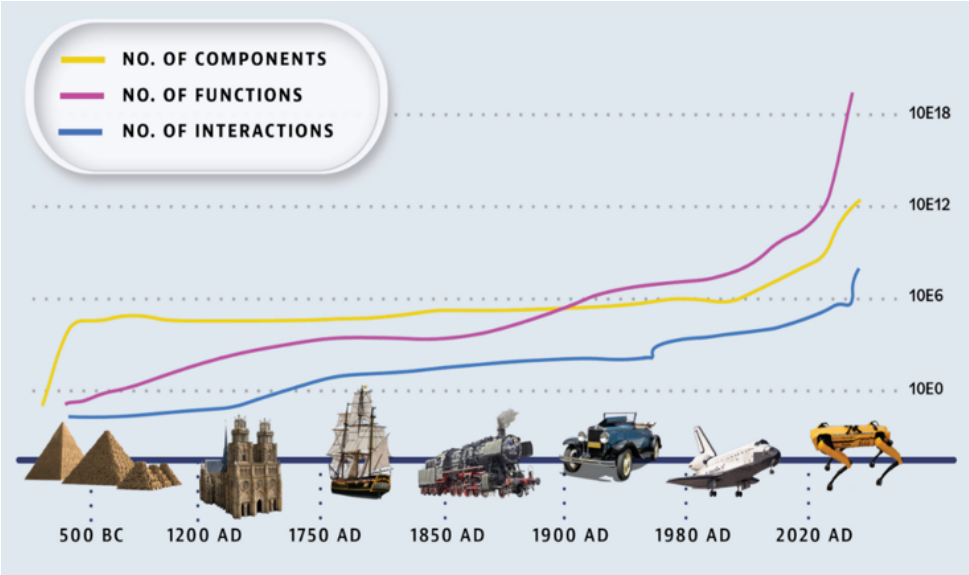


Figure 1: Historical evolution of product complexity in engineering (INCOSE, 2021)

The aircraft lifecycle further amplifies complexity-related challenges. Systems Engineering emphasizes that early lifecycle decisions are critical, as architectural choices strongly influence downstream phases, including manufacturing, operation, maintenance, and disposal. In aeronautics, where product lifecycles often span several decades, the ability to anticipate and manage long-term consequences is essential.

Building on these challenges, the digital transformation of the industry introduces an additional layer of complexity to modern engineered systems. It represents a paradigm defined by the integration of digital technologies such as Cyber-Physical System (CPS), Internet of Things (IoT), advanced data analytics, and Artificial Intelligence into engineered systems (products digital transformation) and industrial processes (production systems digital transformation, or Industry 4.0) (Vial, 2019).

Beyond providing new tools, it fundamentally transforms system architectures, interactions, and lifecycle dynamics. The adoption of these technologies significantly increases system complexity along multiple dimensions:

- **Functional complexity**: As systems gain in autonomy, adaptability, and real-time optimization capabilities, engineers must consider the functional uncertainties of subsystems.
- **Behavioral complexity**: Tighter coupling and feedback between physical processes and digital layers often produces non-linear and time-dependent behaviors.
- **Structural complexity**: The additional hardware, software, sensors, and communication interfaces have to be efficiently integrated within the system structure.

In high-reliability, safety-critical domains such as aerospace, these challenges are amplified. Modern aircraft integrates advanced digital technologies, enhancing performance, efficiency, and flexibility, but simultaneously increasing emergent behaviors, interoperability demands, and lifecycle management difficulties.

Rapid technological evolution contrasts with long development and certification cycles. Such contrast further complicates system oversight across its lifecycle. Thus, the digital transformation acts as both a driver and amplifier of complexity: while it enables new capabilities it also intensifies the challenges faced by systems engineers. Understanding this dual role is key for analyzing how the digital transformation of the industry reshapes not only product systems like aircraft, but also the industrial and engineering systems that produce them.

From a Systems Engineering perspective, production systems are complex systems themselves, integrating physical resources, information systems, human operators, and organizational processes. Industry 4.0 introduces cyber-physical production systems, where physical assets are closely coupled with digital models, sensors, and control software, enabling real-time monitoring, adaptive control, and data-driven optimization.

This integration, however, also amplifies complexity by creating additional interactions, increasing autonomy of production assets, and generating non-linear and emergent behaviors. Production systems then evolve from static, hierarchical structures to dynamic, distributed, and networked architectures, challenging traditional production engineering approaches.

In aeronautics, these trends are particularly pronounced due to highly complex, low-volume, and distributed production processes with strict quality and regulatory constraints. Digital work orders, connected tooling, and real-time quality monitoring offer significant benefits, but also increase the system's complexity, turning the production system into a System-of-Systems (SoS) with interdependent subsystems (e.g. equipments, IT, logistics, and human operators).

This highlights the necessity of applying rigorous SE principles to production systems as well, blurring the traditional separation between product design and production system design.

Industry 4.0 offers substantial opportunities in system integration, adaptability, and lifecycle optimization. The increased availability of data enables improved decision-making, enhanced traceability, and more effective feedback loops across design, production, and operation. These capabilities support core Systems Engineering objectives, including requirements validation, performance monitoring, and continuous improvement.

At the same time, Industry 4.0 introduces critical challenges. Maintaining system consistency across multiple models, data sources, and lifecycle phases becomes considerably more difficult, as heterogeneous tools and stakeholders create fragmented, partial system views.

These tensions are especially pronounced in high-criticality, long-lifecycle, domains such as aerospace. While Industry 4.0 enables predictive maintenance, performance monitoring, and tighter integration between engineering and operations, it complicates certification, verification, and validation, which are central to aeronautical systems engineering, necessitating new tools and methodologies to maintain coherence across product systems, production systems, support systems, and operational environments.

From a research perspective, Industry 4.0 shifts the role of Systems Engineering from designing static architectures toward managing dynamic, data-driven systems that evolve throughout their lifecycle. This evolution underpins the digital transformation of both engineered systems and the discipline of SE itself.

The increasing complexity of engineered systems and the progressive adoption of Industry 4.0 have driven a profound digital transformation of both systems and the engineering processes used to develop them. From a Systems Engineering perspective, this shift moves practices from document-centric approaches toward model-based and data-driven methodologies that preserve

system coherence across the lifecycle.

Traditional document-based Systems Engineering struggles to manage the volume, diversity, and evolution of information in modern, highly interconnected systems. Model-Based Systems Engineering (MBSE) addresses these limitations by placing models at the core of engineering activities, representing requirements, functional architectures, and system structures in a consistent and traceable manner. MBSE supports key principles such as abstraction, viewpoint management, and separation of concerns, while directly addressing complexity drivers such as emergent behavior, interface management, and lifecycle integration (Henderson and Salado, 2021).

MBSE aligns closely with Industry 4.0 concepts, including digital continuity, digital threads, and digital twins, providing a foundation for consistency between system definitions and downstream activities like simulation, manufacturing, and operational monitoring.

In aeronautics, Model-Based Systems Engineering has become strategically essential, enabling early validation of requirements and architectures, improving traceability across lifecycle phases, and supporting impact analysis to reduce risk.

However, MBSE adoption also presents challenges, including integration with existing tools, organizational structures, and regulatory processes. Its effective application requires extending modeling beyond product systems to encompass manufacturing, production, and support systems.

Such approach can be called Concurrent Engineering (CE) as it integrates product, production, and maintenance considerations during the development. This integrated, model-based approach is considered as a critical enabler for managing complexity in the aeronautical industry (Li et al., 2020).

While our position is not developed nor refined, we will consider an established definition of CE for the rest of this chapter.

> According to Verhagen (2015), Concurrent Engineering is defined as a *"systematic approach to the integrated, concurrent design of products and their related processes, including manufacturing and support"* .

The integration of Industry 4.0 technologies and MBSE has highlighted a critical challenge in modern Systems Engineering: the Concurrent Engineering of product and manufacturing systems. The traditional approaches that treat product development and manufacturing system design as mostly independent are no longer adequate for highly complex domains like aeronautics, where strong interdependencies exist between product architecture, manufacturing processes, and operational requirements.

From a theoretical perspective, CE embodies holistic lifecycle integration and emergent property management. Product performance emerges from interactions between design, manufacturing, and operational processes, making System-of-Systems reasoning, architectural analysis, and multi-viewpoint essential aspect of MBSE modeling.

Despite its benefits, Concurrent Engineering poses challenges, including maintaining consistency across multiple models, aligning diverse teams with divergent concerns, integrating heterogeneous toolchains, and complying with strict regulatory requirements.

Overcoming these obstacles requires methodological innovation and organizational adaptation to support cross-domain collaboration. Concurrent engineering represents a central pillar of aeronautical Systems Engineering. By integrating product and production systems within a

model-based framework, engineers can manage emergent complexity, enhance lifecycle performance, and reduce risk, exemplifying the convergence of Systems Engineering theory, through the maturation of MBSE practices, and digital transformation strategies (Dunbar et al., 2023).

1 Research context

1.1 Industrial Chair - ACTE MBSE

In 2017, Airbus launched the Digital Design, Manufacturing, and Services (DDMS) program, to address the challenges of the digital transformation of the aerospace industry. Diverse research and exploration projects were initiated with the objectives of developing innovative ways of working in order to successfully embrace Digital Engineering.

In this context, an industrial chair was launched as a partnership between the University of Lorraine, CRAN (UMR 7039 CNRS) & ERPI (EA/UR 3767) laboratories, and Airbus. This collaboration was framed as a research project named **ACTE MBSE**, involving three PhDs over a five-years period.

This research project studies how **M**odel-**B**ased **S**ystems **E**ngineering answers industrial challenges studied through **A**ctionable, **C**ollaborative, **T**rustworthy, and **E**xecutable perspectives.

- **Actionable:** Traditional MBSE often suffers from being overly academic or isolated. The results of the research thus focus on the pragmatic utility of models. Therefore, efforts should be deployed toward concrete implementation, low-friction deployment in real-world projects, and seamless integration to industrial workflows.
- **Collaborative:** Modern aerospace systems are too complex for a single mind or department to encompass. This axis addresses socio-technical elements of engineering. Breaking down siloed ways of working between discipline and domains are essential to converge toward well-engineered complex systems. Thus, collaborative methods and tools provide a foundation for skilled engineers to work together, develop designs and make collective decisions.
- **Trustworthy:** The aerospace industry involves high standard certifications which become critical stakes. The notion of trustworthiness is therefore of major importance. This research should support this perspective through data integrity, information traceability, and formal verification.
- **Executable:** Aligned with the Digital Engineering transformation, this research introduces executable functionality, advancing beyond conventional descriptive models to deliver active, simulation-based capabilities.

This partnership has permitted the integration into an industrial environment, providing access to insightful stakeholders, methods, tools, and data. This proximity allowed to grasp the reality of the industrial challenges faced in this sector, which were the root of our reflections.

1.2 Research motivation

Recent forecasts confirmed the trend toward an increasing demand of aircraft to be delivered for the 20 next years (42 450 passenger jets, representing a 2% increase from the previous forecast (Hepher, 2025)). Furthermore, the commercial aircraft production market faces increasing pressure from new entrants. These competitors operate without structural and legacy constraints that inherently burden established firms such as Airbus. Indeed, decades of production history

often bind established companies to previous projects, which can impede innovation. Moreover, their production organization is often constrained by complex geopolitical agreements, limiting their operational freedom. This industrial context highlights the necessity for aircraft manufacturers to leverage the new opportunities provided by the digital transformation to bring new aircraft to market with shorter development time, minimal costs and higher design quality.

For manufacturers like Airbus, the sale of their final product is the principal driver of growth. Aircraft must be well designed in order to be sold in a competitive market. However, their efficient manufacturability is also essential to meet market's demand. Ultimately, the ability to produce efficiently a poorly designed aircraft is as detrimental as being unable to produce the best possible aircraft design. Therefore, achieving a balanced solution requires careful trade-offs between aircraft and manufacturing designs.

1.2.1 Airbus digital transformation strategy

Airbus has invested substantial efforts in the digital transformation to support the integration of aircraft and manufacturing system design. During the past decade, new methodologies, frameworks, and tools have been developed to support these concerns. The objectives are to bring together the lifecycle of the entire production system and supply chain in one seamless digital whole, including the aerospace products themselves. By breaking the functional silos, Airbus aims to hold the promise of faster and cost-effective design and production, better services, and improved customer satisfaction (Airbus internal communication, 2025).

This strategy is articulated around three pillars which were identified as key enablers to successfully achieve this digital transformation:

- **Collaborative Design Processes and Digital Continuity:**
  Enabling collaborative design processes and digital continuity is the most important feature for improving safety, certifications, development time and costs. With collective intelligence and new technologies, Airbus aims to erase the boundaries between physical and digital domains and find new levels of efficiency all along the Product lifecycle.
- **Virtual engineering of Product, Manufacturing and Services:**
  Virtual engineering allows new opportunities and levels of automation to achieve original concepts and optimization across Product, Manufacturing, and Service systems.
- **Product Lines (flexible, modular, architecture, standardization, reusability):**
  Moving from dedicated product lines to more reconfigurable industrial elements will allow the flexibility and adaptability required to be attuned to the increasing dynamism of the market.

Through these pillars, Airbus intends to progressively shift from the sole product performance perspective to the digital co-development of products, manufacturing systems, and associated support and services.

1.2.2 Motivation synthesis

The close proximity of this doctoral work with industrial stakeholders, methods, tools, and data, provides the opportunity to study the real-world challenges faced by aircraft manufacturers. This research intends to bridge the gaps between academia and industry by proposing novel approaches to support complex systems development.

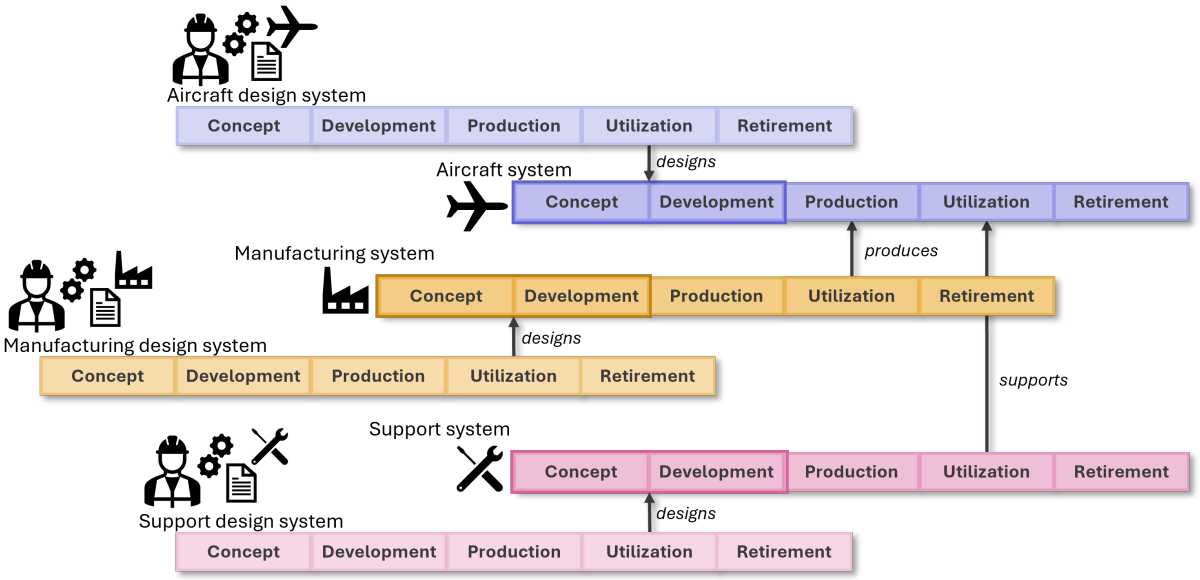


Figure 2: Aircraft and enabling systems lifecycle interactions, inspired from INCOSE (2023)

Aligned with the Airbus digital transformation strategy, we consider that the early collaborative and concurrent development of aircraft and manufacturing systems is key to meet the demands of an increasingly competitive market. This integrated approach ensures global design trade-off analysis, which are crucial for establishing an efficient production of high-quality aircraft. Thus, our core objective is to address this approach by leveraging the opportunities provided by the digital transformation of the aerospace industry.

The typical lifecycle of an engineered system is decomposed in the following phases: *Concept*, *Development*, *Production*, *Utilization*, and *Retirement* (INCOSE, 2023; ISO/IEC/IEEE-24748, 2024). The difficulty of developing all systems in an integrated manner lies within the lifecycle interactions depicted in Figure 2. As illustrated, different lifecycle phases of aircraft, manufacturing, and support systems interact with each other. While the manufacturing system's *Utilization* phase interacts with the *Production* phase of the aircraft, the support system's *Utilization* phase interacts with the *Utilization* phase of the aircraft.

We would like to emphasize that Figure 2 does not express any timed sequence of actions. It only illustrates interactions between various lifecycle phases of the involved systems. Note also that manufacturing and support systems are utilized during an entire program period which does not correspond to one specific aircraft lifecycle.

In addition to these interactions, the digital transformation of each development system introduces new opportunities but also new challenges to the desired approach.

1.3 Industrial problem

Historically, the aircraft development was depicted as an *"over the wall"* process (Mas et al., 2013b; Tang et al., 2014; Kallou, 2023). With this way of working, aircraft engineers gave the complete product design to manufacturing engineers with minimal considerations for later lifecycle phases.

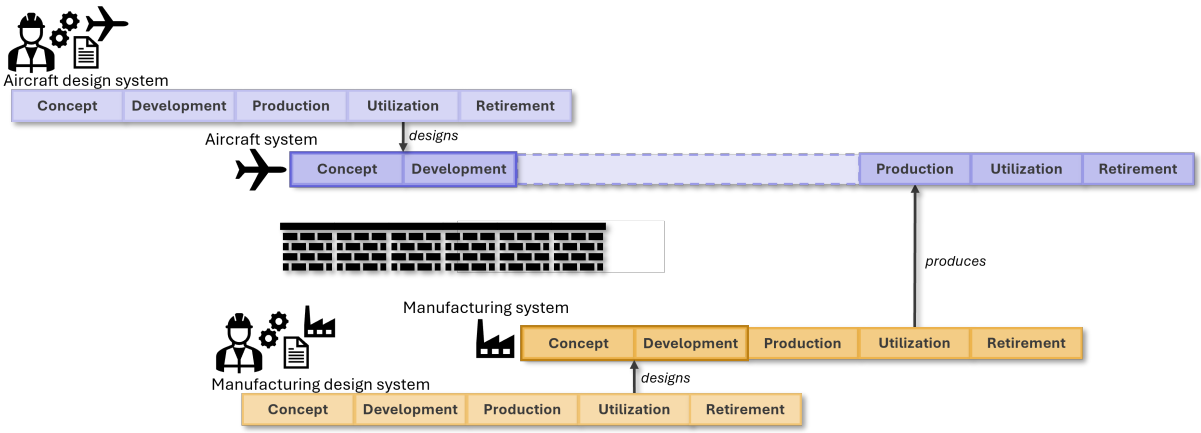


Figure 3: Historical engineering process

This way of working, illustrated in Figure 3, led to the late discovery of defects and weaknesses, necessitating heavy and costly design changes (Polacsek et al., 2017). Although this figure introduces the issues caused by product-driven, sequential development, it is exaggerated for illustrative purposes and does not accurately describe traditional engineering processes.

Nevertheless, this exaggerated process denotes from a different technical cultures between aircraft and manufacturing engineers. During some times manufacturing system design was not considered as an engineering activity with the same degree as product design. These unbalanced considerations led to restricted cross-functional interactions, resulting in a sequential, product-driven workflow.

Consequently, this way of working delayed aircraft production and necessitated extensive and costly design revisions late in the development lifecycle.

Figure 3 has introduced the industrial problem of product-driven sequential development, and delineated objectives for an enhanced process through parallel manufacturing engineering activities and high-level impact analysis.

However, addressing sequential development does not resolve strict product-driven consideration. Ideally, bidirectional exchanges between product and manufacturing engineers should be the basis for a balanced global development of such complex systems.

From this industrial problem introduction, this doctoral work is dedicated to support the paradigm shift of product-driven, sequential development toward a more collaborative and concurrent engineering.

Benefiting from a close collaboration with industrial partners, we have the opportunity to understand this industrial problem through a real-world context. Thus, we designed a series of interviews to refine the problem and identify the actual difficulties and challenges, as well as potential solutions.

1.3.1 Interview series

Grounded in the context of a new program development, this study was positioned at the intersection of three major organizational domains: Product engineering, Manufacturing engineering, and Methods & Tools. As shown in Figure 4, the extensive consultation of a broad spectrum of stakeholders with diverse professional backgrounds and positions has permitted the collection of unique points of view.

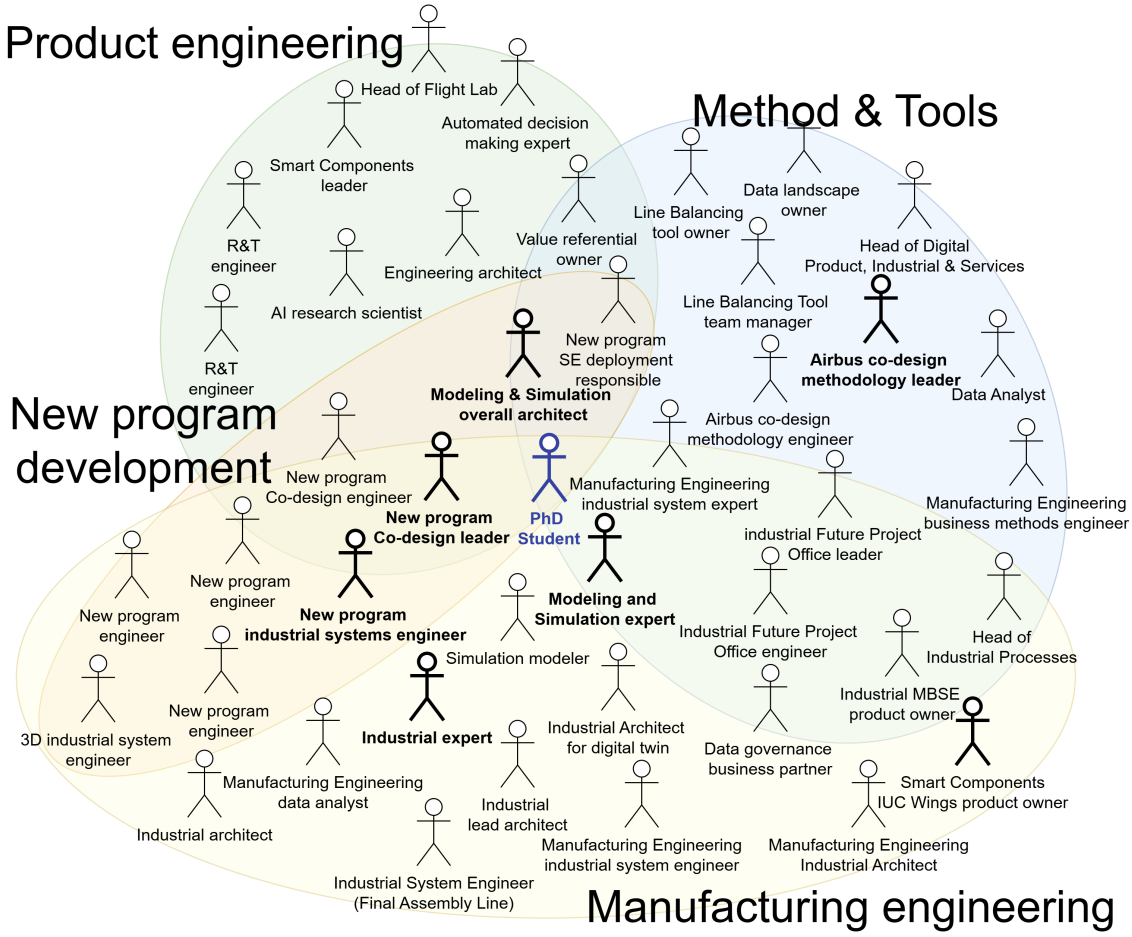


Figure 4: Industrial interactions within Airbus

It can be noted that key stakeholders, distinguished in bold in this figure, became regular focal points for the rest of this research.

Individual semi-structured interviews were employed as the primary interaction format. This approach was selected for two principal reasons when engaging the industrial partners. First, to facilitate candid feedback: individual and informal discussions allowed participants to express their perspectives honestly, unconstrained by peer influence or pressure from conflicting viewpoints. The second rationale addressed logistical efficiency. Recognizing the demanding schedules of the industrial partners, individual meetings represented the most viable approach for resolving incompatible agenda schedules, thereby facilitating participation.

The interviews intentionally maintained a tone closer to informal discussions rather than following a rigid protocol. This approach intended to facilitate meaningful digressions, allowing participants to share rich insights from their industrial experience. While maintaining this flexible atmosphere, each interview was structured around the following key thematic points:

- **Research Objectives**: Clarification of the study's aims.
- **Understanding of the problem**: Eliciting the participant's conceptual definition of concurrent engineering and its related problems.

- **Implementation of concurrent engineering**: Mapping current practices and activities.
- **Enhancing concurrent engineering**: Identifying blocking points and perceived levers for improvement.
- **Future of concurrent engineering**: Exploring strategic foresight and long-term vision.

The interview protocol was structured to guide the conversation through the different phases of this investigation. The initial point aims to establish context by outlining the research objectives, specifically clarifying that this study seeks to understand the inherent challenges of integrating aircraft and manufacturing system design, rather than to prescribe a specific solution.

The first substantive question then served a diagnostic purpose, determining the participants' understanding of key terminology (e.g. concurrent engineering, co-development, co-design), which revealed a significant variance in their definitions. The main body of the interview then explored the practical application of concurrent engineering within their operational context. Specific questions focused on current processes, inter-departmental interactions, and known difficulties. Follow-up questions were systematically employed to investigate the root causes of the identified issues and leads for improvement.

The concluding segment of the interview gathered participants' perspectives on potential resolutions and their strategic vision for the future of concurrent engineering. The collective findings from these exchanges pointed to three primary areas of concern:

1. **Cultural and process resistance**: Even with formal guidelines in place, the "over-the-wall" mentality remains a persistent cultural difficulty. Legacy workflows and historical practices continue to exert a strong influence on current processes, departmental interactions, and individual behaviors.
2. **Systems Engineering skills maturity deficits:** A second area of concern is the skill deficit caused by the rapid rollout of SE and digital methods. This lack of proficiency makes it difficult to apply new collaborative frameworks and tools effectively, ultimately stalling the progress of digital continuity and cross-functional collaboration.
3. **Knowledge loss**: Discussions frequently highlighted the inefficiencies caused by insufficient knowledge capitalization. Decades of design and production have generated vast amounts of data and decisions, yet the rationale is rarely tracked, preventing re-use and effective knowledge capitalization.

These points are rooted in the complexity of the on-going digital transformation strategy. This context, combined with the high degree of complexity of aircraft and manufacturing system design, represent a major challenge to the effective production of well-engineered products.

By addressing the concerns listed above, collaborative processes and a synchronization of the engineering phases of each system lifecycle would support globally optimized aircraft and manufacturing systems.

Nevertheless, it highlights technical and organizational issues that shall be the starting point of this research activity.

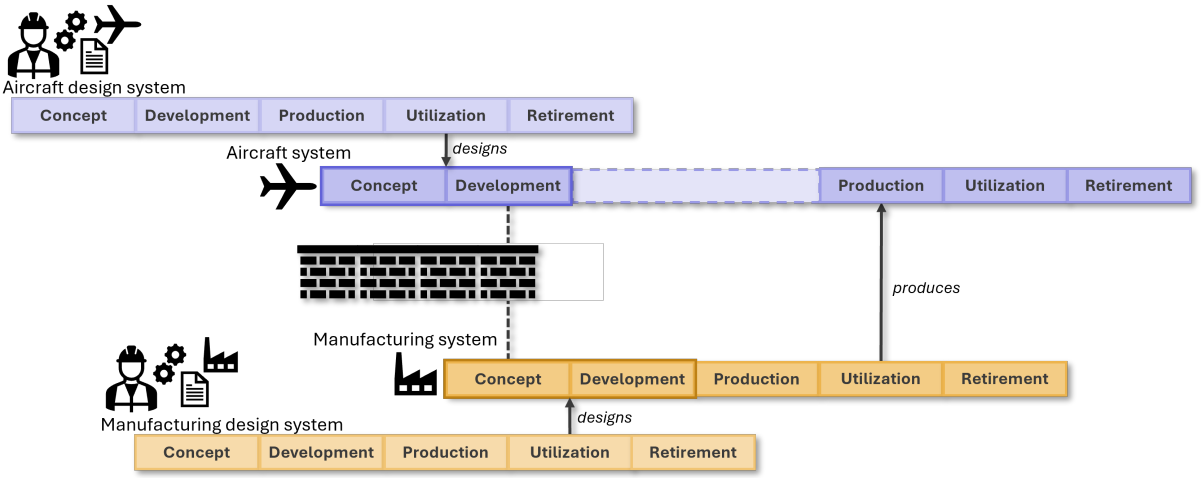


Figure 5: AS-IS - Engineering process with "over the wall" mentality

1.3.2 Industrial problem synthesis

Series of interviews allowed us to better grasp the concrete difficulties faced by aircraft manufacturers. The collection of diverse viewpoints refined our understanding of the industrial problem and its root causes. As shown in Figure 5, the development of aircraft and its corresponding manufacturing system is not a sequential process but rather a desynchronized one. The central problem lies in the timing of the inter-domain collaboration. Specifically, the manufacturing system's concept stage only starts after the aircraft's concept stage has been finalized. This late involvement leads to critical design decisions that do not adequately incorporate manufacturing considerations. Consequently, the current collaboration between these domains yields primarily minor adjustments based on impact analysis, rather than true concurrent engineering.

Challenges inherent to cultural and process resistance, lack of digital maturity, and knowledge loss, form a structural wall obstructing the collaboration required to synchronize the design phases.

Refined from the current design process shown in Figure 5, we depicted through our industrial interactions the desired aircraft-manufacturing design illustrated in Figure 6. This co-design process is characterized by unified co-conception and co-development processes that would replace the desynchronized individual engineering phases of the aircraft and the manufacturing system.

The unified approach to these engineering activities is essential for driving global designs. When integrated into collaborative engineering processes, the alignment of design stages becomes more seamless, allowing for rapid iterations, enhanced responsiveness and faster convergence.

2 Research methodology and outline

2.1 Design Science Research Methodology

Given the industrial challenges and the research context, this study exploits the new opportunities offered by the digital transformation to address key organizational issues for complex

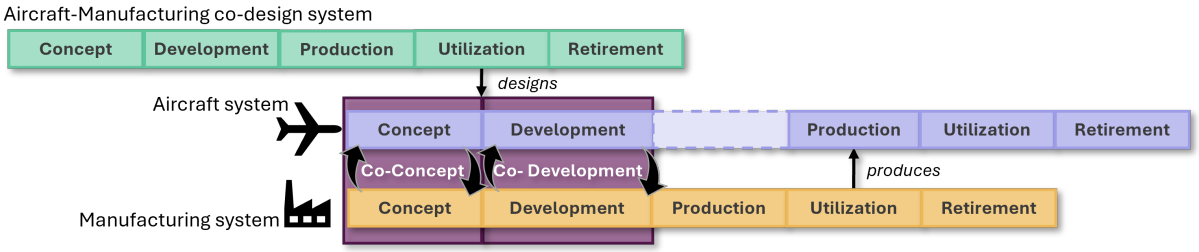


Figure 6: TO-BE - Aircraft-Manufacturing co-engineering process

system design such as cultural and process resistance, lack of digital maturity, and knowledge loss.

Achieving such objectives is inherently challenging due to the deeply interdisciplinary nature of the problems involved. To ensure both a structured approach and scientific rigor, the Design Science Research Methodology (DSRM) has been selected as the foundational framework for this research. Rooted in Computer Science and Engineering, the DSRM focuses on solving organizational problems (Peffers et al., 2007). Its fundamental objective is to create innovative artifacts such as constructs, models, methods and instantiations to solve practical problems and generate new knowledge (Hevner et al., 2004; Gregor and Hevner, 2013). This approach is characterized by an iterative process of problem identification, solution design, development, evaluation, and refinement. Emphasis is put on the evaluation of the developed artifacts to ensure both practical relevance and theoretical advancement (Vom Brocke et al., 2020).

The use of the DSRM for this study is justified as this research addresses a real-world problem within a complex engineering domain with organizational challenges. Furthermore, the collaboration between academia and industry involves a practical integration of this research for a result scientifically grounded but also applicable in practice. Finally, the artifacts created by this study are intended to improve existing processes and extend design knowledge. All these points perfectly align with the fundamental objectives of the DSRM.

As illustrated in Figure 7, this method offers several entry points. Nevertheless, its nominal iterative process sequence begins by **identifying the problem**. This step requires a thorough understanding of the problem space and should result in a clear definition of the problem breakdown. Next, the researcher **defines objectives of a solution** which have to be theoretically grounded and aligned with the problem identification. The objectives can be quantitative (e.g. by defining metrics to assert that a new artifact is better than current ones) or qualitative (e.g. by describing how a new artifact would bring capabilities addressing the problem identified).

The **design and development** of the artifact then iterates, guided by the established theory, until the objectives are met. For each iteration, the artifact's value is demonstrated in a concrete, real-world context. This **demonstration** leads to an **evaluation** that assesses how effectively the artifact fulfills the objectives, which determines the need for further iterations. Finally, **communication** is essential to share the research results, both to the academic community and, in a more accessible format, to the industrial partners.

The DSRM structure orients the development of a viable artifact with technology-based solutions to address important and relevant business problems. The designed artifact has to rigorously demonstrate its utility, quality and efficacy through robust construction and evaluation methods (Hevner et al., 2004). The objective is to improve the current engineering practices in the industry while contributing to the state of the art. Thus, results verification and validation should address both the scientific quality and the suitability for industrial deployment. Applied

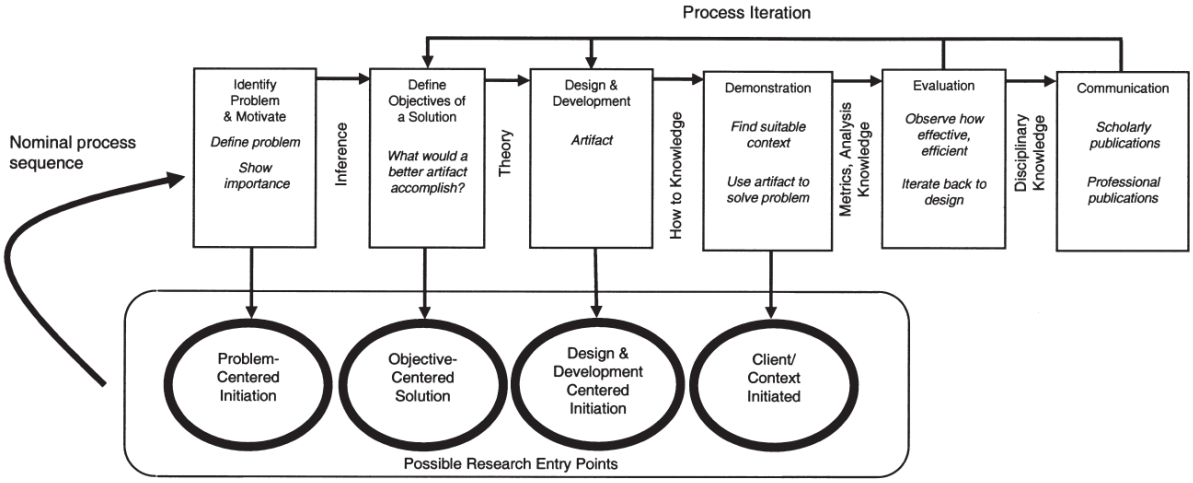


Figure 7: DSRM process sequence (Peffers et al., 2007)

in an industrial context, this methodology permits to perform iteration loops for the artifact's development, demonstration, and evaluation with problems of increasing complexity.

The DSRM classifies contributions into three distinct levels, defined by their degree of abstraction and theoretical maturity (Gregor and Hevner, 2013). They range from specific instantiations (Level 1), such as new products and processes, to more abstract components constituting the basis of emerging design theories (Level 2). These components can be constructs, design principles, models, methods, or technological rules. Ultimately, Level 3 contributions are well-developed design theory about the phenomena under study.

The remainder of this study will focus on defining, designing, demonstrating, and evaluating contributions categorized as Level 1 and Level 2.

2.2 Research outline

As illustrated in Figure 7, this doctoral work enters the DSRM by the problem-centered initiation. The problem addressed by this thesis is the desynchronization of the conceptual design phases of aircraft and manufacturing system. Figure 8 provides the outlines of this document.

The present chapter addresses the **problem identification**. From the initial research context, industrial problems were identified through semi-structured interviews with industrial partners. Root issues comprising systems complexity, digital transformation strategy, and organizational challenges were identified to address the industrial problem. The end of this chapter will infer these industrial root causes to their related scientific problems in order to orient the literature review conducted in Chapter 2.

Chapter 2 holds a literature review structured around the identified scientific problems. Each axis is concluded by a gap analysis that highlights provided opportunities and limitations. This chapter concludes by defining **objectives of a solution** for the scientific problems through our research theory composed of hypothesis and core questions.

Chapter 3 details the **design and development** of this thesis's main contributions. Artifacts such as frameworks, methods and models are elaborated in order to address the scientific

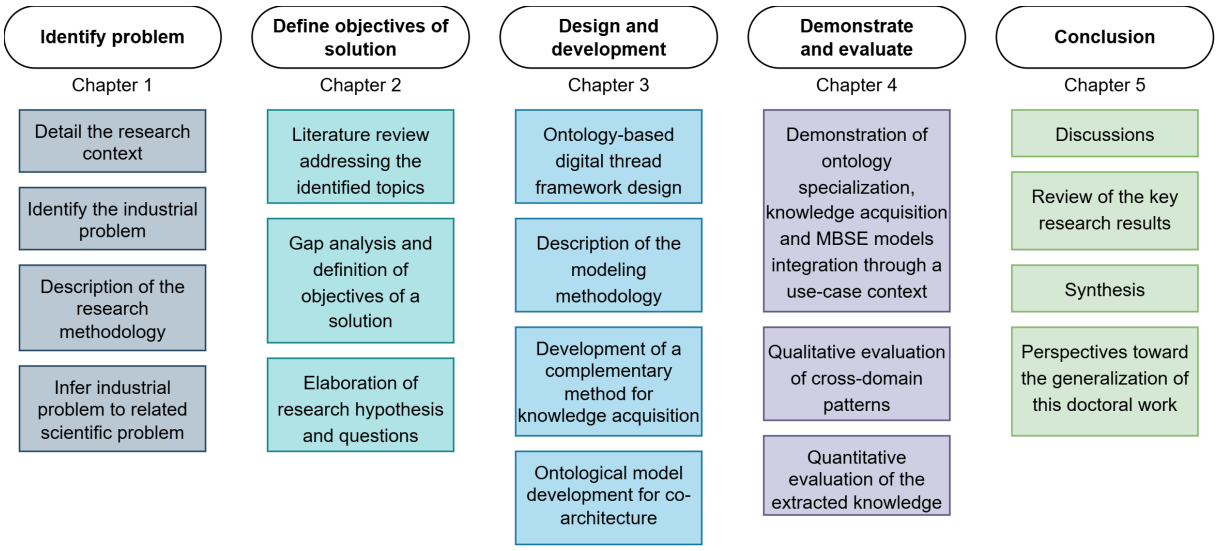


Figure 8: Research outline following DSRM structure

problems by answering the research questions.

Chapter 4 **demonstrates and evaluates** the artifacts developed in the previous chapter through a case study grounded in industrial reality. Frameworks are implemented, methods are applied, and models are refined and instantiated. Both qualitative and quantitative evaluation permit to demonstrate that the resulting artifacts effectively answer the initial problem.

Finally, chapter 5 synthesizes key information for a better **communication** of this study. Additional discussions add more depth and nuances to the results of this research, our contributions are summarized, and perspectives identify future research axes that can be built on this thesis.

3 Conclusion

The concurrent engineering of aircraft and manufacturing systems is a strategic approach intended to avoid costly, late-stage design modifications by identifying a global optimal solution during the early design phases.

Despite the recent emergence of supporting technologies, the practical implementation of this integrated design paradigm remains challenging. To identify the root causes of these difficulties, this research conducted extensive interviews with a significant number of industrial stakeholders. The interviews allowed to identify several primary challenges, beginning with the inherent complexity of the systems involved.

Aircraft and manufacturing systems are complex systems characterized by numerous parts, functions, and interfaces. This complexity is increased by the strong interdependencies between the two systems. Furthermore, the large size of engineering teams and the heterogeneous digital environment required for such projects introduces significant interoperability issues, which complicate communication, understanding, and coordination. Finally, a substantial barrier to efficient concurrent engineering is that a significant proportion of critical engineering knowl-

edge remains tacit and unformalized within experts' minds, making its systematic reuse highly resource-intensive.

The identified industrial issues translate directly into three core scientific problems. First, there is the fundamental difficulty of implementing Concurrent Engineering with two complex systems characterized by strong interdependencies. Additional complexity is caused by multi-level interoperability issues (syntactic, semantic, and organizational) which hinder proper collaboration. Finally, effective knowledge capitalization plays a key role, for systematically capturing and reusing unformalized, critical engineering knowledge.

The development of novel methods and models supporting complex system design is therefore essential to the effective Concurrent Engineering of aircraft and manufacturing systems. Through MBSE methodology, ensuring interoperability and allowing the capture, formalization, sharing, and execution of knowledge, these new artifacts may effectively allow the synchronization of design phases while shortening iteration loops.

Consequently, the primary focus of this research is to support complex system design while resolving interoperability issues and enabling effective knowledge capitalization through the emerging opportunities offered by the digital transformation.

Chapter 2

Literature review

Following the Design Science Research Methodology, the previous chapter has identified industrial problems and highlighted their importance to this research context. This chapter will develop and address the scientific problems inferred in the previous chapter by conducting a literature review, analyzing gaps and building a theory to define **objectives of a solution** for the synchronization of design phase between complex systems.

Throughout the exploration of diverse academic fields, the resulting literature review intends to position this dissertation across several axes and disciplines. This chapter is oriented by the paradigm shift from product-driven sequential development toward a more collaborative and concurrent engineering process. More specifically, it relies on the digital transformation to support modeling and simulation activities, interoperability issues, and knowledge representation.

1 Introduction

As stated in the previous chapter, aircraft and their enabling systems are highly complex systems with a considerable number of parts, functions, and relationships (Mas et al., 2021). Such complex systems necessitate dedicated methods and processes to efficiently manage their development. Systems Engineering (SE) has grown to address these needs both in academia and industry. SE 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"* (ISO/IEC/IEEE-15288, 2023). From requirement engineering to verification and validation, SE provides standardized processes to collectively address the complexity of modern systems.

However, the last decades have witnessed a continuous trend of increasing complexity in system development. Nowadays, needs of mass customization in product families, establishment of globalized supply chain sensitive to disruptions, increased focus on environmental considerations and user experience, increasing the complexity of product development. Such evolutions have pushed the limits of traditional SE practices, underlining the need to develop new approaches for developing such complex systems.

The digital transformation of the industry has introduced the Digital Engineering (DE) paradigm. The socio-technical and cultural changes triggered by this paradigm shift, the application systems based on it, and especially, their production network have introduced both new opportunities and new challenges for complex system design.

We identified in Chapter 1 that the synchronization and the integration of design phases between aircraft and manufacturing systems was one of the main industrial endeavors for shorter

development time, minimal costs and higher design quality. This axis is also of major importance in the academic engineering community.

2 Product-Manufacturing design synchronization and integration

As stated previously, the synchronization and integration of the design activities of products and manufacturing systems is a major concern for both industrial and academic communities.

Before developing on this point, we would like to clarify the terminology used for the manufacturing system. Across the literature, various names are employed to refer to this enabler system. *"Production system"*, *"industrial system"*, *"manufacturing system"* are equally valid. We have chosen to use the term manufacturing system as it refers to manufacturing engineering processes necessary for developing this system. This includes manufacturing processes, assembly processes, transportation processes and many more. Therefore, for the remainder of this study, we will use the term *manufacturing system*

Product and Manufacturing system design integration has become key in competitive engineering sectors as it benefits from reduced time to market and improved global development costs and quality. Ideally, companies should integrate all systems involved in the lifecycle of their product. *Product*, *Manufacturing*, and *Support* systems are usually the trinity of system design integration.

Nevertheless, the considerable challenges faced by this integration often lead the industry and the research communities to reduce the scope of their efforts toward more attainable objectives. Therefore, a significant part of the research involved in the integration of system design across lifecycle phases focuses on the two phases yielding the most immediate return on investment: Product design and Manufacturing phases. We would like to emphasize that, although the integration of Product and Manufacturing system design is usually the focus of research efforts, other studies address the integration of other phases with the ultimate objective of integrating the entire product lifecycle within the design activities.

Within the aerospace industry, Mavris et al. (1998) stated 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). For commercial aircraft, as for any other complex product, the integration of various disciplines as well as the integration lifecycle phases represent a global trend toward an improved design process.

While the paradigm is widely shared within the aerospace industry, plethora of diverse approaches try to address it. We will focus on an approach intending to shift from a sequential mode of product development to a more iterative and evolutionary mode as identified with our industrial partners: *"concurrent engineering"*.

2.1 Concurrent engineering definitions

Concurrent Engineering (CE) 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 way of working aims to avoid the late realization that a product needs design changes that could cause considerable impacts on global development time, costs, and quality. Ma et al. (2008) add a notion of parallelization of developments by defining its principles as: *"Achieving concurrency and close-loop evolution in product development and manufacturing processes via a tight integration of applications and parallel engineering"*. It is

Keyword	Paper published since 2022
"Integrated Product Process Development"	21
"Integrated Product Development"	1650
"Concurrent Engineering"	10900

Table 1: Google Scholar specific keyword search

distinguished from the traditional sequential product development by iterative global trade-off decision making. As Concurrent Engineering laid down vast guidelines, diverse approaches for its implementation have emerged with also various substitute and alternative concepts providing some nuances.

Concurrent Engineering is often considered as a synonym with Simultaneous Engineering. Although, some researchers highlight that, in CE, engineers concur on a solution (originating from a conflict of at least diverging perspectives). On the contrary, Simultaneous Engineering can be seen as a way of working where the systems are developed simultaneously without any conflict to resolve in perfect cooperation (Putnik et al., 2021). We consider that Simultaneous Engineering can be particularly difficult in large organizations such as Airbus. This notion of conflict resolving is important to us as we observed that the aircraft engineers will tend to propose the best aircraft design with few manufacturing considerations while the manufacturing engineers will fight for an optimized production system even if it becomes detrimental to the aircraft design. With such distinct cultural views, the whole point of CE is then to establish satisfactory trade-offs toward an integrated global design.

In the literature, the concepts of CE and Integrated Product Development (IPD) are also closely related. While often used interchangeably, it appears that they convey some nuances. While Concurrent Engineering laid generic principles of concurrent work and cross-functional teams, IPD addresses a greater focus on business strategy and customer input (Fahl et al., 2020; Disselkamp et al., 2023). Integrated Product-Process Development (IPPD) is a specific management technique related to the US Department of Defense (DoD) that leverages CE and Systems Engineering (SE) to promote open discussion and innovative thinking resulting in superior products, more efficient processes and, ultimately, a more satisfied user (Sutton, 1998). However, it seems that this term lost popularity among the research community during recent years according to a quick search analysis on Google Scholar (shown in Table 1).

With the digital transformation of the industry, Collaborative Engineering has stemmed from Concurrent Engineering, promoting effective communication with stakeholders in different locations. Part of Product Lifecycle Management (PLM) systems, it leverages information management processes to share data and automate tasks throughout the product's life (Wognum and Curran, 2012). Lu et al. (2007) have added more nuances to the collaborative paradigm by the distinction between coordination, cooperation, and collaboration. According to the authors, *Collaboration* not only involves shared resources (as in *Cooperation*), and shared outcomes (as in *Coordination*), but most importantly, shared goals.

Within Airbus, the terms concurrent engineering and co-development are often employed without distinction. Concurrent Engineering was significantly employed during the A380 program with the introduction of new collaborative tools. More recently, the concept of co-development remains the most used according to our observations as it is an umbrella term for co-engineering, co-design, and co-validation activities, "co" standing for both Concurrent and Collaborative.

Given all these definitions, we consider that the terms addressing the most closely the identified scientific problems are at the intersection of Concurrent Engineering and Collaborative Engineering. Therefore we will employ the term Collaborative and Concurrent Engineering

(CCE) for the rest of this dissertation.

We define Collaborative and Concurrent Engineering as: a systematic and multi-disciplinary approach to the development of products and their enabler systems, considering all lifecycle issues simultaneously and characterized by concurrent workflows with shared resources, outcomes, and goals. It leverages collaborative information management processes in short iteration loops to support satisfactory trade-offs reconciling divergent perspectives from multi-organizational teams into a single, integrated global design.

2.2 Related concepts

Whereas Collaborative and Concurrent Engineering comprises various principles, a significant number of other concepts are related, overlapping, or encompassing it. This section aims to position related concepts to our work to better discriminate the subject of this dissertation. We feel that concepts such as Design for X (DfX), Configuration Management (CM), and Product Lifecycle Management (PLM) are important to discuss and position within our work.

2.2.1 Design for X (DfX)

Design for X is an approach similar, yet distinct from CCE. They share similar objectives as they consider and integrate future lifecycle issues during product design. The letter "X" indicate a specific capability where the most renowned is Design for Manufacturing and Assembly (DfMA) but can be declined to a great variety of domains (Benabdellah et al., 2019).

As our research focuses on the integration of Product and Manufacturing system design, one can consider that the DfMA from Barbosa and Carvalho (2013) or the Conceptual Design for Assembly (CDfA) from Formentini et al. (2022) might fall under the scope of this dissertation. Although effective, these approaches can be distinguished from CCE regarding two points. Firstly, while such approaches aim to anticipate issues originating from a future design phase, the development of the involved systems remains sequential. This way of working can therefore still yield integration errors, or at least miss opportunities for better global design solutions. Secondly, these approaches are dedicated to a specific lifecycle phase (or capability). Although we reduced the scope of this dissertation to design products and manufacturing systems, CCE considers all lifecycle issues simultaneously.

2.2.2 Configuration Management (CM)

Configuration Management (CM) is defined as *"a management discipline applied over the product's life cycle to provide visibility into and to control changes to performance and functional and physical characteristics"* (Hirshorn et al., 2017). CM is closely related to CCE as it ensures that a product's design, documentation, attributes are consistent and controlled from conception throughout retirement. It emphasizes traceability, version control, and management of changes to complex systems, facilitating regulatory compliance and ensuring that customers receive products that meet requirements (ISO/IEC/IEEE-10007, 2017). CM is considered as a methodological enabler of CCE as it provides structured variant management practices and data governance processes aligned with concurrent workflows (Stekolschik, 2020; D'Souza et al., 2016).

This discipline, however, goes by pair with Product Lifecycle Management (PLM) systems that implements it.

2.2.3 Product Lifecycle Management (PLM)

Product Lifecycle Management (PLM) is defined as *"the business activity of managing, in the most effective way, a company's products all the way across their lifecycles; from the very first idea for a product all the way through until it is retired and disposed of"* (Stark, 2022). Whereas, CM is a product-centered discipline, PLM is an organization-wide philosophy that comprises the concept of CE, IPD, CM and many more.

Mas et al. (2015, 2021) have delineated the specifications of future PLM systems. In these papers, the authors identify the necessity to incorporate knowledge to support the Configuration Management and the digital engineering of product and processes in a collaborative approach.

2.3 Collaborative and Concurrent Engineering in early design phase

CCE offers the best opportunities during the early design phases. As illustrated in Figure 9, the design decisions made during the conceptual phase commit 70% of the total lifecycle cost while incurring only 8% (INCOSE, 2015). 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 product during the conceptual design phase, while the committed costs are low and the design freedom is high.

An aircraft lifespan can reach 50 years from the first conceptualization to the disposal. Without considering early R&D, the average development time of a commercial aircraft is 7.5 years between the launch of a new program to the first aircraft entry into service (Mas et al., 2015). Such long lifecycles of complex products therefore involve tremendous costs with a relentless inertia.

The integration of aircraft and manufacturing system design has been identified for several decades to reduce the overall development time, control the total costs, and improve the design quality.

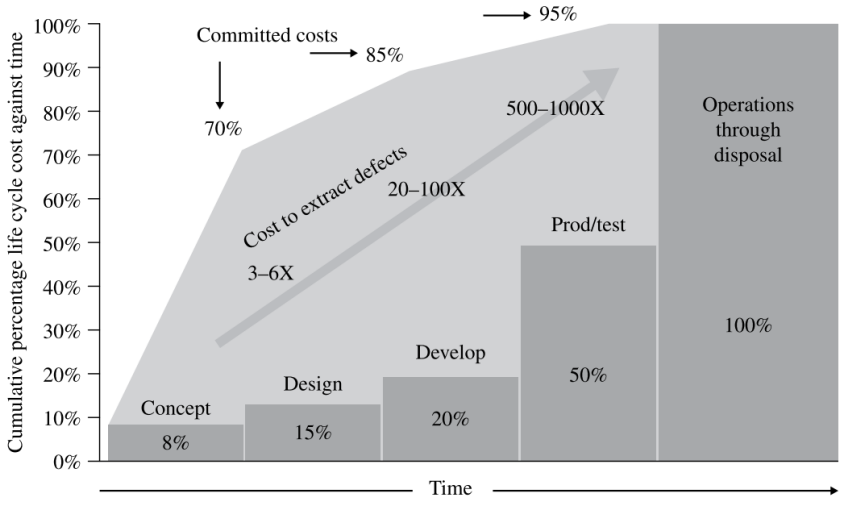


Figure 9: Committed Lifecycle costs against time (INCOSE, 2015)

Therefore, the rest of this doctoral work focuses on the integration of commercial aircraft and manufacturing system design during the conceptual design phase to improve the overall development time, costs, and quality. The operational and disposal phases are considered out of the scope to this research albeit they bear a significant importance for aircraft design.

Following the concurrent engineering paradigm, parallelizing the design of aircraft and manufacturing systems would assist program leaders by providing a better vision of the global system in the earliest stages. By integrating and aligning these two disciplines throughout a single design process, one could improve the development time, costs and quality of all systems.

During the conceptual design phase, the main deliverables are the architectures of the systems. The system architecture process consists of defining the structure and behavior of complex systems to meet their operational and functional needs. As system architecture is an abstract description of entities and relationships between them, it can be described as a model involving engineering artifacts linked by relations.

However, implementing Collaborative and Concurrent Engineering (CCE) during the conceptual design phase is fundamentally challenging due to the abstract nature of early-stage information and the multiplicity of potential solutions. These challenges makes it difficult to assess the global impact of design decisions, thus hindering the synchronization of different development streams.

The core of the problem lies in the lack of explicit background data, assumptions, and varied perspectives, forcing a heavy reliance on the time-consuming and experience-based intuition of individual engineers (Murman et al., 2001; Zhang et al., 2020; Formentini et al., 2022). This constraint limits manufacturing engineers to evaluating only a few simplified cases for defining initial processes and resources.

Therefore, the conceptual design phase highlights a need for extensive knowledge and information traceability to support heavily-dependent expert-based impacts assessments.

Nevertheless, the emergence of Digital Engineering has introduced the development of formal models for both product and manufacturing system design to overcome these limitations. Such models provide the analytical and decision-making framework necessary to effectively support a truly collaborative and concurrent engineering environment (Mas et al., 2013a).

2.4 First gap analysis

The Product-Manufacturing design synchronization and integration is a major endeavor for complex systems engineering sectors. Addressing such concern, this study focuses on Collaborative and Concurrent Engineering approaches. Part of the Product Lifecycle Management philosophy, CCE allows for considerations of all lifecycle issues through concurrent workflows with shared resources, outcomes, and goals.

The implementation of CCE presents the most benefits when applied at the earliest time possible. Short iteration loops of global trade-offs permit to reconcile divergent perspectives into a single, integrated global design toward efficiently-manufacturable, well-designed products.

However, implementing CCE in early design phase raises significant challenges. Because early-stage information is abstract with a multitude of potential solutions and interdependencies, assessing the impact of cross-domain design changes is a challenging task that relies heavily on specialized expert judgment.

The Digital Engineering paradigm shift offers compelling ways to develop complex interdependent systems while supporting cross-domain impact assessment. However, this paradigm shift also comes with new cultural and socio-technical challenges.

3 Digital Engineering

Digital Engineering (DE) is transforming the industry with new engineering processes fostering the elaboration and reusability of digital models. In opposition to the traditional document-

centric and paper-based ways of working, digital models can be easily shared and edited supporting collaborative engineering processes while enhancing information cohesiveness.

As shown in Figure 10, Digital Engineering is a large concept encompassing diverse fields and domains (Suprun and Elsawah, 2026). Sony and Naik (2020) have characterized it as a socio-technical and cultural transformation as it involves interactions between people and technologies, from which emerge what can be called a digital culture within organizations.

DE remains an on-going transformation with significant endeavors remaining. Shown in Figure 11, a roadmap orienting the research for Digital Engineering in complex system development was delineated by McDermott and Verma (2022). The five major axes identified are: Models for decision-making, Authoritative source of truth, Technological innovation, Collaborative environment, and Workforce culture.

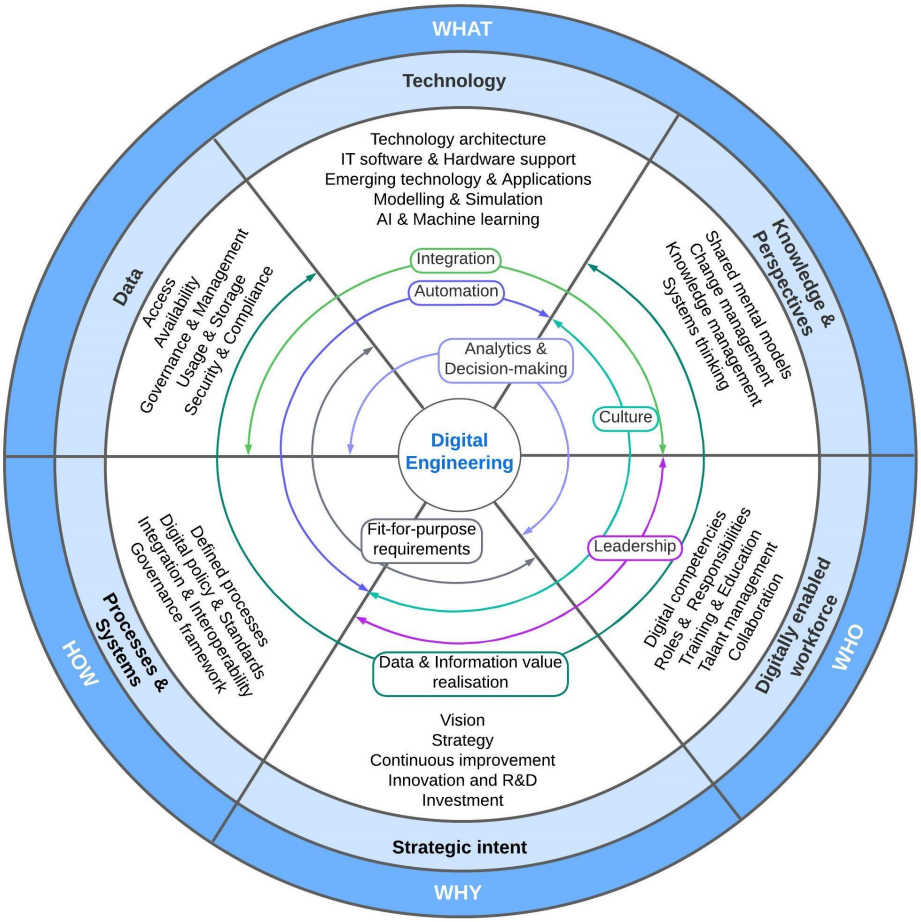


Figure 10: SEBoK Digital Engineering wheel (Suprun and Elsawah, 2026)

This roadmap also defines incremental states of DE maturity. These DE stages are respectively: data integration, semantic integration, augmented engineering, and finally, fully implemented Digital Engineering. As stated previously, the most important side of this paradigm shift is collaborative capability of DE. The authors highlight that the integration of digital models with technological innovations such as Semantic Web Technologies (SWT), ontologies, and machine learning, provides a framework for enhanced and automated decision-making.

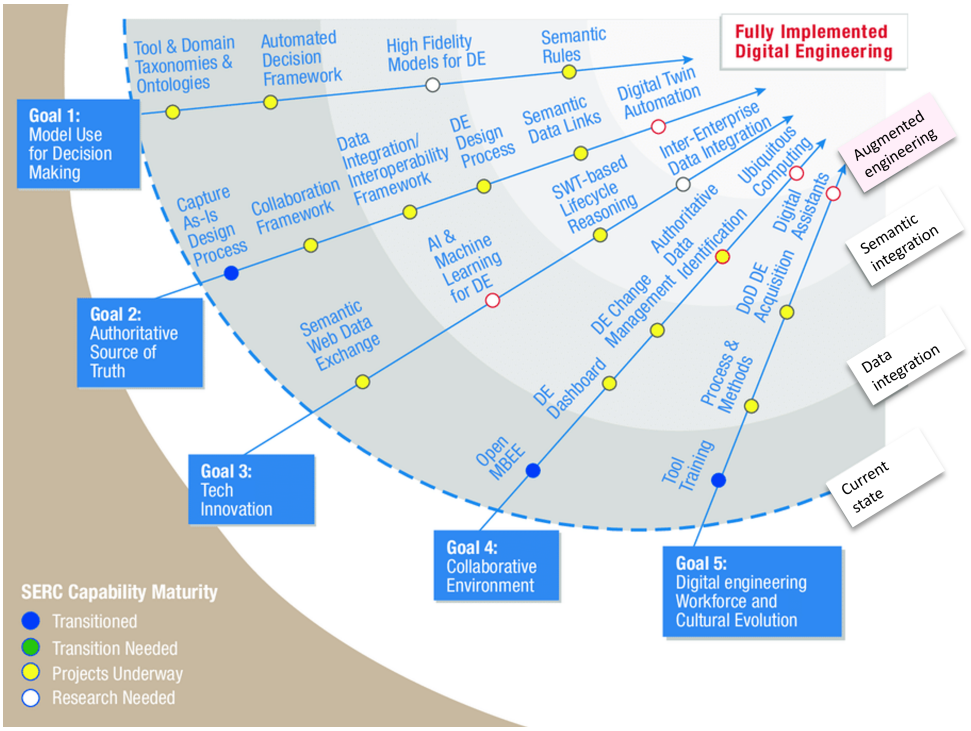


Figure 11: Digital Engineering roadmap example (McDermott and Verma, 2022)

The envisioned maturity increments follow a classical path: first integrate the involved data, then integrate meaning and context, and finally, integrate high-end knowledge representation, reasoning and simulation.

Finally, all engineering data and information shall be available seamlessly in a shared source of truth enabling efficient communication across domains and disciplines during the whole lifecycle. However, this fundamental transformation of engineering activities relies significantly on the cultural adoption of the workforce across the organization.

These new ways to analyze, integrate, automate, and support decision-making have deeply transformed traditional engineering activities toward digital engineering activities such as CAD, MBSE, or MDAO. Whereas CAD and MDAO mostly address later design phases, the scope of MBSE addresses the conceptual design phase.

3.1 MBSE for Concurrent and Collaborative Engineering

Aircraft and manufacturing systems are becoming increasingly complex with multi-disciplinary environments. Their development is supported by Systems Engineering (SE) which provides standardized processes to collectively address the complexity of modern systems. Activities such as requirement analysis, architectural design, implementation, integration, verification, and validation, constitute the core of SE.

During the past decades, most industries have witnessed the combination of SE principles with digital models, introducing Model-Based Systems Engineering (MBSE). Shifting from a document-centric approach 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"* (INCOSE, 2015).

MBSE has been developed to model the system's requirements, functions, behaviors, and structures. The most common MBSE language employed is SysML (System Modeling language) which is an extension of UML (Friedenthal et al., 2014). By addressing the inconsistencies of the document-centric way of working, MBSE thrives with the complexity of the engineered systems (Akundi and Lopez, 2021). Menshenin et al. (2021) have integrated MBSE with PLM approaches, demonstrating the importance of such methodology for handling complexity and uncertainty for complex product design.

More recently, MBSE has been leveraged to transform traditional manufacturing system design into a multi-disciplinary and collaborative environment for enhanced decision-making toward optimized products and processes (Akundi and Lopez, 2021).

The rise of MBSE comes with new capabilities incorporating Collaborative and Concurrent Engineering and collaboration aspects. According to Topper and Horner (2013), this methodology supports collaboration between various stakeholders through a shared reference, a standardized modeling language and information traceability for complex system design. In this sense, MBSE facilitates CCE through the modeling of requirements and system architectures while automatic cascading design changes for systematic exploration of the design solution (Bruggeman and La Rocca, 2023).

In the current state of the literature, CCE and MBSE are applied in complementary but siloed ways. Despite the lack of integration of these two methodologies, they ultimately support similar objectives: enhancing the design of complex systems through improved communication across disciplines, integrated system development processes, traceable design decisions, and flexible information structures. Vizitiu et al. (2025) provide a nuanced understanding of the current state and trends in concurrent design via MBSE.

In the aerospace industry, Li et al. (2020) leverage MBSE with other disciplines to optimize the design of aircraft and manufacturing systems while guaranteeing compliance with the requirements. In this paper, the authors propose a *Requirement-Functional-Logical-Physical* decomposition to model interdependencies between product features and production processes, enabling information traceability and impact analysis between domains.

3.2 Digital Thread concept

The Digital Thread is a concept belonging to the Digital Engineering. It is considered as the backbone of the majority of the new methods and tools emerging with the digital transformation such as Model-Based Systems Engineering (Bonar and Hastings, 2024).

In the aerospace, Lee et al. (2012)) highlighted the need to quickly assess and visualize the impact that changes in system design and factory configuration have on aircraft performance, production rate, backlog, and profitability. Siedlak et al. (2018) bring the idea of a digital thread linking the various models with the goal of accelerating design time and enabling trade-offs across traditionally isolated disciplines. In this paper, the authors use the MInD framework (Manufacturing Influenced Design (Ceisel et al., 2012)) which is a framework that leverages MBSE with more detailed modeling techniques (e.g. physics-based models and discrete-event simulations) across disciplines during early design.

Tuegel et al. (2017) define the Digital Thread as *an extensible, configurable and component enterprise-level analytical framework that seamlessly expedites the controlled interplay of authoritative technical data, software, information, and knowledge in the enterprise data-information-knowledge systems, based on the Digital System Model template, to inform decision makers throughout a system's life cycle by providing the capability to access, integrate and transform disparate data into actionable information*". The word *"authoritative"* in this definition refers to

the concept of Authoritative Source of Truth (AST) which has been previously mentioned as one of the main axes of Digital Engineering transformation (McDermott and Verma, 2022).

According to Smith et al. (2022), AST is *"the capability (composed of a combination of tools, people, processes, and rules) that gives definitive answers (backed up by business rules for the relevant organization) to queries (requests for information) about a target system. The answer to a query comes in the form of digital artifacts"*. Authoritative Source of Truth is the essence of the Digital Thread for the capability to provide the right information to the right stakeholder at the right time.

In complex engineering contexts, there is rarely a single AST (Zhang et al., 2024). Instead, there are multiple authoritative technical data sources depending on the domain and discipline (e.g. MBSE repositories for system architecture, PLM for product structures, Enterprise Resource Planning (ERP) tool for inventory information, etc...). In Digital Engineering, the digital thread links all local AST into a coherent vision across the lifecycle (Bajaj et al., 2017).

Digital threads have been employed to integrate heterogeneous manufacturing systems with MBSE product architecture (Hedberg et al., 2016; Bonar and Hastings, 2024). However, the need to link models and artifacts across environments and lifecycle phases raises concerns of interoperability as a key endeavor in order to benefit from its capabilities.

Dunbar et al. (2023) proposed a digital thread framework integrating MBSE to support concurrent engineering. Based on meta-models, it leverages aligned data interfaces to enable tool-to-tool interoperability across diverse domains. The resulting digital thread achieves model integration and interoperability capabilities through the use of Semantic Web Technologies (SWT) and ontologies. This framework unveils compelling ways to address interoperability issues within Digital Engineering.

3.3 Second gap analysis

MBSE presents compelling capabilities to support Collaborative and Concurrent Engineering in the aerospace industry. Through the use of digital models, engineers can easily collaborate with standardized engineering processes addressing the complexity of the involved systems. Used in a collaborative manner, MBSE environment allows for information traceability, multi-disciplinary views, and diverse degrees of abstraction.

Furthermore, the digital continuity enabled by MBSE provides a seamless cascade of information toward improved design consistency and early errors detection. This paradigm also permits to easily reuse and edit models, fostering innovation and reducing repetitive tasks while supporting a clear versioning.

However, integrating the design of aircraft and manufacturing systems often reveals a critical gap in Systems Engineering processes and modeling maturity. Indeed, the utilization of SE and MBSE was historically concentrated on aircraft design only. As manufacturing engineering only recently begun to employ these methodologies and tools, a significant disparity in experience and skill sets has emerged between the two domains (Mas et al., 2018).

Despite initiatives to bridge this gap, inconsistent MBSE maturity levels remain a major obstacle to successful CCE practices (Akundi and Lopez, 2021). This challenge is further compounded by a trend toward customized modeling techniques, which complicates cross-domain alignment (Wortmann et al., 2017).

Although recent efforts have sought to standardize systems engineering terminology, persistent methodological differences continue to necessitate labor-intensive model linkage and maintenance (Miller, 2022).

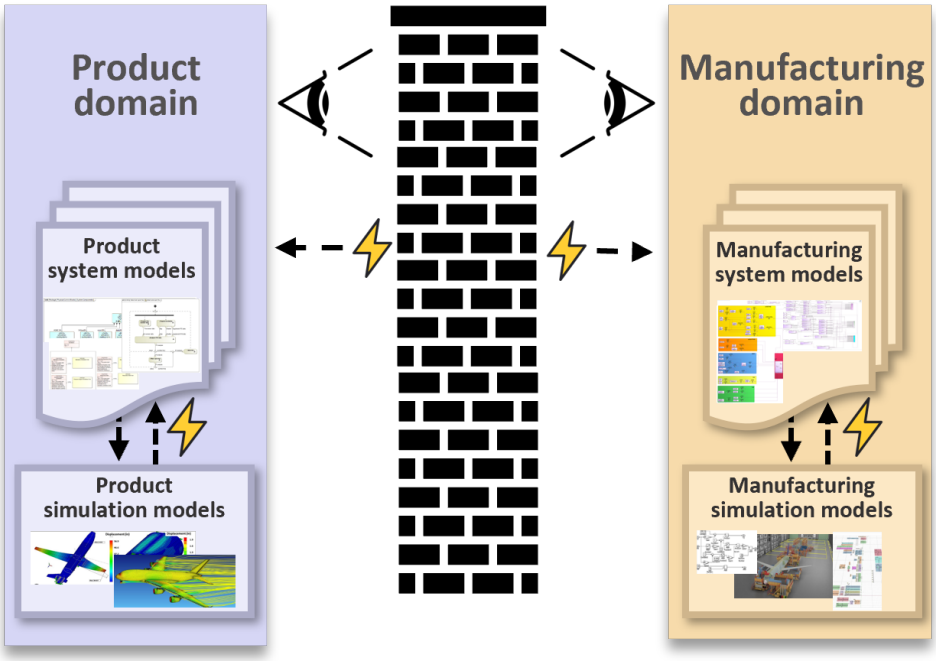


Figure 12: Synchronization and Interoperability issues

Consequently, such integration issues among architecture models lead to problems of communication, understanding and operation between the engineers involved (Lu et al., 2021).

Figure 12 illustrates the issues identified in our industrial context regarding the use of MBSE for CCE. The first problem found during our observations resides in remaining siloed way of working between aircraft and manufacturing system engineers. With reduced visibility toward cross-domain projects, the collaborative design activities are hindered by communication, understanding and coordination issues causing the desynchronization of design activities.

The second problem, as identified by Siedlak et al. (2018), is the necessity of using simulation models, even in early design phase. This need introduces problems of interoperability between MBSE environments and the other third-party tools.

Concerns toward data integration and linkage maintenance for MBSE in a Collaborative and Concurrent Engineering context have highlighted the need for a more flexible and comprehensive solution (Li et al., 2020; Bruggeman and La Rocca, 2023). While Madni and Sievers (2017) identified ontologies as a way to enhance MBSE by interfacing between architectures and supporting tradespace evaluations while ensuring semantic consistency, Dunbar et al. (2023) have implemented ontologies at the basis of a digital thread framework integrating cross-domain MBSE approaches.

Therefore, it appears that ontologies offer interesting capabilities to provide enhanced comprehension toward MBSE artifacts bridging modeling maturity gaps. Furthermore, employed with Semantic Web Technologies, they represent a flexible communication medium toward interoperability between customized frameworks and third-party tools.

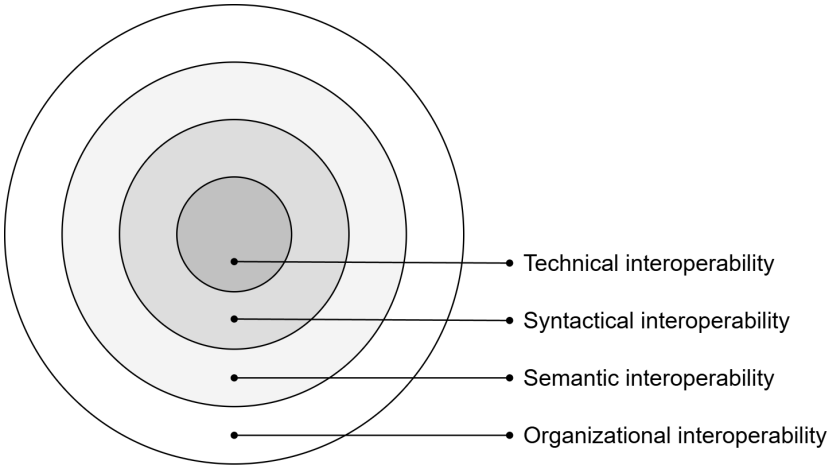


Figure 13: Interoperability degrees inspired from Van Der Veer and Wiles (2008)

4 Ontologies for Collaborative and Concurrent Engineering

Ontologies are defined as the *"formal description of knowledge as a set of concepts and relationships used to represent an area of concern"* (Saeed et al., 2017). Initially used in the Semantic Web, they have since been extended to a variety of other domains. They play a fundamental role in information exchange and knowledge management across distributed environments.

In complex systems engineering sectors with multidisciplinary stakeholders, the vocabulary employed tends to rapidly evolve within each engineering process. Technical terms, acronyms, and homonyms are thus widely employed across engineering disciplines. However, their meaning tends to remain confined in their specialized communities. Discrepancies of understanding, therefore emerge as an additional blocking point to collaboration between disciplines.

Ontologies bring key capabilities to support Collaborative and Concurrent Engineering (CCE) during the conceptual design phase. On one hand, through a common conceptualization, they enable 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 (Da Silva Serapião Leal et al., 2019).

4.1 Ontologies for interoperability

As illustrated in Figure 13, interoperability is declined with incremental degrees: technical, syntactic, semantic, and organizational (Van Der Veer and Wiles, 2008). The core technical interoperability relies on infrastructure protocols for data exchange between hardware and software. As this is basically enabled by any digital tool, we do not consider it relevant in our scope.

Syntactic interoperability builds upon technical interoperability enabling communication between softwares through data formats. The semantic interoperability adds a common understanding toward the interpretation of the data exchanged. Finally, organizational interoperability is the ability for organizations to communicate and transfer meaningful information across various information systems, infrastructures, geographic regions, and cultures. Organizational interoperability depends on successful technical, syntactic and semantic interoperability.

Combined with Semantic Web Technologies (SWT), ontologies provide capabilities addressing both syntactic and semantic interoperability (Ranatunga et al., 2025). With standard machine-

readable formats and query protocols such as RDF/XML and SPARQL, they provide a graph-based flexible data exchange agnostic to tool-specific format (Dunbar et al., 2023). Furthermore, ontologies defining common classes, properties and constraints can support heterogeneous data alignment while mapping local terms to shared concepts. These capabilities thus provide the means to communicate between diverse data formats while conveying a shared meaning.

Madni and Sievers (2017) identify ontologies and SWT as a way to enhance Model-Based Systems Engineering through flexible interface between architecture models and trade-offs analysis (syntactic interoperability) while maintaining a semantic consistency (semantic interoperability). Hu et al. (2022) have used ontologies as a central part of the MBSE methodology, by leveraging a semantic core to integrate 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. (2013) to improve interoperability and knowledge sharing across product and manufacturing system design.

For complex systems modeling, Sanya and Shehab (2015) leverages the definition of domain-specific ontologies in a modular manner to access interdisciplinary knowledge while easily managing the complexity. Consequently, in order to ensure the compatibility between diverse domain-specific ontologies, the definition of a top-ontology such as Basic Formal Ontology (BFO) allows the description of concepts aligned on a shared schema (ISO/IEC/IEEE-13586, 2021). Some industrial practices also leverage the utilization of a middle-ontology such as IOF-core (which refers to BFO) in order to align industrial conceptualizations in extended enterprise contexts (Hu et al., 2022; Arista et al., 2023).

IOF-core has been developed as a standardized suite of ontologies to support the digital manufacturing industry and aims to become an official standard at the end of its development (Drobnjakovic et al., 2022). With capabilities to exchange information between heterogeneous sources in a tool-agnostic format while conveying a shared conceptual knowledge across distributed environments and organizations, ontologies and SWT are enablers for syntactic, semantic and organizational interoperability.

Comparable aspects have been addressed by Dunbar et al. (2023), which incorporated Semantic Web Technologies to favor model integration and interoperability. In this paper, 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 capabilities.

Such knowledge representation and reasoning capabilities permit to consider ontologies not only as an interoperability enabler, but also as a support for Knowledge-Based Engineering (KBE).

4.2 Ontologies for Knowledge-Based Engineering

As stated in Section 2.3, the conceptual design phase is characterized by a high degree of abstraction with limited knowledge about the systems of interest. Therefore, the capture, modeling, and reuse of knowledge that supports design decisions is key to support early Collaborative and Concurrent Engineering.

Knowledge-Based Engineering (KBE) is defined as *"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). KBE promotes the acquisition and reuse of knowledge facilitating cross-functional collaboration by centralizing system information and design rules. Consequently, KBE systems supports decision-making through

the effective propagation of design modifications across components and systems, encompassing diverse domains.

Bruggeman et al. (2024) proposed a generic model to capture and organize knowledge for automatic manufacturing considerations during the conceptual design of aircraft structures. This model has helped to identify trends and rank manufacturing concepts, thereby supporting trade-off decisions. Adopting a comparable approach, Szejka et al. (2024) employed ontologies and semantic technologies to identify inconsistencies between product and manufacturing system design while ensuring information interoperability.

Dunbar et al. (2023) leveraged ontologies as a reasoning layer to infer knowledge based on heterogeneous data sources. Through Description Logic (DL), reasoners part of the SWT stack can automatically enrich the described knowledge by discovering how new relations between elements. Nevertheless, the authors mention a high-effort cost to capture the initial knowledge and establish cross-domain links. In this sense, Sun et al. (2024) identifies ontologies as a mean to acquire, manage, and transfer tacit knowledge for complex system design.

Although exhibiting encouraging capabilities, these approaches remain locally specialized and frequently lack reusability and adoption (Kuegler et al., 2023). High costs of both implementation and maintenance, coupled with lack of robust knowledge acquisition techniques, knowledge management and formalization methods were identified by the authors as issues impeding the development and adoption of generic KBE approaches. Concurring with this statement, Ameri et al. (2022) state that the interoperability problem in the industry is still unresolved because they are developed on local needs, failing to consider a wider scope of application. The authors identify the need for a consistent use of ontologies for data access and reasoning across the product lifecycle.

4.3 Ontology-Based Engineering methods

The increasing trend of KBE approaches employing ontologies for a unified knowledge representation has introduced Ontology-Based Engineering (OBE) (Lentes, 2025). OBE leverages explicit specifications and structured conceptualizations for improved knowledge representation and reasoning. OBE enhances complex system design by allowing domains to be modeled via axiomatic definitions and taxonomic structures, thus embedding enriched knowledge within the engineering process. Complex system design activities are supported by OBE methodologies which use ontology models to enhance collaboration through knowledge capture, management, and sharing (Mas et al., 2025).

Through ontologies, Curran et al. (2010) proposed a methodology for early and continuous use of multidisciplinary knowledge leading to more accurate estimation of manufacturing consequences.

Mas et al. (2018) proposed an OBE methodology named Models for Manufacturing (MfM) that leverages an agnostic approach for knowledge capture and reuse to support complex manufacturing system design. This methodology was employed at the core of the MBSE environments in successful industrial applications (Hu et al., 2022; Zheng et al., 2022; Arista et al., 2023).

For example, MfM has been leveraged by Zheng et al. (2022) to establish a semantic-driven tradespace framework by converging ontology engineering and MBSE to optimize the digital continuity and interoperability in aircraft manufacturing system design. In this context, the ontology serves as a semantic core to integrate the modeling, simulation and requirement management activities. The authors state that ontologies are a powerful tool for knowledge representation and formalization by capturing domain knowledge in a persisting way that is compatible with MBSE framework and the perspective of human common sense. Thus it can serve as a trusted

knowledge base, a cross-domain bridge, and a mediator for interoperability in manufacturing engineering.

In a similar context, Arista et al. (2023) integrate experts' knowledge to support manufacturing system design via semantic integration and ontology reasoning. In this paper, the authors propose a manufacturing system design tradespace leveraging MBSE through MfM's guidelines (Mas et al., 2018) in order to structure and manage ontologies for interoperability and knowledge enrichment. Within the developed application ontology, assembly system domain knowledge, industrial requirements and information about the system architecture model were integrated allowing to greatly re-use captured knowledge for complex system design.

While there are yet open questions related to the knowledge extraction from different knowledge sources, the MfM methodology provides a generic and structured approach to provide shared conceptualizations, a common understanding and reasoning capabilities based on ontologies. Incorporated at the core of Model-Based Systems Engineering, MfM offers a convincing OBE approach to support early Collaborative and Concurrent Engineering (CCE) (Arista et al., 2023).

4.4 Third gap analysis

Ontologies and Semantic Web Technologies (SWT) present compelling capabilities to be integrated at the core of MBSE methodology and Digital Threads.

Firstly, by serving as an interface for MBSE artifacts, they provide a graph-based flexible data exchange medium agnostic to specific tool formats or modeling languages. Acting as a bridge between cross-domain MBSE frameworks and the rest of the digital suite, they enable syntactic interoperability.

Further, by describing common classes, properties, and constraints, they provide a unified conceptualization enabling a shared understanding among the various teams involved, thereby achieving semantic interoperability.

Also, used as a shared reference, ontologies and SWT provide the means to coordinate across distributed environments and organizations which achieve organizational interoperability.

Secondly, ontologies have a significant knowledge representation and reasoning capabilities which are essential to support Collaborative and Concurrent Engineering (CCE) during the conceptual design phase. Ontologies grew in importance within the Knowledge-Based Engineering (KBE) community leading to emergence of Ontology-Based Engineering (OBE).

OBE methodologies define structured approaches for knowledge capture, formalization, and reuse supporting decision-making for complex system design.

The OBE methodology named MfM presents interesting advantages such as its proximity with MBSE environments and its numerous industrial applications. By placing OBE as a central part of the MBSE methodology, both shortcomings related to MBSE interoperability and adoption can be addressed.

Nevertheless, the studied papers highlighted open questions regarding knowledge acquisition toward diverse sources. For now, most approaches consider experts as their main knowledge source, which can become a resource-intensive and time-consuming process. As shown in Figure 14, the considerable amount of data generated with DE has raised new needs for methods incorporating knowledge from both experts and historical records.

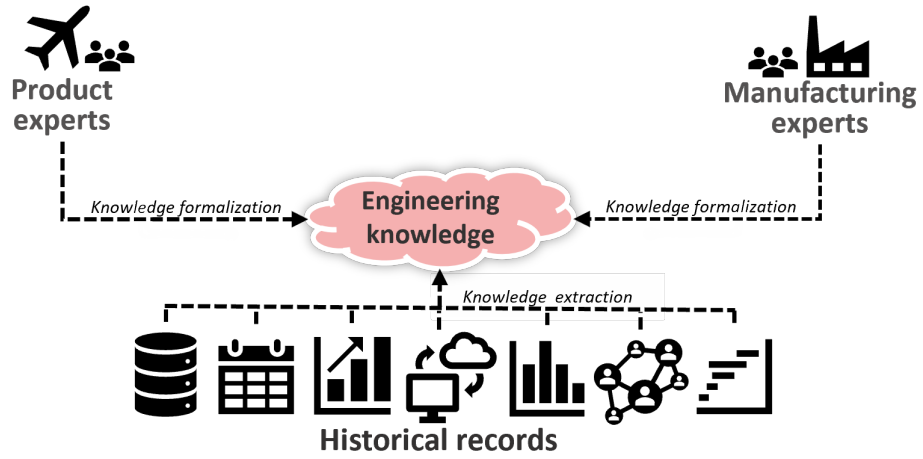


Figure 14: Knowledge acquisition from diverse sources

5 Knowledge for product design

In the field of product design, Chandrasegaran et al. (2013) propose a knowledge classification (illustrated in Figure 15a) through three dimensions: *Tacit vs Formal*, *Product vs Process*, and *Compiled vs Dynamic*. While these dimensions offer a robust and comprehensive framework for general knowledge description, the specific needs of early-stage Collaborative and Concurrent Engineering necessitate a more nuanced informational layer.

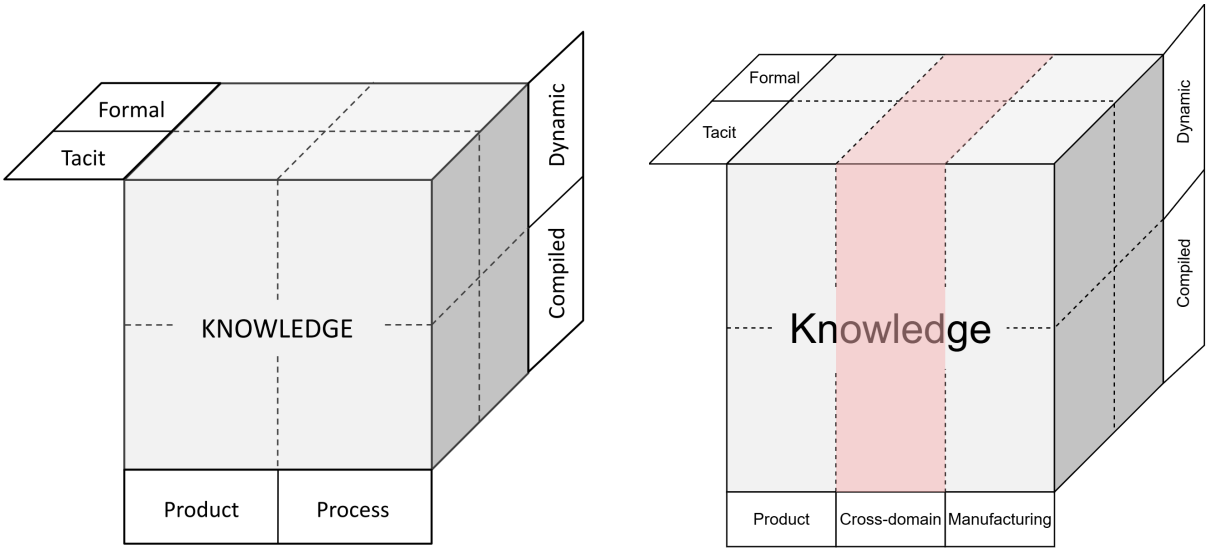
Consequently, we would like to refine this classification in Figure 15b to more accurately reflect the specificity of knowledge within early CCE context. The objectives here are not to pursue the philosophical goal of defining what is knowledge, but rather to delineate the specific concepts essential to our discourse.

- Product/Process dimension: While considering the integration of Product and Manufacturing system design, the dichotomy Product/Process knowledge is not satisfactory. We propose to add a band representing *"Cross-domain"* knowledge that links both product and process artifacts (e.g. knowledge about the production cost of a product system).
- Tacit/Formal dimension: Within the Knowledge Management (KM) literature, diverse degrees of expressivity exist. The most common classification encountered during our study was the *Explicit/Implicit/Tacit* decomposition (Jensen et al., 2007; Pozzali, 2008). Whereas distinctions exist between *Implicit* and *Tacit* knowledge, we can align with the decision of the original figure to simplify the taxonomy by subsuming implicit knowledge into a larger *"Tacit"* category. Similarly, we consider that adopting *"Formal"* as a synonym for *"Explicit"* remains a sufficient descriptive degree for the rest of this dissertation.

Thus, this study will focus on the acquisition of *cross-domain* knowledge, whether it is *formal* (e.g. *compiled* in technical documentation or *dynamically* available from sensors), or *tacit* (e.g. *compiled* in interview recordings or *dynamically* existing experts' minds).

5.1 Knowledge acquisition

Knowledge acquisition is a key enabler of Knowledge Management. Acting as a primary process, it is indispensable to the further activities of formalization, structure, and redistribution



(a) Knowledge dimensions (Chandrasegaran et al., 2013) (b) Knowledge dimensions for CCE

Figure 15: Knowledge classification refinement proposal

(Kuegler et al., 2023).

The traditional activity of knowledge acquisition has considered human experts as their main source for a long time. Nevertheless, the explosion of data quantity induced by the digital transformation of the industry has raised more questions toward the extraction of knowledge from large databases.

Within the literature, various terms referring to knowledge acquisition are used, each conveying certain nuances. The main dichotomy lies between knowledge capture, elicitation, and formalization, which considers humans as the source of knowledge, and knowledge extraction from technical data. Knowledge acquisition encompasses all these terms without distinction.

This section addresses traditional expert-centric approaches as well as more recent data-driven techniques to finally explore how they can be combined.

5.1.1 Expert-centric knowledge elicitation

Regarding expert-centric knowledge elicitation, two methods are widely established within the literature: MOKA and CommonKADS

The Method and tools Oriented to Knowledge-based engineering Application (MOKA) is based on informal and formal models (Stroke, 2001). This methodology leverages models as a mean to record and formalize the experience from expert's minds and identify the overlying knowledge structure and rationale. The most famous component of the MOKA methodology is the ICARE informal model describing Illustrations, Constraints, Activities, Rules and Entities.

Another methodology is the Common Knowledge Acquisition and Design System (CommonKADS), yielding knowledge models providing a conceptual description of problem-solving functions and data (Schreiber, 2000). This methodology leverages UML as modeling language to structure the captured knowledge and share it across an organization.

Regarding the capture phase of the Knowledge-Based Engineering lifecycle, MOKA and CommonKADS employ both similar approaches. They use models and informal interviews with ex-

perts to acquire and formalize engineering knowledge with a conceptual degree of description (Sureephong et al., 2007).

In Collaborative and Concurrent Engineering context, several studies have adopted a similar protocol to identify key parameters and their impact across domains, based on qualitative analysis by experts (Avnet and Weigel, 2010; Eckert and Stacey, 2014; Wang et al., 2021; Arista et al., 2024). These approaches require experts from various backgrounds to capture industrial knowledge through multiple working sessions.

In addition to the working time involved, the domain-specific semantics, communication skills, and cognitive biases make the capture of insightful and consensual knowledge a real challenge. It demands significant efforts in preparation, interaction management, knowledge curation, and subsequent re-formalization.

Nevertheless, 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.

5.1.2 Data-driven knowledge acquisition

In the aerospace sector, surrogate modeling has emerged as a robust approach for simulating both aircraft performance metrics and supply chain outputs (Tang et al., 2014; Dasari et al., 2019).

Tang et al. (2014) investigated the critical factors governing the integration of aircraft and supply chain architectures during the conceptual design phase. The authors used a synergy of Design of Experiments (DoE) and sensitivity analysis to identify primary cross-domain driver attributes. This methodology facilitates more informed data-driven decision-making during the high-level description degree of early design stages.

Nevertheless, the trustworthiness of outputs from data-driven methodologies employing AI is a central concern, particularly due to the black box nature of many models. When such approaches are used to design critical system such as aircraft, their explainability becomes essential.

Consequently, interpretable machine learning models such as Random Forest (RF) can be exploited for both classification and regression activities (Dasari et al., 2019; Bénard et al., 2021). Several approaches allow for the extraction of concise rule sets from the inner structure of trained RF models.

Following a similar logic, Decision Tree (DT) algorithms were employed by Ali et al. (2018) to derive manufacturing rules. However the authors highlight the need to bridge automatic data-driven knowledge generation with manual knowledge curation.

Thus, an approach for scalable, hybrid knowledge capture blending human expertise with computational methods has been proposed to improve knowledge management practices across various industries (Li, 2024).

A survey of hybrid expert systems between 1988 and 2010 has also unveiled Hybrid Knowledge Systems based on fuzzy neural networks (Sahin et al., 2012). Nevertheless, most of these hybrid experts systems are hybrid in their utilization of knowledge rather than in their method of acquisition. In practice, most hybrid frameworks maintain a rigid dichotomy: conducting expert-centric elicitation and data-driven extraction as independent, parallel processes.

The hybrid notion within the context of data-driven acquisition remains a nuanced topic. As all data-driven extraction studies are inherently designed and oriented by humans, the primary

concern is not whether expert influence exists, but rather its degree of application.

6 Final gap analysis

The considerable consequences of unexpected design changes has highlighted the necessity to anticipate issues across all lifecycle phases from the initial conceptualization of a complex product. However, this task is hindered by the increasing number of parts, functions, and interface, leading to interoperability problems as well as a lack of global perspective and knowledge.

A significant part of the research field addresses the integration of product and manufacturing system design because of the most immediate return on investment. While ultimately, all enabler systems should be considered in a Collaborative and Concurrent Engineering context, the scope of this study aims to support the integration of engineering activities between the aircraft design and its manufacturing system design.

Implementing Collaborative and Concurrent Engineering during early design phases offers opportunities of low total committed costs with high design freedom. Thus, this study shall privilege the integration of the engineering activities in early stage such as the conceptual design phase.

While this integration is challenging, the industry digital transformation and the development of Digital Engineering provide compelling ways to address it.

MBSE approaches have brought key capabilities to support early Collaborative and Concurrent Engineering between aircraft and manufacturing systems. Through standardized engineering processes, information traceability and multidisciplinary views, digital models allow to manage the high complexity of systems of interest.

Enhancing the traditional document-centric way of working, digital system models provide shared resources in a collaborative environment. Consequently, the augmented access, sharing, and reusability capabilities of system models foster innovation and alternative design studies.

Within the aerospace industry, more detailed modeling techniques (e.g. physics-based models and discrete-event simulations) are employed alongside of MBSE development. Therefore, the need to link the various models across diverse digital tools and environments has emerged under the concept of Digital Thread.

Digital threads integrate data, information, and knowledge to inform any stakeholders for accelerating design and enabling trades across traditionally isolated disciplines. However, this leads to cumbersome interfaces between across domains and tools which, combined with discrepancies of modeling maturity, yields significant interoperability concerns that could hinder CCE if they remained unaddressed.

Ontologies and Semantic Web Technologies are standard means to enable interoperability between heterogeneous sets of softwares. Used as a central part of the MBSE methodology, they provide convincing approaches to enhance Digital Engineering environments.

While serving as a flexible graph-based communication medium, they allow for a unified understanding, agnostic to any specific framework or tool format. Used as a shared reference, they ensure the means to coordinate between teams across diverse multi-disciplinary teams in extended enterprise context.

Ontologies have also a strong knowledge representation capability which addresses the need to rely on time-consuming and experience-based intuitions of individual engineers inherent to the abstract nature of information and the multiplicity of potential solutions from the conceptual

design phase.

Therefore, ontologies can be leveraged at the core of Knowledge-Based Engineering activities to centralize system information, domain knowledge and design rules with reasoning capabilities. The resulting enriched insights allow for engineers to assess cross-domain impact during the early stages of system design. Thus, structured methods to capture, model, and reuse knowledge, are crucial to support design decisions during early CCE.

Opportunities were identified to build upon established transversal OBE methodologies and expand their knowledge acquisition techniques in a complementary manner. Indeed, the industry digital transformation and the advancements in AI have provided new opportunities toward knowledge capture from incrementally large databases. Consequently, there is a need to blend human expertise with automatic data-driven practices in order to benefit from the experience and intuition of experts as well as the robustness and scalability of machine learning and big data.

In conclusion, ontologies address the syntactic, semantic, and organizational interoperability concerns arising from heterogeneous digital engineering environments. Employed at the center of the MBSE methodology, which permits to collaboratively manage system complexity, they act as a bridge between tools, stakeholders, and more importantly, domains. Through reasoning capabilities and structured approaches to capture, formalize, and reuse domain knowledge, ontologies provide engineers enriched insights to conduct early impact assessments for trade-off analysis. A specific focus is identified toward the combination of human expertise with data-driven techniques leveraging large databases to integrate experts' intuition with the robustness and scalability of machine learning approaches.

Therefore, this research identify the need for an ontology-based digital thread framework to support knowledge-driven Collaborative and Concurrent Engineering during the conceptual design phase of a new aircraft.

6.1 Industrial state of practice

While the previous sections have conducted a review of the literature, the close proximity of this research with the industry allows for complementary insights toward the state of practice, which can differ from academic fields.

The adoption process of new approaches, methodologies, or technologies, is determining for successful achieving paradigm shifts such as Digital Engineering transformation. Through the rich interactions and exchanges with industrial partners, we had the opportunity to examine more in depth certain points of the state of practice within our organization.

6.1.1 Social dimension

As stated previously, the DE transformation is a cultural socio-technical process (Suprun and Elsawah, 2026). Collaborative and Concurrent Engineering further complicates this landscape by integrating diverse team members from disparate domains, disciplines, and nationalities. Consequently, despite the presence of standardized engineering processes and structured methodologies, stakeholder interactions must be analyzed through the lens of sociological dynamics.

Discussions with industrial partners highlight a persistent challenge: the *"over-the-wall"* mentality. Departmental silos often impede collaboration, where product engineers prioritize design excellence while manufacturing engineers focus strictly on industrial efficiency. Therefore, the activity of performing global trade-offs is all the more sensitive and must be supported by strong evidences.

This phenomenon highlights a problem rarely addressed in the engineering community: social interactions play a key role when tight collaboration activities are involved. In large organizations such as Airbus with numerous departments, teams, and disciplines, social interactions should be considered for effective CCE.

6.1.2 Modeling skills maturity gap

Model-Based Systems Engineering has been a recurring topic during our industrial interactions as it plays a central part in the scope of this doctoral work and in Airbus's digital transformation strategy. As identified in the previous chapter, our industrial collaboration permitted to observe that despite the company-wide Digital Engineering transformation strategy, maturity discrepancies regarding MBSE modeling skills were a significant obstacle to cross-domain collaboration.

As stated previously, the manufacturing engineers have been using SE/MBSE methodologies for a significantly shorter amount of time than aircraft engineers. This create additional challenges in term of interface and interoperability between models.

Furthermore, despite the establishment of a common framework, its significant complexity and rapid rollout underline a lack of modeling proficiency, which ultimately stalls the progress of digital continuity and cross-functional collaboration (Kozak, 2024).

6.1.3 Knowledge capitalization

Airbus has been designing and producing aircraft for more than fifty years. A considerable amount of knowledge has been acquired during this period. Practical know-how, experienced engineering processes, rationale of design decisions, history of commercial strategies and their outcomes are extremely valuable to such organizations.

Critical risks of knowledge loss arise when engineers leave the company or simply retire. The current knowledge capitalization processes remain at human level through completion of standardized forms. However, the explosion of data quantity during the past decades accumulates considerable amounts of unexploited information for knowledge capitalization.

Consequently, complementary approaches considering large industrial datasets as source for knowledge capitalization are of major importance to keep and reuse the accumulated experience of the organization.

7 Research hypothesis and questions

Following the previous literature review and industrial state of practice, we are able to build a theory to address the identified problems.

Research hypothesis. *"Early Collaborative and Concurrent Engineering can be supported by ontology-based approaches through MBSE integration and enriched by knowledge acquisition blending expert-centric and data-driven techniques."*

In order to validate or not this hypothesis, we will try to answer to following research questions:

- **RQ1:** How collaborative and concurrent engineering activities can be supported through the integration of MBSE and ontology-based approaches?

While MBSE provides a robust structure for managing complex system architectures, it often lacks the semantic depth required to move beyond static diagrams toward a shared understanding that facilitates real-time synchronization. By integrating MBSE with formal ontologies, this research aims to bridge diverse engineering domains with enhanced knowledge representation and reasoning capability in a collaborative environment.

- **RQ2:** How to combine human experts and industrial databases for hybrid knowledge acquisition approaches?

Knowledge in industrial environments is often separated between high-fidelity industrial databases (quantitative and explicit) and the heuristic insights of human experts (qualitative and tacit). This research investigates the synthesis of these distinct sources into a singular and cohesive knowledge base. The challenge lies in developing a hybrid acquisition pipeline for structuring the nuanced decision-making logic of senior engineers supported by real-world data.

- **RQ3:** How to incorporate the acquired knowledge to support the collaborative and concurrent engineering activities?

Once knowledge is acquired and structured, it must be actionable within the engineering workflow. This question focuses on the mechanisms of knowledge incorporation into the engineering environment. The goal is to transform the digital environment from a passive recording tool into an active decision-support system that leverages historical records and human experience to guide the concurrent engineering process.

- **RQ4:** To which point incorporated knowledge is relevant in new product development context?

The development of new complex engineered systems with innovative technologies highlights issues of knowledge reuse. Perspectives toward knowledge transfer from past programs to future projects encompass this final question.

8 Chapter conclusion

This chapter has provided a comprehensive literature review, positioning the current dissertation within the broader academic discourse. By synthesizing various methodologies concerning the integrated development of complex products and their associated manufacturing systems, this review has established Collaborative and Concurrent Engineering (CCE) as a cornerstone concept of this research.

While the early-stage application of CCE introduces additional challenges toward collaboration and knowledge sharing, it also offers the greatest opportunity to converge engineering processes for reduced development time, controlled costs, and enhanced design quality.

The analysis of the cultural and socio-technical transformation incurred by the Digital Engineering has permitted to highlight the Model-Based Systems Engineering methodology and the concept of digital thread as fundamental enablers for CCE. Nevertheless, while they provide essential capabilities for complex system design in a collaborative manner, they also come with significant interoperability concerns between disciplines, tools and domains.

To address these concerns, ontologies and Semantic Web Technologies are widely considered as standard technologies enablers for syntactic, semantic, and organizational interoperability.

Furthermore, their inherent formal knowledge representation and automated reasoning capabilities facilitate the implementation of Knowledge-Based Engineering.

By resolving the interoperability limitations of DE and supporting engineers with enriched, cross-domain insights for design-change assessment, Ontology-Based Engineering (OBE) methods provide compelling ways to integrate MBSE and knowledge to support CCE during the conceptual design phase.

Finally, this chapter addressed the evolution of knowledge acquisition within the KBE/OBE. In a complementary manner to the traditional expert-centric techniques, the considerable amount of industrial data generated with the Digital Engineering transformation has unveiled extensive considerations toward more statistical approaches.

Interpretable machine learning techniques have been identified as a critical bridge between expert-centric formalization and data-driven extraction. These methods provide verifiable evidence and a degree of expressivity that is formally compatible with ontology structures.

In accordance with the Design Science Research Methodology (DSRM), the following objectives of solution can be delineated from this literature review:

- The first objective is to utilize Model-Based Systems Engineering (MBSE) for aircraft and manufacturing system architecture design. Through standardized engineering processes, multi-disciplinary views, and information traceability, engineers shall work on models collaboratively, describing complex systems while managing different degrees of abstraction.
- The second objective is to integrate these MBSE architectures with the rest of the Digital Engineering suite. By employing SWT and ontologies as a flexible interface providing shared and agnostic conceptualizations, they ensure interoperability capabilities. Beside providing means for enhanced communication, understanding, and coordination, they also allow for knowledge reasoning supporting early CCE.
- The third objective is to benefit from our industrial collaboration to explore knowledge acquisition approaches blending expert-centric and data-driven techniques. By leveraging from both human intuition and large databases' robustness, we aim to acquire cross-domain design rules, which, incorporated into ontological models, support system design and global trade-offs.

By achieving and integrating these objectives, the resulting framework shall enable engineers to collaboratively refine the architectures of both aircraft and their manufacturing systems. Used as the core of the MBSE methodology, ontological models would serve an interoperability backbone across the broad Digital Engineering environment. Ultimately, this integration would also facilitate cross-domain impact analysis, providing stakeholders enriched insights to conduct global trade-offs during the critical conceptual design phase.

Chapter 3

Ontology-based Digital Thread framework

Following the Design Science Research Methodology, the previous chapters have defined the problem of early Collaborative and Concurrent Engineering and conducted a literature review in order to build a theory toward the enhancement of CCE practices.

This theory has established that Model-Based Systems Engineering is a fundamental methodology for the development of complex systems such as aircraft and manufacturing systems. By integrating standardized engineering processes from Systems Engineering with the model-centric paradigm of Digital Engineering, MBSE allows for multi-disciplinary views, information traceability, and complexity management in a single source of truth.

While these capabilities are essential for CCE, significant challenges have been observed in contexts of collaboration between product and manufacturing engineers during the conceptual design phase. Arising concerns of interoperability, knowledge sharing, and high-effort cross-domain links maintainability were highlighted as hindering the successful Collaborative and Concurrent Engineering of aerospace systems (Szejka et al., 2024; Hu et al., 2022; Li et al., 2020).

Ontology-Based Engineering approaches address interoperability issues by providing a common conceptualization with a shared understanding. Furthermore, their knowledge representation and reasoning capabilities permit enriched insights supporting cross-domain impact assessment.

Thus, this chapter aims to **design and develop** an artifact integrating MBSE and OBE methodologies while incorporating knowledge acquired from hybrid sources.

The developed artifact is an ontology-based digital thread framework, designed to seamlessly integrate cross-domain design activities and incorporate both semantic and engineering knowledge to directly support critical trade-off decisions during the conceptual design phase.

The following sections detail the diverse modules composing the developed framework, the methodology followed for the elaboration of such framework, and a proposal of a complementary methods regarding hybrid knowledge acquisition using expert-centric knowledge formalization and data-driven knowledge extraction.

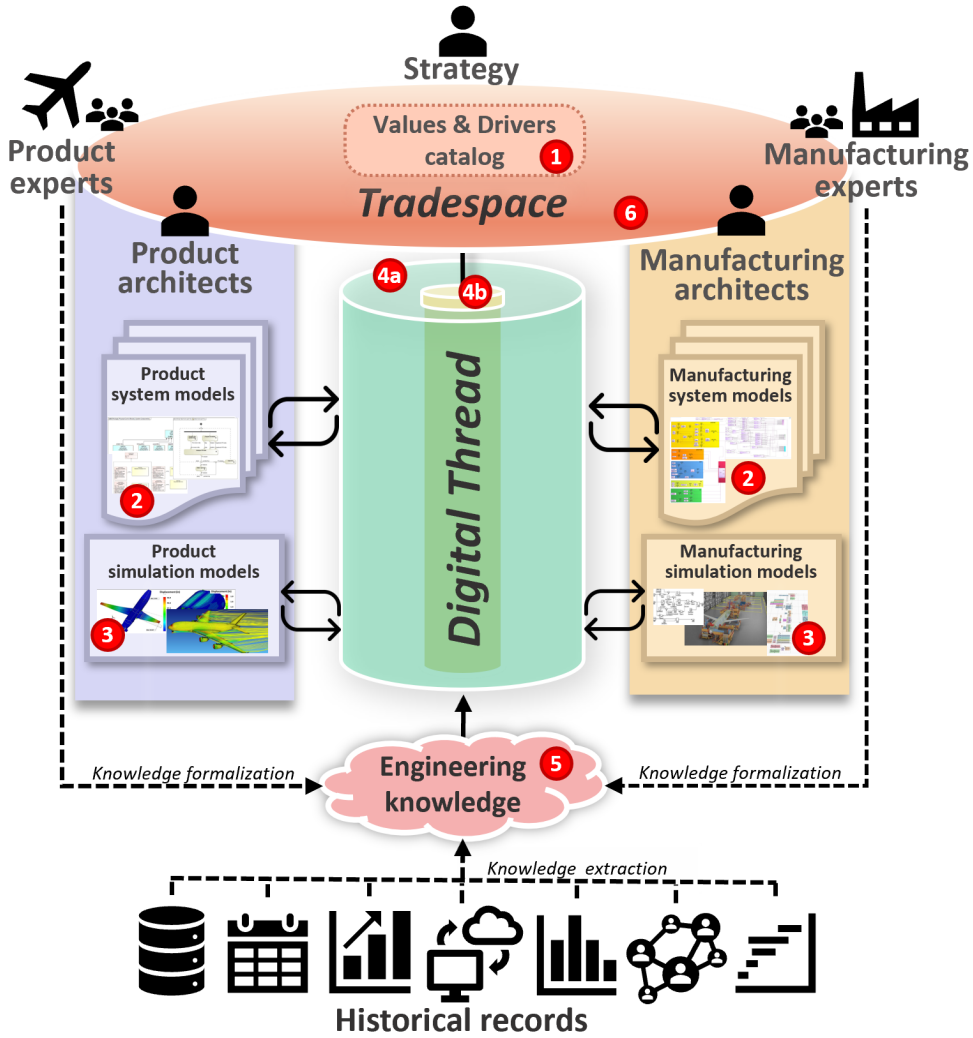


Figure 16: Ontology-based digital thread framework

1 Framework description

The proposed ontology-based digital thread framework, illustrated in Figure 16, consists of six key modules: *Values & Drivers catalog (1)*, *System models (2)*, *Simulation models (3)*, *Digital Thread (4)*, *Engineering knowledge (5)*, and *Tradespace (6)*. The interactions and specific purposes of each of these modules are described in the following subsections.

1.1 Values & Drivers catalog

Following Integrated Product Development (IPD) principles, the Values & Drivers catalog (identified as '1' in Figure 16) addresses business and customer value drivers as key needs guiding the development of the aircraft and its manufacturing system.

Its purpose is to develop the right product by considering the whole lifecycle scope. By defining a common set of values and drivers, this module strategically orients the development of each system toward converging tracks at the initial development stage.

Subsequently, strategic stakeholders must establish a hierarchy among these values and

drivers, from which, top-level program requirements and objectives are cascaded and trade-offs are evaluated.

1.2 System models

System models (identified as '2' in Figure 16) are the cornerstone of engineering activities. During the early design phase, both product and manufacturing engineers use the MBSE methodology to model their requirements and system architectures. The use of standardized engineering processes, typically realized with modeling languages such as SysML, provides a structured approach necessary for the development of complex systems.

By using a decomposition similar to the Requirement-Functional-Logical-Physical (RFLP) proposed by Li et al. (2020), engineers from product and manufacturing domains can collaborate on both systems of interest with multi-disciplinary views connected to the design requirements. With these digital system models, engineers can efficiently handle complexity and trace the impact of design changes through comprehensive information tracking.

The application of SE principles and RFLP modeling supports both physical and functional integrations, ensuring that manufacturing requirements can be verified during the aircraft design phase.

1.3 Simulation models

Simulation models, ranging from basic tools to complex multi-physics simulation softwares (identified as '3' in Figure 16), use data from MBSE architectures for domain-specific analysis. Their results encompass from aircraft aerodynamic studies to manufacturing flow simulations. Such models are used to verify requirement compliance and rank various alternative architectures.

These simulation models allow engineers to effectively explore the design solution space while directly supporting global trade-off decisions. Later in the system lifecycle, these models can also be employed as parts of *Multi-Disciplinary Analysis and Optimization (MDAO)* and *Design of Experiments (DoE)* activities for more in-depth, refined optimizations.

The seamless data exchange pipeline, which provides the inputs from the MBSE environment and propagates the outputs of these simulations, is fundamentally ensured by the core component of this framework: the Digital thread.

1.4 Digital thread

Interfacing with all the other modules, the Digital thread is the core of the framework. It is constituted of a knowledge base (identified as '4a' in Figure 16) which is structured by an ontological core ('4b' in Figure 16).

The knowledge base relies on Semantic Web Technologies (SWT) to serve as a communication medium between engineers and also between the digital tools. Following W3C standards such as Resource Description Framework (RDF) and Ontology Web Language (OWL), it can be employed with graph-based queries, offering freedom and flexibility regarding information exchanges. These mechanisms address the issue of answering diverse stakeholders concerns and any specific tool input data format, thereby achieving syntactic interoperability.

Furthermore, the ontological core establishes a controlled vocabulary with a taxonomic structure and shared conceptualizations. The resulting common understanding enables semantic interoperability between engineers from various domains, different formalisms, and diverse degrees of abstraction.

Considered a shared reference, the Digital thread also furnishes the means to coordinate among all involved stakeholders through robust information traceability. By enabling communication, understanding, and coordination, it addresses the organizational interoperability which is at the center of the collaborative engineering paradigm.

Additionally, the knowledge representation and reasoning capabilities of ontologies permit the integration of rule-based engineering knowledge supporting early cross-domain impact analysis for trade-off decisions.

This approach shares similarities with the work presented by Dunbar et al. (2023); Zheng et al. (2022); Arista et al. (2023) which leverage frameworks integrating elements close to ontology-based digital threads. Nevertheless two principal distinctions can be drawn. Firstly, this framework is dedicated to Collaborative and Concurrent Engineering (CCE) activities during the conceptual design phase and its associated challenges. Secondly and more importantly, the considerations for knowledge acquisition leveraging diverse types of knowledge sources are emphasized in this thesis. This distinction is further developed in the next module: Engineering knowledge.

1.5 Engineering knowledge

Engineering knowledge (identified as '5' in Figure 16) is formalized from expert implicit or tacit knowledge, via questionnaires, workshops, or modeling sessions. Further, data-driven techniques are conducted on explicit knowledge stored in industrial databases. The primary goal of this Engineering knowledge is to support engineers for early system analysis, and achieve faster iteration cycles.

Despite considerable efforts to develop robust knowledge acquisition methods within traditional Knowledge-Based Engineering (KBE) and Ontology-Based Engineering (OBE) approaches Kuegler et al. (2023), the explosion of data quantity raises new concerns about extracting knowledge from large databases. An increasing number of research projects are envisioning the integration of big data and AI approaches with traditional knowledge acquisition techniques (Mas et al., 2025; Li, 2024).

This doctoral work focuses specifically on the identification and formalization of cross-domain knowledge through a novel knowledge acquisition strategy. This strategy, combining both expert-centered and data-driven techniques, represents a main contribution of this research and is detailed in Section 3.1.

Such novel hybrid knowledge acquisition method permit to enrich existing Ontology-Based Engineering (OBE) approaches by identifying and formalizing cross-domain knowledge elements into the ontological core ('4b' in Figure 16).

This methodology exploits expert-centric modeling sessions to identify what we call *knowledge patterns*, which then guide systematic data-driven studies. By applying interpretable machine learning models to large-scale industrial datasets, this approach extracts explicit and verifiable *"if-then"* engineering rules providing enriched insights to all stakeholders. Furthermore, these executable rules facilitate robust cross-domain impact analysis during the conceptual design phase toward global trade-off decisions.

1.6 Tradespace

The tradespace (identified as '6' in Figure 16) acts as a virtual collaborative environment for all stakeholders (Strategy, Product architects and Manufacturing architects), enabling multi-attribute explorations for concurrent design, specifically between aircraft and manufacturing

system design.

Stakeholders define trade-off studies to be performed using the Values & Drivers catalog. Leveraging the captured cross-domain engineering knowledge, a design space is proposed, triggering modeling and simulation activities for different MBSE architecture options. The tradespace, system models, and simulation models are orchestrated by the digital thread.

By integrating various trade studies, each linked to system and simulation models, this module drives the convergence of system architectures to achieve the best global system performances.

1.7 Framework synthesis

This ontology-based digital thread framework acts as a bridge between aircraft and manufacturing system design. A critical aspect is the link of the MBSE environment with the rest of the digital software tools for design and trade-off studies. This central integration establishes a unified direction to drive model-based engineering activities across the organization.

Through MBSE's structured approach for system development, engineers can effectively address the complexity of aircraft and manufacturing system design with standardized processes, multi-disciplinary views, different degrees of granularity and information traceability, in a collaborative manner.

Furthermore, the linked simulation models and cross-domain knowledge captured provide complementary analysis material, allowing to rank alternative architectures during the design process. Short iteration loops are then supported with early trade-off decisions converging toward a global optimum.

At the center of this framework, the ontology-based digital thread serves as a communication medium with flexible queries answering any stakeholders concerns or input data format. Providing a shared understanding with a controlled vocabulary and a taxonomic structure, the resulting conceptualizations act as a single source of truth, allowing each team from different locations or culture to coordinate within a complex organization.

Through communication, understanding, and coordination, this framework leverages respectively syntactic, semantic, and organizational interoperability Zarko et al. (2017) for complex system engineering in a collaborative context.

Moreover, by centralizing system information and design rules into an ontological core with reasoning capabilities, this digital thread provides enhanced insights for early cross-domain impact analysis, thereby supporting CCE in short iteration loops.

Ultimately, this ontology-based digital thread acts as the support orchestrating Model-Based Engineering activities for early CCE of complex systems in a digital enterprise.

2 MfM Methodology

The literature review of Chapter 2 has identified the OBE methodology named Models for Manufacturing (MfM) in order to realize the ontological models composing the digital thread of this framework.

This doctoral work follows MfM for the following 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 methodology focuses on domain knowledge capture of processes and system behaviors, rather than traditional ontology engineering methodologies which only aim at semantic interoperability. As this a topic is also covered by MfM, This methodology seems to be the most suitable for the problem at hand.
- Thirdly, this method has demonstrated its value through numerous industrial implementations Zheng et al. (2022); Arista et al. (2023); Szejka et al. (2024). As this doctoral work is conducted in a similar context, the arguments toward adoption and reusability of OBE, seen the previous chapter, support for the use of this methodology.
- 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 detailed in Section 3.

2.1 MfM description

Models for Manufacturing (MfM) is an Ontology-Based Engineering (OBE) methodology developed to support complex manufacturing system design. By defining a structured approach to manage ontologies, MfM helps to capture functions, behaviors and semantics of the systems of interest. Used at the center of MBSE environments, this methodology provides a shared conceptualization, a common understanding and knowledge representation capabilities that supports engineering activities.

As illustrated in Figure 17, MfM is based on a 3LM (3-Layers Model) with each layer independent for modularity and maintainability aspects. The *Data layer* comprises any stored information, such as technical documents, legacy and operational databases, and the cloud. The *Service Layer* gathers all the services employed for the defined objective (here the co-architecture of aircraft and manufacturing systems). It can be modeling tools, simulation tools, dashboards, and other. Nevertheless, the core layer of MfM is the *Ontology layer* which interfaces between the two other layers while representing knowledge and design information in an agnostic way. The *Ontology layer* is composed of four ontological model types: *Scope*, *Data*, *Behavior* and *Semantic* models.

The limits of the ontology application are defined by the *Scope model*. Key concepts and deliverables emerge from this definition and are developed in the *Data model* which describes their taxonomic structure and their properties. The *Behavior model* represents how the concepts from the *Data model* interact with each other. Finally, the *Semantic model* ensures seamless interfaces between the other layers.

MfM describes engineering activities with two phases: the ontology development phase, which leverages its own data and services to elaborate the *Ontology layer* as *Data*, *Behavior* and *Semantic models*. These models are then instantiated in specific use-case contexts, during the ontology instantiation phase. This phase, in turn, uses its own context-specific *data* and *service* elements.

The correspondence between the MfM 3LM and the proposed Digital Thread framework is illustrated in Table 2. During the ontology development phase, expert knowledge and historical records are exploited from the data layer to capture functions, behaviors and semantics of the systems of interest. The *Scope*, *Data*, *Behavior* and *Semantic* models are subsequently derived from the captured knowledge to compose the ontological core of the digital thread (4b in Figure 16). During the ontology utilization, the populated knowledge base (4a in Figure 16) contains the instances of MBSE artifacts, their simulation results, their interfaces, and related engineering rules. In addition, tools for system modeling, simulation, and dashboarding, rely on the

knowledge base but can also necessitate some auxiliary databases (2, 3 and 6 in Figure 16).

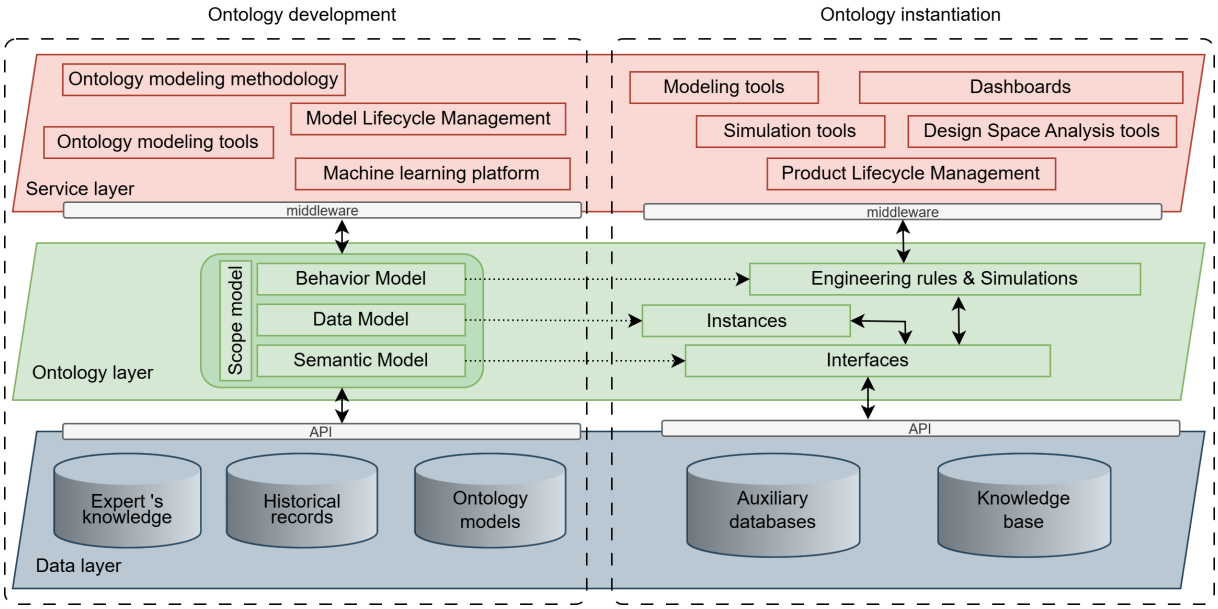


Figure 17: 3LM framework adapted from Mas et al. (2025)

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

Table 2: Correspondence between the proposed framework and MfM

2.1.1 Current knowledge base in manufacturing system design

The following ontologies have been developed through MfM and form the current knowledge base for system engineering activities. Their function is to support the design of products and the manufacturing systems across different contexts and maturity stages.

1. The work of Mas et al. (2013a) defines an ontology to aid the assembly line design process. Using a preliminary breakdown of the "As-Designed" product structure (functional view of the product), it supports the definition of an "As-Planned" product structure (product workshare between partners/contractors) and the "Build Process" of a final assembly line.
2. The Industrial System Design (ISD) ontology was developed by Arista et al. (2023) to support manufacturing system design at global manufacturing system level, including resources reusability concepts in a worldwide industrial network. Building on the preliminary 'As-Designed' product structure, it helps to define the 'As-Planned' product structure before making the make/buy decisions for the supply chain design. Thus, the authors leverage

the 'Build Process' as a top-sequence of manufacturing and logistics operations between potential sites using global logistic means.

3. The Eco-efficiency ontology, elaborated by Oliva et al. (2020), addresses sustainability and eco-efficiency in the industrial assembly processes, introducing an eco-efficiency dimension along with the traditional criteria, cost and time, currently used for optimization.
4. The Reconfigurable Manufacturing System Design (RMSD) ontology, described by Arista et al. (2024), supports the specificities of reconfigurability principles within the manufacturing system design at concept phase in a collaborative engineering process.
5. The Manufacturing Quotation ontology from Skrzek et al. (2023) focuses on knowledge related to manufacturing costs of metal sheet parts for new product design.

The Co-Architecture Ontology described in the next section enriches this knowledge base with models addressing Collaborative and Concurrent Engineering process during the conceptual phase of aircraft design.

2.2 Co-Architecture ontology development

This section implements MfM to develop the ontological core of the digital thread identified as "4b" on Figure 16). This development intends to answer the identified concerns toward the co-architecture engineering process between product and manufacturing engineers.

This ontology is developed in a generic manner to provide a common basis for diverse applications of the proposed framework. Therefore, we emphasize that while the following ontological models establish the basis of knowledge representation about Collaborative and Concurrent Engineering, they are intended to be specialized in specific use-case contexts before being instantiated.

Morales-Palma et al. (2022) has proposed meta-models for common specifications regarding MfM. The authors define a formalism using SysML to facilitate the elaboration of the four ontological models at the center of the MBSE methodology. With these meta-models, MfM allows to overcome one of the main issues hindering the development of KBE systems by providing a modeling structure easily readable by humans while remaining concise and consistent across projects.

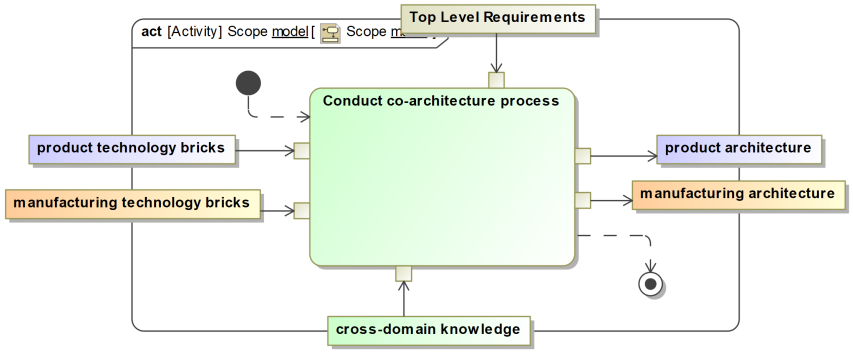
Ontology development following the MfM methodology is conducted through four models: *Scope*, *Data*, *Semantic*, and *Behavior*. This research has benefited from a close collaboration with Airbus partners, permitting to organize iterative modeling sessions with experts from aircraft and manufacturing domains. The models presented in this section are the results of these sessions.

2.2.1 Scope model

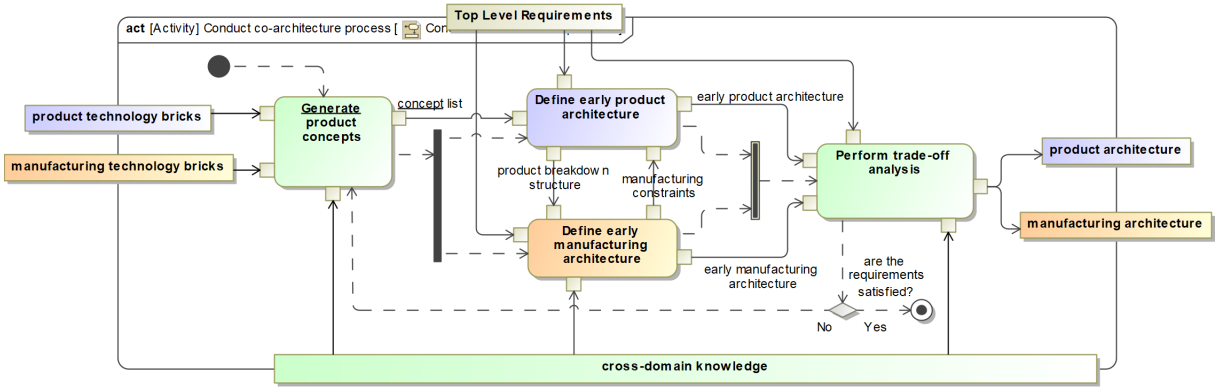
The formalization of stakeholders, activities and deliverables permits a common comprehension of the co-architecture process. The *Scope model* encompasses the activities involved for conducting co-architecture between aircraft and manufacturing system design. The main delineated concepts orient and delimit the development of the rest of the ontology.

Figure 18a shows the black-box view of the *Scope model*. As shown in the figure, top-level requirements, and technology bricks from each domain are the first inputs of this model. Cross-domain knowledge is a support mechanism for this activity and the outputs are the product and manufacturing architectures.

Figure 18b shows a white-box view of the *Scope model*. Its first sub-activity is to generate product concepts from AS-IS capabilities with combination of technology bricks. This initial step is grounded in the Configuration Management methodology. Cross-domain knowledge supports



(a) Scope model - black box view



(b) Scope model - white box view

Figure 18: Scope model

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 provided to product engineers for the early development of their architecture. Then, close iteration loops begins between product and manufacturing engineers where the former share product breakdown structures while the latter determine manufacturing constraints. Such short iteration loops during early design phase are supported by cross-domain knowledge which permit enhanced insights of design choice impact assessment.

Finally, trade-off studies are performed between the diverse envisioned architectures using top-level requirements as evaluation criteria. Perspectives on requirements that are difficult to assess in early stage are supported by cross-domain knowledge. If no pairs of architectures satisfy the requirements, engineers return to concept generation, applying all the lessons learned.

The key takeaway of this *Scope model* is the emergence of a co-architecture activity, encompassing product and manufacturing activities. With a higher degree of abstraction than architecture process, it has sub-activities such as product concept generation and trade-off analysis which do not belong to one specific domain, thus avoiding unbalanced decision power during design choices. Additionally, cross-domain knowledge supports almost every step of the process.

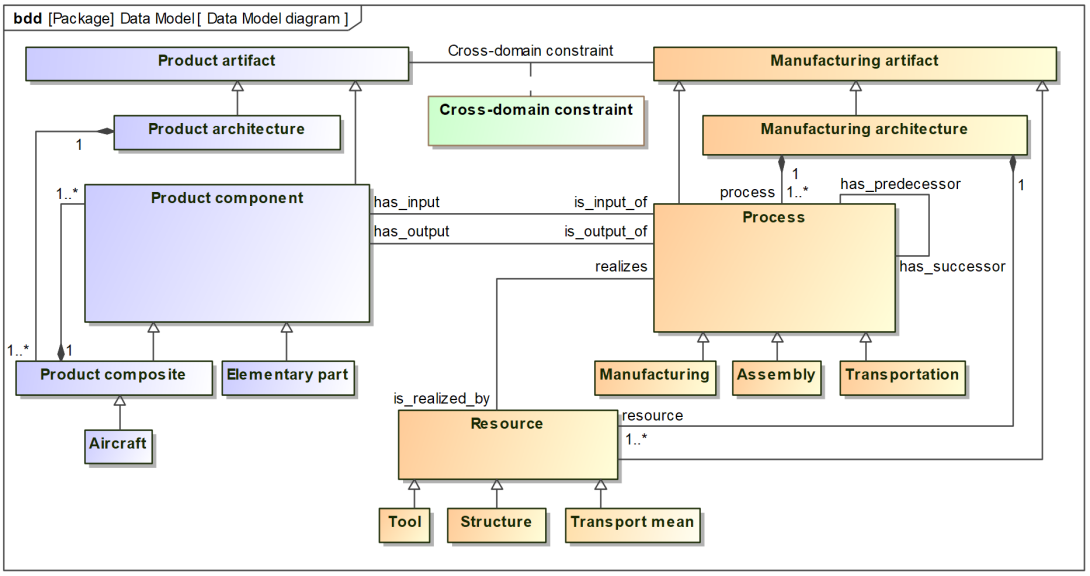


Figure 19: Data model

2.2.2 Data model

In early CCE context, the *Data model* defines the concepts and relationships involved in product and manufacturing architectures. The *Data model* is agnostic to any tool, framework, or modeling language.

As the main focus is on the interactions between aircraft and manufacturing engineering domains, the Product-Process-Resource (PPR) decomposition (Cutting-Decelle et al., 2007) has been selected for the taxonomy structure. The PPR decomposition is widely adopted across industry and provides a high modularity capability for the representation of products and manufacturing systems.

The *Data model* illustrated in Figure 19 has no intent of being exhaustive. Instantiated in use-case contexts, it shall be extended with additional classes and properties in a modular manner as argued by Sanya and Shehab (2015). For both reusability and interoperability concerns, the development of ontologies across disparate domains benefits from high-level alignment provided by a top-ontology (Dunbar et al., 2023).

While Basic Formal Ontology (BFO) is currently the standard (ISO/IEC/IEEE-13586, 2021) for top-level ontologies, several industrial applications employ the BFO/IOF-Core structure (Zheng et al., 2022; Arista et al., 2023, 2024). IOF-core is constituted of a standardized suite of middle-level ontologies supporting the digital manufacturing industry and aims to become an official standard at the end of its development (Drobnjakovic et al., 2022). Thus, all concepts delineated in the *Data model* should be aligned with the BFO/IOF-core structure.

The relationships with most importance are those which connect product and manufacturing domains. In early Collaborative and Concurrent Engineering, such relationships define interactions and interfaces between product and manufacturing architectures.

While product components are inputs and outputs of manufacturing processes, an additional relationship has emerged during our exchanges with the experts. Indeed, the concept of cross-domain constraint between any product and manufacturing artifacts has been identified as key for concept generation, architecture development, and trade-off analysis.

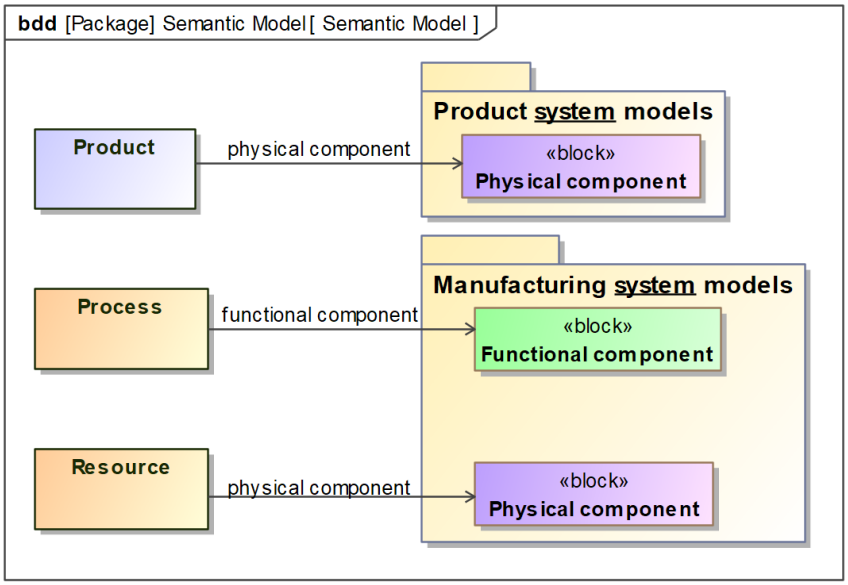


Figure 20: Semantic model

2.2.3 Semantic model

The *Semantic model* is the primary interface between MBSE architectures and the ontology. Its purpose is to map each concept and property from the *Data model* to their corresponding MBSE artifacts. Therefore, this model is highly specialized according to the use-case application and the corresponding *Data model*.

Nevertheless, the *Requirement-Functional-Logical-Physical* decomposition Li et al. (2020) selected as a MBSE reference permits the development of a first abstract model. As illustrated in Figure 20, *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.

2.2.4 Behavior model

In CCE context, the *Behavior model* should represent how the systems of interest interact with each other. Nevertheless, this kind of knowledge is difficult to acquire and formalize, especially in early design stage. Although open questions remain regarding the acquisition of such knowledge, new opportunities are emerging due to the explosion of data volumes (Big Data) and advancements in interpretable statistical models (AI).

In this sense, we propose an additional contribution to this thesis: a hybrid knowledge acquisition method that integrates experts and large datasets of historical records as knowledge sources.

3 Hybrid knowledge acquisition method

The digital transformation of the industry and the advancements of Artificial Intelligence bring new opportunities toward knowledge acquisition. Over the past decades, vast quantities of data have been compiled in heterogeneous formats, often without any specific intent for future

knowledge sharing. These datasets represent a compelling opportunity for knowledge capitalization.

However, the "blind" application of conventional data mining techniques often fails to yield actionable insights. The perspectives and intuitions of domain experts remain essential for interpreting data variety, mapping the cross-domain interdependencies, and driving the extraction of design rules.

This section proposes an original approach that has the potential to enrich the current knowledge acquisition process within MfM, particularly for the elaboration of the *Behavior model*. Blending expert-centric and data-driven approaches, it leverages human expertise to drive data-mining techniques which benefit from the robustness and scalability of large databases. As illustrated in Figure 21, 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 cross-domain early 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 addresses the development of the *Behavior model* of the *Ontology layer*. Functioning in a complementary manner to more traditional knowledge acquisition methods, it can be regarded as an enrichment of the MfM methodology.

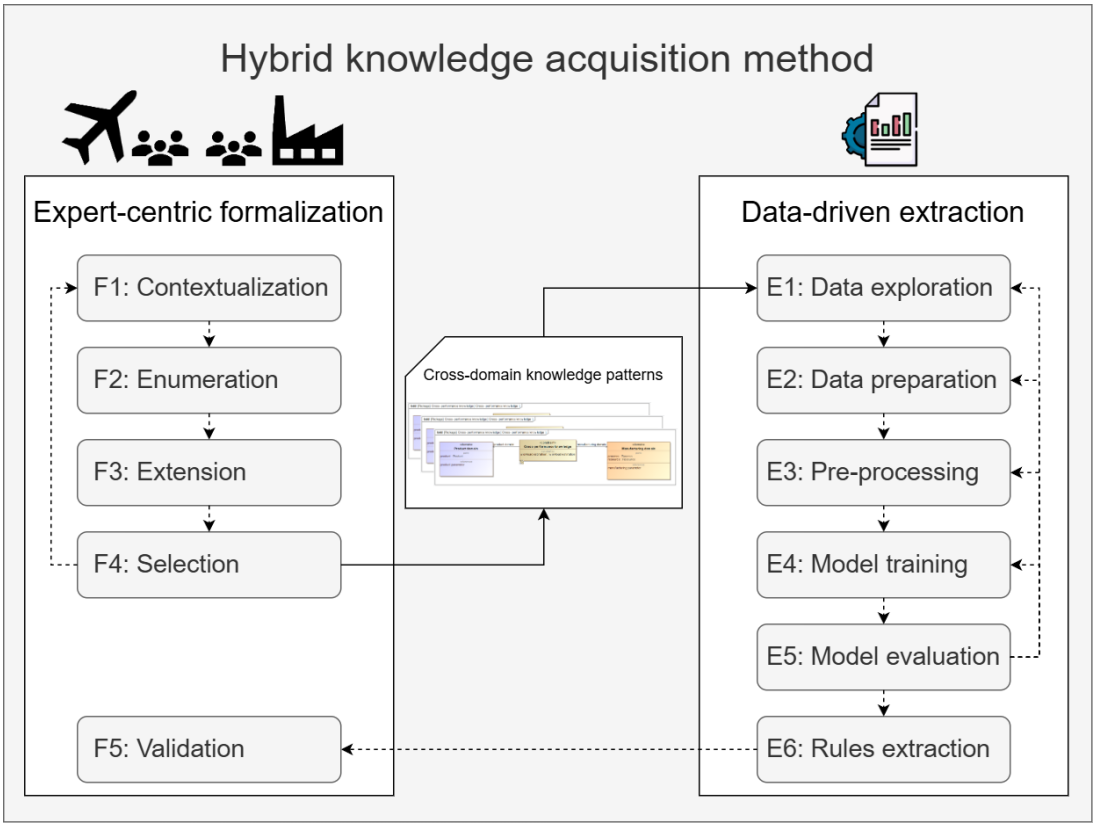


Figure 21: Hybrid knowledge acquisition method

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.

Product and manufacturing architects usually have a good intuition about these types of knowledge even if they might need help formalizing them. This list aims to be completed, corrected, and strengthened along each iteration.

As illustrated in the left part of Figure 21, the expert-centric formalization consists of five distinct steps:

- Contextualization (F1): A first contextualization phase is performed with the diverse domain experts to present the research objectives and scope of knowledge to be captured. This step is mainly supported by the *Scope model*, which helps to formalize and reach a common understanding about the addressed issue between different domain experts with diverse backgrounds and points of view. Nevertheless, any MfM models can be used as support material at this stage. This step results with a preliminary list of cross-domain knowledge patterns which will be the core resource of the following activities.
- Enumeration (F2): The enumeration step holds a discussion about the identified patterns. Refining each description, the experts take more time to assess the patterns' validity. All patterns deemed valid are added as elements of the *Behavior model*.
- Extension (F3): With the previous steps, experts have gained a clearer understanding of this knowledge formalization practice. They can then add new patterns that come to mind.
- Selection (F4): This phase concludes the first part of the expert-centric formalization. The domain experts perform a ranking of the validated patterns regarding their relevance in the early CCE process. The selected patterns are used as input to a data-driven knowledge extraction studies.
- Validation (F5): Each data-driven extraction process results in engineering rules. During this final step, domain experts validate such rules before being incorporated into the *Behavior model*.

3.2 Data-driven extraction

Data-driven studies aim to derive explicit engineering rules from large databases of historical records, using a cross-domain knowledge pattern.

In this regard, these studies employ conventional data science technique in order to train interpretable machine learning models such as *Decision Trees* or *Random Forests* (Ali et al., 2018; Dasari et al., 2019; Bénard et al., 2021). Such models offer to extract explicit *if-then* rules from their inner structure. Extracting explicit engineering rules not only benefits human validation of captured knowledge, but also enables them to be expressed in MBSE and ontology environments for knowledge execution and reasoning.

As illustrated in the right part of the Figure 21, the data-driven extraction is composed of six steps:

- Data exploration (E1): A rigorous investigation is conducted across the data sources of the organization to find the pattern's concepts and parameters.

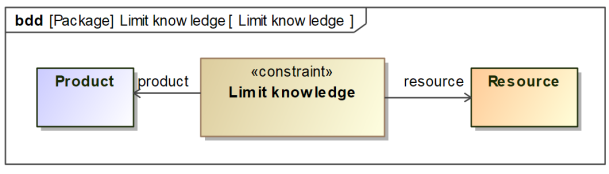
- Data Preparation (E2): As the knowledge patterns link concepts from product and manufacturing domains, the information is often stored in heterogeneous formats. Thus, transformation and joining processes may be needed to prepare the data into a homogeneous input dataset.
- Pre-processing (E3): Once the data preparation is done, conventional pre-processing techniques are applied to facilitate the learning process while avoiding undesired biases (Zheng and Casari, 2018). Some of the most common pre-processing techniques are data cleaning, outlier management, dataset balancing, value normalization and feature encoding.
- Model training (E4): As expressed before, the core of this approach relies on the interpretable machine learning models such as *Decision Trees* or *Random Forests* (Ali et al., 2018; Dasari et al., 2019). The processed dataset is then used to train such models while keeping a portion dedicated to the evaluation of the training process.
- Model evaluation (E5): Subsequently, different metrics are employed on the evaluation subset. The training process is considered successful if the metrics results satisfy a predefined threshold. If the model does not satisfy the expected threshold, either iterations are conducted on the previous steps, or the learning process is considered unattainable with the available data.
- Rules extraction (E6): Finally, if the training process has been validated, the rules extraction process is performed by conducting the algorithm adapted the the chosen model.

It is important to note that, as the MfM methodology itself, this hybrid knowledge acquisition method is an iterative process employed to mature the ontological core and knowledge extracted.

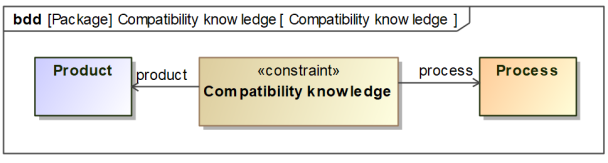
3.3 Behavior model as cross-domain knowledge patterns

As previously stated, the *Behavior model* describes how elements from product and manufacturing domains interact between each other (e.g. constraints or design rules for impact assessment). This thesis has leveraged the hybrid knowledge acquisition method described in Section 3 for the elaboration of generic *Behavior model* elements.

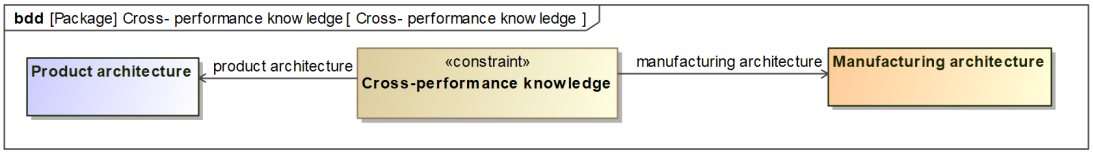
Some of the resulting patterns are shown in Figure 22. While remaining at a high degree of abstraction, they link concepts from the *Data model*, creating additional relationships between aircraft and manufacturing MBSE architectures.



(a) Limit knowledge



(b) Compatibility knowledge



(c) Cross-performance knowledge

Figure 22: Generic cross-domain knowledge patterns

Although some patterns address relationships between specific concepts such as product/resource for *limit knowledge pattern* and product/process for *compatibility knowledge pattern*, other patterns describe more abstract relationships such as the *cross-performance knowledge* which can involve any artifact from product and manufacturing architectures.

Similarly to the *Data* and *Semantic models*, *Behavior model* aims to be specialized in dedicated use-case contexts with instantiated models and resulting rules.

4 Discussion and conclusion

4.1 Discussion

As illustrated in Figure 23, the development of these ontological models are part of the MfM methodology.

Although they could, the proposed generic models are not intended to stand as yet another ontology as plenty already exist in this domain. Their development is intended to be specialized in use-case specific contexts. However, some interesting ideas have already emerged from these simple models.

The first noticeable element is the global co-architecture activity from the *Scope model* (shown in Figure 18a). This common activity, neither driven by product, nor by manufacturing engineering concerns, is the cornerstone of global collaborative engineering processes. This highlights the need for unbiased design decisions toward the best pair of product and manufacturing architectures. Furthermore, it initiates a more long-term vision that shall incorporate both system models in a single vision and MBSE model.

This approach, significantly reducing the siloed way of working, is yet unfortunately hindered by the performance issues of such a gigantic model. Moreover, the modeling maturity discrepancies between domains remain an obstacle to effective CCE in MBSE environment.

The second worth-mentioning element belongs to the *Data model*. Although the conceptualization of product and manufacturing architectures remains simple by following the Product-Process-Resource decomposition, the emergence of cross-domain constraint between product and manufacturing artifacts has oriented the development of the *Behavior model*.

Beside from our hybrid knowledge acquisition method to formalize and extract these constraints, we envision further Semantic Web Technologies such as Shapes Constraint Language (ShaCL) and Semantic Web Rule Language (SWRL) to enforce the captured knowledge in an executable manner.

Also, as these models have been developed generically and are quite abstract, they are not specific to the aerospace industry and could be employed in any other complex system engineering industry.

4.2 Conclusion

This chapter has introduced a framework designed to facilitate Collaborative and Concurrent Engineering (CCE) between product and manufacturing domains, particularly during the conceptual design phase of complex systems like aircraft. Following the DSRM, the proposed artifacts (framework, method, and models) address the scientific problems identified in the previous chapter to support our theory. Our proposed framework integrates five modules around

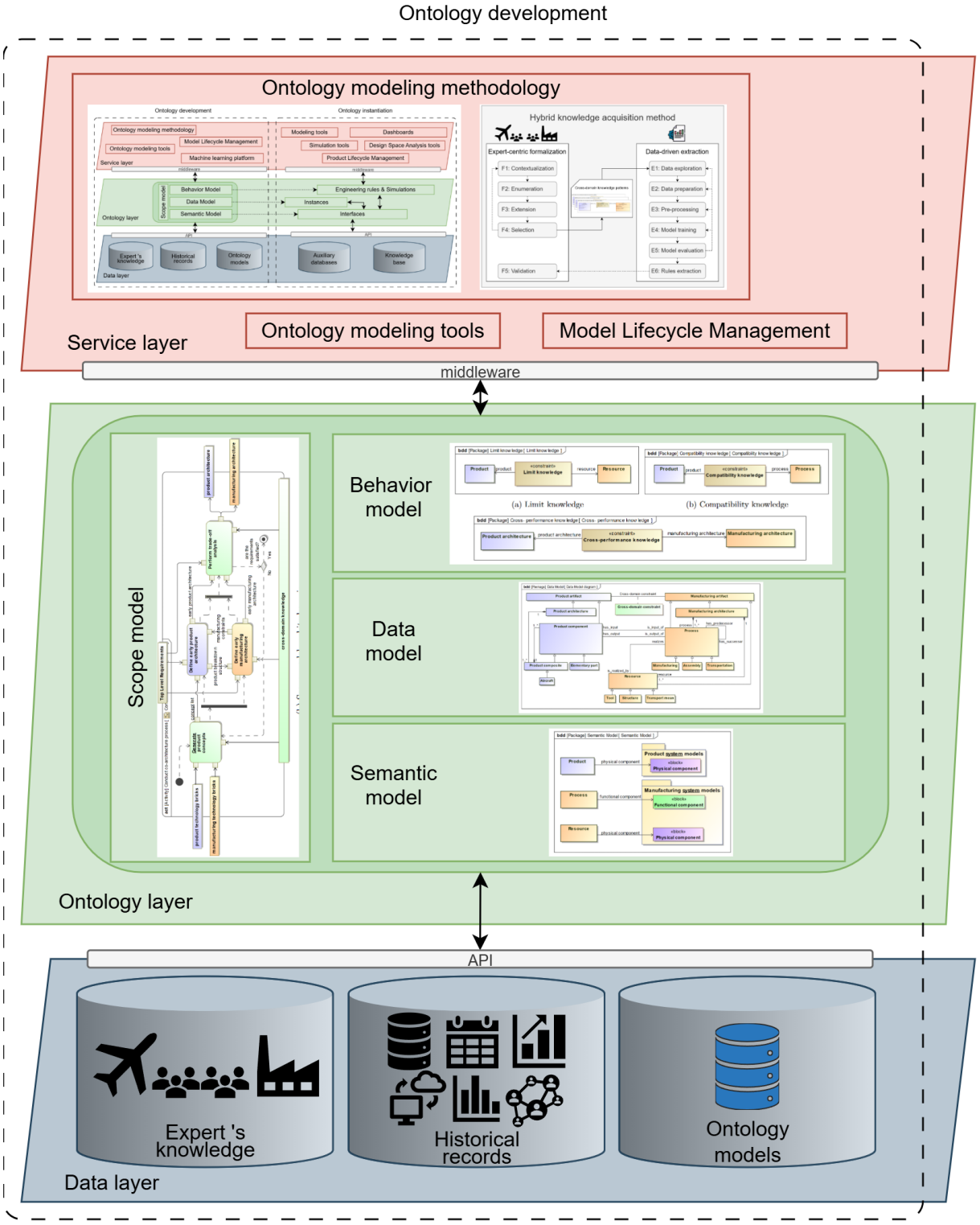


Figure 23: MfM's ontology development for CCE

the core of the framework: an ontology-based digital thread.

The *Values & Drivers catalog (1)* defines common tracks for initiating system design with an aligned vision. It also serves as a prioritization reference for trade-off analysis.

The *System models (2)* are the cornerstone of this framework as they enable the execution of Systems Engineering processes through digital models. Facilitating the complexity management of the systems of interest with various degrees of abstraction, they provide a collaborative environment with multidisciplinary views and information traceability. While these models are the initial point of engineering activities, they need to interface with other models with further specialized simulation capabilities.

The *Simulation models (3)* are the diverse tools or simulation software applications outside the Model-Based Systems Engineering environment. Each having unique input/output data format, their interoperability with the *System models* is of primary importance.

The core of the framework is the digital thread composed of a *Knowledge base (4a)* and its *Ontological core (4b)*. Through Semantic Web Technologies, it provides syntactic, semantic, and organizational interoperability by interfacing with the other models in an agnostic format. Furthermore, its knowledge reasoning capabilities allow for enriched insight toward cross-domain impact assessment.

The *Engineering knowledge (5)* enriching the digital thread can be formalized with domain experts and extracted from large industrial databases. This knowledge is crucial to shorten the iteration loops during the early design phase when lots of hypothesis remain open and engineering decisions rely on empirical experience.

The *Tradespace (6)* receives the necessary information from the *System models*, *Simulation models*, and conduct trade-off analysis supported by the *Value & Drivers catalog* with enriched insight of the *Engineering knowledge*.

Our contributions were focused on the development of the *Digital thread (4)* and the acquisition of the *Engineering knowledge (5)*. The ontology development was conducted by following an Ontology-Based Engineering methodology named MfM which leverages iterative modeling sessions with domain experts to capture relevant knowledge. This development resulted in four ontological models: *Scope, Data, Semantic,* and *Behavior*. This generic development provides a common basis for future specialized developments in use-case specific applications.

The *Scope model* has describes the activities involved during early CCE as a co-architecture process. This common ground supports unbiased decisions toward a global optimum between product and manufacturing engineering. The defined activities rely on cross-domain knowledge to be executed in short iteration loops.

The *Data model* defines the key concepts and relationships by following the Product-Process-Resource decomposition. This agnostic representation ensures a common conceptualization among engineers from distant disciplines.

The *Semantic model* ensures the interface between MBSE artifacts and the *Data model*. For these generic models, it only serve as a bridge between the PPR concept and the RFLP decomposition.

The *Behavior model* represents and describes complex interactions between systems. The development of this model has raised questions toward knowledge acquisition solely from expert formalization. This led us to our final contribution: a hybrid knowledge acquisition method centered on cross-domain knowledge patterns.

Proposed as a complementary knowledge acquisition approach to MfM, this method aims

to combine human's experience and intuition with the learning scalability and robustness of machine learning techniques.

This approach was driven by the explosion of industrial data without knowledge capitalization. Benefiting from iterative modeling sessions with domain experts, key concepts and attributes are formalized as knowledge patterns. Subsequently, these patterns are employed as a guide for data-driven studies, permitting to extract implicit engineering knowledge for early cross-domain impact analysis.

Chapter 4

Case study

Following the DSRM, this chapter **demonstrates and evaluates** the contributions proposed in Chapter 3. More specifically, it implements the developed framework, methods, and models through a real-world case study. By leveraging the industrial collaboration in which this thesis is included, we were involved in a project that allowed for a robust demonstration of this research's applicability and utility.

Thus, the rest of this chapter is focused on a project addressing the early co-architecture of next-generation hydrogen fuel tanks. Our main interactions took place with modeling and simulation architects, industrial systems engineers and the project co-design leader. The development and the instantiation of a Co-Architecture Ontology is conducted by implementing the MfM methodology. The resulting models form the ontological core of the digital thread.

Among these models, the *Scope Model* formalizes the co-architecture process and its stakeholders, the *Data Model* defines key concepts and properties from product and manufacturing domains as a taxonomic structure, the *Semantic Model* interfaces with the MBSE architectures by mapping *Data model* concepts to their corresponding MBSE artifacts, and finally, the *Behavior Model* leverages a hybrid knowledge acquisition method to establish generic, rule-based knowledge patterns for cross-domain early impact.

Ultimately, these models instantiated with both MBSE architectures are extracted into the digital thread, providing a graph-based agnostic interface between other tools of the Digital Engineering ecosystem.

1 Problem statement

1.1 Project context

Within the project in which this research was included, Model-Based Systems Engineering models were being developed for both the product and manufacturing systems. However, architects encountered significant difficulties to iterate through the co-architecture process. Specifically, issues concerning interoperability between the MBSE environments and simulation models hindered impact analysis activities.

Although a prior effort-intensive custom solution was implemented to extract the necessary information from the MBSE architectures, it required a substantial number of steps per iteration, resulting in a cumbersome process and data linkages difficult to maintain.

Furthermore, after each successful extraction, manufacturing architects faced another challenge: the *Workload* estimation. The *Workload* is the cumulated amount of work-time required

to produce an aircraft component. *Workload* estimation is one of the initial steps of the manufacturing architecture activity. Based on a high-level process sequence, manufacturing architects estimate workloads, define product lines, and allocate human resources. After balancing production lines and aggregating everything through Value Stream Mapping (VSM), early architectures can finally be evaluated.

Thus, the *Workload* estimation constitutes the cornerstone of the manufacturing architecture process as all manufacturing performance metrics can be cascaded directly from this activity via diverse analytical tools. The engineers involved in this project have identified *Workload* estimation as their main bottleneck because it remains heavily reliant on empirical experience and necessitates extensive iterations of consultation with domain experts.

1.2 Objectives of a solution

After the analysis of this project context, we concluded that facilitating information exchange between the diverse digital environments and shortening the time required for workload estimation would allow for much closer iteration loops. This, in turn, would enable a faster convergence between product and manufacturing architectures toward a globally more optimal solution.

The following sections aim to develop and instantiate the ontological core of the digital thread framework described in Chapter 3. Following the MfM methodology, this work intends to provide the infrastructure to achieve interoperability between the existing MBSE architectures and external simulation tools. Additionally, the hybrid knowledge acquisition method, also described in the previous chapter, is conducted to elicit engineering rules for facilitating workload estimation with the express purpose of reducing the duration of architectural iteration cycles.

2 Ontology development - MfM specialization

The models proposed in the previous chapter were meant to be specialized in specific use-case contexts. This allows to address precise objectives without introducing unnecessary complexity in the general ontology.

The specialization of the *Scope model* is deemed unnecessary, as no engineering activities unique to this use-case were identified. If this precise use-case had required specific engineering activities and interactions, the scope would have been specialized to reflect the involved co-architecture processes.

The *Data model* requires rigorous specialization to capture all concepts and attributes inherent to this project. This domain-agnostic representation serves as the cornerstone of the ontology, establishing a shared knowledge structure that formally describes the architectures of each system of interest.

Also, as the *Behavior model* delineates the complex cross-domain interactions occurring between aircraft and manufacturing system architectures, it requires a dedicated specialization toward the identified key interactions: the workload estimation.

Finally, the *Semantic model*, positioned at the intersection of ontological development and instantiation, ensures seamless interoperability and traceability between the MBSE architectures and the broader ecosystem of digital tools.

One can keep in mind that these models represent different views of the same concepts. Therefore, ontology development and specialization activities are part of an iterative and parallel process. Thus, the identification or emergence of a given concept of attribute for one model can

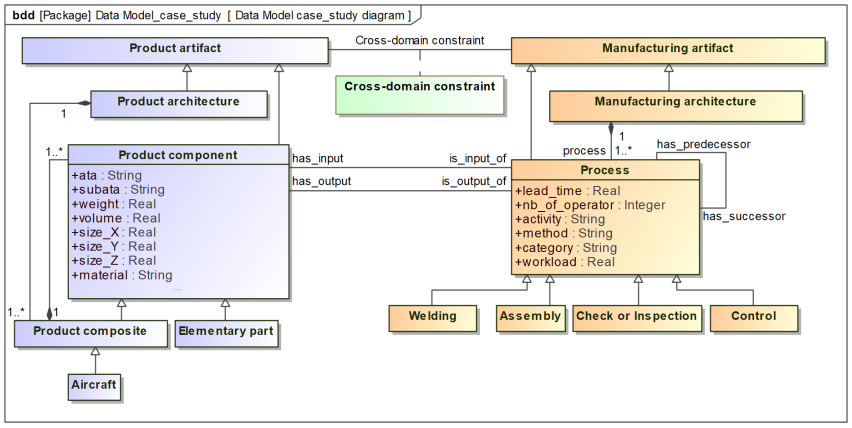


Figure 24: Data model

trigger its propagation to the other models. Each ontological model are developed and specialized through modeling sessions with the domain experts and key stakeholders of the use-case.

2.1 Data model

The *Data Model* describes the concepts and attributes involved in this project. Given the current early stage of project maturity, *Resource* management was not considered as a part of this study. The development of MBSE models therefore focused exclusively on *Product* and *Process* concepts.

As depicted in the Figure 24, a *Product* is characterized by essential properties including its shape, mass, material, and ata. *Products* serve as both inputs and outputs for *Processes*, which are specialized into four categories: *Welding*, *Assembly*, *Check or Inspection*, and *Control*. Furthermore, each *Process* is defined by properties such as its *successor*/*predecessor* relationships and its *workload*.

2.2 Behavior model

The *Behavior Model* describes the cross-domain interactions between aircraft and manufacturing artifacts. In the context of this case study, the focus is put on the *Workload estimation* knowledge to address the bottleneck identified in the problem statement (see Section 1).

In order to elaborate the *Behavior Model*, we leverage the hybrid knowledge acquisition method outlined in Chapter 3 to extract executable engineering rules related to *Workload estimation*. *Workload estimation* is categorized as a cross-performance knowledge (seen in Figure 22c).

As the remainder of this section involves sensitive information from an internal project, note that any technical data has been modified for confidentiality purposes. Nevertheless, these modifications have been conducted with the intention of preserving coherence. The authors emphasize that the focus here is on the general approach rather than specific technical outcomes.

2.2.1 Expert-centric formalization

A new series of interviews was conducted with diverse domain experts, including manufacturing preparators, industrial system experts, material experts and industrial architects. This

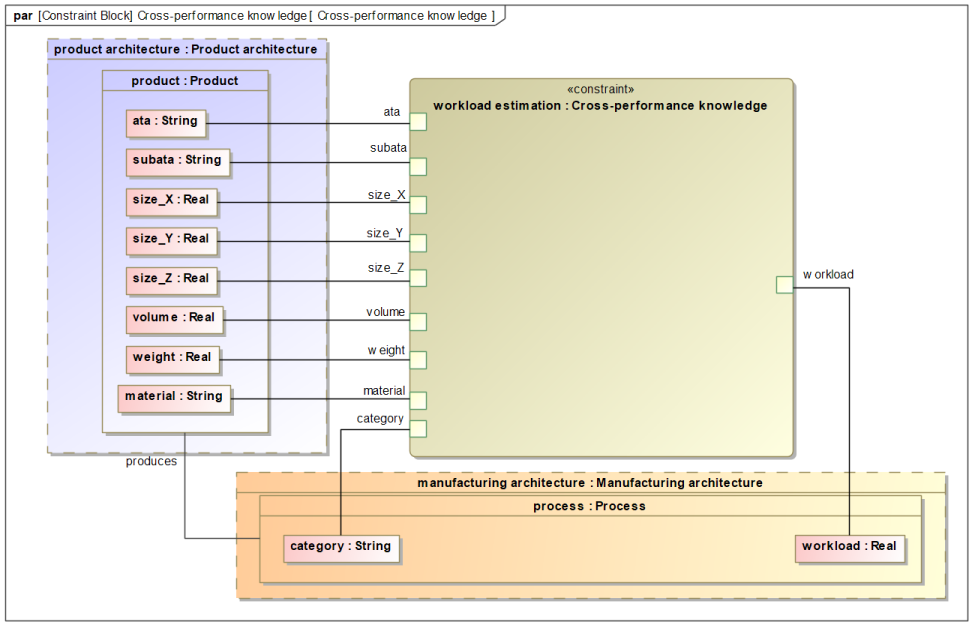


Figure 25: Workload estimation pattern as Behavior model component

iterative expert-centric formalization yielded significant results by identifying concrete cross-domain parameters *(e.g. weight, volume, material and process category)* from the product and manufacturing domains that play a significant role in workload estimation. The resulting cross-domain pattern associated with workload estimation is illustrated in Figure 25.

It is important to note that the identified parameters were not unanimously considered essential by all experts for workload estimation. For instance, not all experts and stakeholders agreed on the involvement of the *material* parameter. A decision was made to initially retain this parameter, with the option to remove it later if its inclusion proved to be a source of complications.

This identification process served to formalize the concepts and attributes essential to workload estimation. Consequently, this model brings value describing additional cross-domain links between MBSE architectures. By formalizing impact relationships between systems, the information traceability capability of MBSE environments has the potential to help the identification of effective levers supporting early co-architecture activities.

During the final step of the human-centric formalization, the experts directed us toward relevant data sources. Such suggestions have supported the second phase of the hybrid knowledge acquisition method which aims to instantiate this pattern from historical records. Specifically, most information concerning the Product was accessible in a particular legacy database, while the Manufacturing information was maintained within the company's Enterprise Resource Planning (ERP) tool.

2.2.2 Data-driven extraction

Guided by the established workload estimation pattern (Figure 25), the data-driven extraction phase was initiated. This approach intends to leverage the robustness and scalability of machine learning models applied on large scale datasets. More specifically, its aims to extract explicit rules of implicit knowledge through interpretable models such as Random Forest (RF)

(Dasari et al., 2019) or Decision Tree (DT) models (Ali et al., 2018).

Data exploration (E1): A thorough exploration of a substantial part of the organization's data sources found traces of the parameters identified by the workload estimation pattern. Based on the guidance of experts consulted during the previous human-centered phase, we prioritized data from recent programs due to its relative recentness, which supported enhanced data reliability.

- Product information: Through CM databases and digitalized drawings' meta-data, the targeted information was found at a *Design Solution* granularity level.
- Manufacturing information: The absence of an explicit *workload* parameter necessitated to find a variable tracking the process time. Within the ERP, concepts such as *Routings* and *Work Orders* were identified with such information.
  - A *Routing* represents a generic list of operations defining the overall product build process.
  - A *Work Order* is a specific instantiation of a *Routing* for an individual aircraft.

Although the *Work Order* database contained a significantly larger number of instances, consultation with domain experts strongly advised against its use due to unreliable processing time information. Indeed, the timestamps of *Work Orders* can significantly differ from reality due to the way operators register this information.

Consequently, we selected the *Routing* dataset, accepting the trade-off of a smaller sample size (approximately 50,000 instances) in exchange for the assurance that the time information was measured using the rigorous and reliable MTM-UAS (Methods-Time Measurement Universal Analyzing System) standard. This decision therefore prioritizes data quality and measurement rigor over considerable data volume.

Data preparation (E2): The subsequent challenge was the integration of the identified sources of information. The datasets were stored in heterogeneous formats with no explicit link between each other (e.g. product engineering data from the legacy database and manufacturing engineering data from the ERP system).

To create a unified and meaningful input for the machine learning training, significant preparation activities are required:

- **Transformation:** Converting the disparate data structures and formats into a common, standard representation (e.g. unit homogenization between Kg and g, Hours and Minutes).
- **Aggregation:** Summarizing or combining related data points to the appropriate level of detail required for workload estimation (e.g. summing the measured process time of all operations in a *Routing*).
- **Filtering:** Removing irrelevant data out of the scope of the model's training (e.g. keeping only *Routings* relative to the recent programs).
- **Joining:** Establishing synthetic or derived linkages between the datasets (e.g. matching Product IDs in the *Routing* data with corresponding attributes in the Product drawing data).

These collective transformation, aggregation, filtering, and joining activities were essential to achieve a homogeneous and meaningful input dataset comprising all the targeted parameters for workload estimation learning.

Pre-processing (E3, loop 1): From an initial input dataset comprising 21,846 data points, standard pre-processing techniques are applied to reduce biases and favor the expected machine learning training (Zheng and Casari, 2018).

Data cleaning: Initial checks were performed to identify and address incorrect or missing data. This involved scrutinizing logical inconsistencies:

- **Missing values:** A significant number of lines in the input dataset can have at least one missing value. Dealing with missing values can be achieved either by removing the whole line or by filling the missing data point with a synthetic value. This choice depends on the importance of the feature involved. Less critical features can be filled synthetically to preserve the information contained in the rest of the line while others might justify a simple line removal.
- **Incorrect values:** Data points with logically impossible characteristics, such as negative values for parameters like *volume* or *weight*, were removed.
- **Outlier values:** Data points with excessive *workload* values were flagged as outliers. According to domain experts, any workload exceeding 2,500 Industrial Minutes (IM) was considered as an outlier. While these data points may not all be fundamentally incorrect, they represent rare exceptions that could introduce significant bias and impede the model learning process.

Categorical features balancing: Then, the dataset is balanced to address the issue of categorical values occurring too infrequently. These non-representative instances can introduce noise into the training process. While a 1% heuristic is frequently applied for such thresholds, the iterative nature of our pre-processing revealed that this value resulted in an excessive number of columns during a subsequent encoding phase. Consequently, a more strict threshold of 1.5% was adopted to maintain a manageable feature space while ensuring the inclusion of statistically significant categories.

This balancing is illustrated in Figure 26, where we see the initial distribution of ATAs and SubATA values. As a high variation in such parameters would introduce noise in the dataset, the categories less represented shall be excluded. The removal of a few will thus greatly improve the stability and distribution of such features. We see here that we keep mostly ATA 92 (Electric installation), 53 (Fuselage), 57 (Wings), and 21 (Air conditioning) chapters.

Discrete features segmentation: Afterward, due to the intention to leverage the SIRUS algorithm (Bénard et al., 2021), all discrete features are segmented to their closest 10th quantile. This value stabilization helps to define common thresholds in order to regroup the Random Forest rules and extract the most frequent ones.

Categorical Features encoding: To ensure a proper comprehension by the machine learning model, the categorical features were subsequently encoded. The two most common encoding techniques are the *Label Encoding* and the *One-Hot Encoding*.

- **Label Encoding:** Assigns a numerical value (1, 2, 3, etc...) to each category. The main drawback of this technique is that it may generate an artificial hierarchy or ordinal relationship that does not exist in reality.



(a) Initial ATA/subATA distribution

(b) Balanced ATA/subATA distribution

Figure 26: Example of categorical data balancing

Initial dataset of 21,846 lines	
Pre-processing technique	Total remaining lines
Data cleaning	9,339 lines
Categorical features balancing	7,413 lines
Discrete features segmentation	7,413 lines
Categorical features encoding	7,413 lines
Train/test split (85%/15%)	6,301 & 1,112 lines

Table 3: Data volume engaged in pre-processing

- **One-Hot Encoding (Privileged):** This technique generates a new boolean column for each distinct categorical value. A 1 in such column indicates that the data point belongs to that specific category while a 0 indicates the opposite. This method effectively represents categories without imposing any misleading ordinal relationships.

  However, it generates a larger feature space (more columns) and might cause complexity issues when numerous categories are involved.

In order to avoid any unwanted ordinal relationship generated by the *Label Encoding* technique, and supported by the previous *Categorical features balancing* step which reduced significantly the number of distinct categories, the *One-Hot Encoding* was selected, resulting in a a total of 231 columns (discrete features included).

Train/Test split: Finally, the fully pre-processed dataset was split into two subsets: a training set and a test set. This is a crucial step in machine learning methodology to ensure the model's generalizability. By intentionally keeping the test subset separate and out of the training process, the primary objective is to avoid a phenomenon known as "overfitting".

Overfitting occurs when a model learns the training data, including its noise, instead of learning the logic behind it. While this produces excellent results on the training data, it significantly reduces the model's ability to make generic predictions when presented with new data.

As *Random Forest* models are not overly susceptible to overfitting, and because our pre-processed dataset does not contain an extremely large number of lines, the target size of the test set was specified around 1000 data points. This allowed us to allocate 85% of the data for the model training while keeping 15% as a testing set (1112 data points).

The pre-processing techniques employed and their resulting number of line in the input dataset are summarized in Table 3. One can notice that a considerable part of the initial dataset was removed during the *Data cleaning* step (more than 50%). This was mainly due to the *Weight* feature, often missing in the source databases, which was considered as an important feature.

Model training (E4, loop 1): After the pre-processing step, a *Random Forest Regressor* model has been iteratively trained and with the *coefficient of determination (R^2)* and the *RMSE* as primary performance metrics.
R^2, quantifies the proportion of the variance in the dependent variable that is predictable from the independent variables. To put it more simply, it represents a measure of how well a regression model explains the variability of the data around its mean.

The formula for the coefficient of determination described in Equation 3 as the inverse of the unexplained variation *(SSres)* over the total variation *(SStot)*, thereby yielding a result between 0 and 1. The unexplained variation *(SSres)* being the sum of the squares of errors described in Equation 1 where f is the prediction and y is the actual data point. The total variation *(SStot)* is the sum of the squares of the differences between the actual data points and the mean as described in Equation 2.

$$SS_{res} = \sum_i (y_i - f_i)^2 = \sum_i e_i^2 \tag{1}$$

$$SS_{tot} = \sum_i (y_i - \bar{y})^2 \tag{2}$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{3}$$

However the consideration of what constitutes a "good" R^2 is heavily dependent on the context. Some studies require values extremely close to 1, and others might find 40% as an acceptable threshold. For the specific task of early workload estimation in this project, consultations with domain experts established an R^2 threshold of 70% as the criterion for demonstrating a correct model fit to the data. It is important to note that the aim of this project is not to be highly precise, but rather to perform quick approximations that enable short iteration loops.

Nevertheless, relying only on a percentage metric like R^2 can remain abstract for some stakeholders. To provide a more concrete and interpretable measure of model performance, we included the *RMSE* as complementary metric. *RMSE*, as defined in Equation 4, represents an absolute measure of the mean error.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - f_i)^2} \tag{4}$$

By using the same units as the predicted *workload* values (IM), it allows stakeholders to grasp the magnitude of the prediction errors. However, as this metric is highly sensitive to outliers, it is rarely used as the main metric of regression models.

Through the definition of a dual-metric standard, incorporating an R^2 greater than 70% and a RMSE inferior to 300 IM, we established both relative and absolute measures for determining the successful completion of the training process. This combined assessment ensures that the

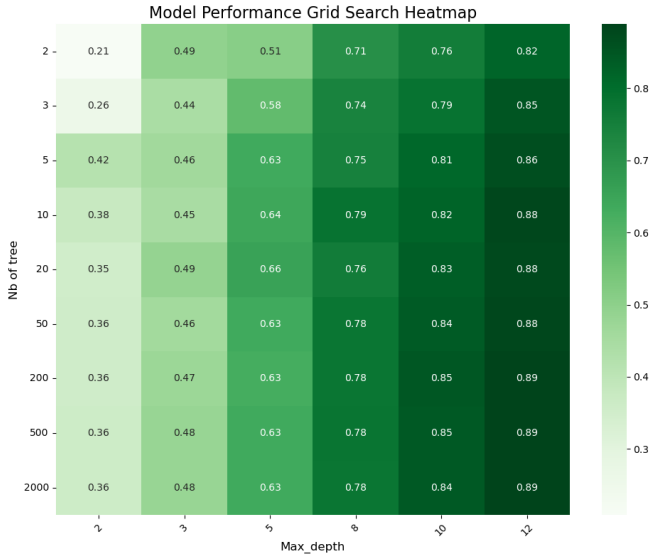


Figure 27: Grid Search analysis heatmap

Hyperparameter name		Hyperparameter value
$n_estimators$	=	200
max_depth	=	12
$bootstrap$	=	$True$
$max_features$	=	"$sqrt$"
$criterion$	=	"$squared_error$"

Table 4: Random Forest hyperparameter values

model not only explains a significant portion of the data variance but also maintains a practically acceptable level of estimation error.

With these performance metrics established, a Grid Search analysis is executed to systematically finetune the hyperparameters of the *Random Forest Regressor* model. This optimization process involves exploring key parameters such as the number of decision trees in the forest (named "estimator") and their maximum depth.

As illustrated in the Figure 27, various sets of hyperparameter values were iteratively evaluated through systematic cross-validation. This rigorous approach ensures that the selection of optimal hyperparameters is based on stable performance metrics across five data folds. Such hyperparameter values are detailed in Table 4.

Model evaluation (E5, loop 1): The testing set, which was kept out of the training phase, was then employed to demonstrate the machine learning model's capability to generalize on new data. As illustrated in Figure 28, the measured *workload* values are compared against their associated predictions. The accuracy of these predictions (represented by the blue data points) is visually confirmed by their proximity to the central red line (representing perfect prediction).

Thus, the model demonstrated strong performance, achieving a R^2 of 94% and a $RMSE$ of 165 IM. While a concrete trend can be easily noticed, the plot also indicates the presence of a few outliers with error increasing on high workload values. By meeting the predefined metric requirements ($R^2 > 70\%$ and $RMSE < 300$ IM), this evaluation confirms the successful learning process for early workload estimation.

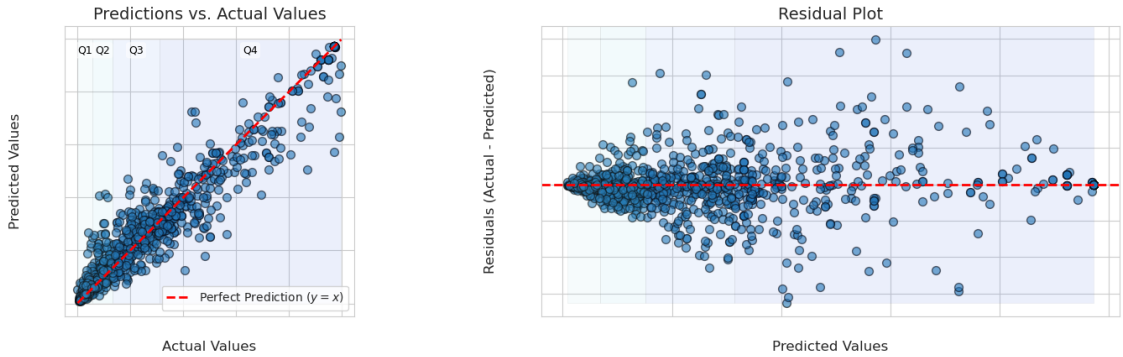


Figure 28: Random Forest Regressor evaluation

Rules extraction (E6, loop 1): Once the successful learning process is confirmed, the stakeholders can already use the model (considered as a "black box") as an additional simulation tool. However, our approach leverages interpretable machine learning models to extract the learned knowledge in the form of *if-then* rules, which can then be incorporated into MBSE environments and ontology models.

The SIRUS algorithm proposes to extract a stable rule set imitating the behavior of the trained Random Forest model by 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 rule set has to be used for each prediction by averaging the results of each rule.

As seen previously, SIRUS relies on the segmentation of discrete features toward their closest 10th quantiles to stabilize the splits of each tree with homogeneous values. Then, each path of each tree is collected, treated, and aggregated into the resulting rules listed in Table 5.

The coherence and industrial relevance of the extracted rules for early workload estimation were initially confirmed through a qualitative validation with industrial experts. However, as a rigorous follow-up confirmation, a quantitative validation was executed on the testing set, mirroring the assessment methodology used in the previous step.

The results were considerably below our expectations with $R^2 = 38\%$ and RMSE = 7782 IM. While considering an error in our implementation of the SIRUS algorithm, we identified that the nature of SIRUS induces the emergence of shallow rules (mostly with depth of one, two, and rarely, three degrees).

In the context of this specific workload estimation problem, with our input data, it turns out that the maximum tree depth is a key hyperparameter. As shown in Figure 27, satisfactory results only start to be achieved with a depth of eight degrees.

Although the extracted individual rules appear logical, the complete, complex knowledge

Frequency	Rule body	Rule head	
0.21	IF volume $\leq$ 1,618,204,019.5 mm^3	THEN workload = 789.04 IM	ELSE workload = 2,204.72 IM
0.19	IF size_Z $\leq$ 4,421.3 mm	THEN workload = 944.6 IM	ELSE workload = 4,331.9 IM
0.12	IF category = "assembly"	THEN workload = 3,614.4 IM	ELSE workload = 1,322.7 IM
0.11	IF ata = "21"	THEN workload = 326.7 IM	ELSE workload = 1,403.6.84 IM
0.08	IF weight $\leq$ 9,556.4 g	THEN workload = 886.6 IM	ELSE workload = 1,642.5 IM
0.07	IF size_Y $>$ 1,516.1 mm	THEN workload = 1,626.6 IM	ELSE workload = 634.4 IM

Table 5: Most occurring extracted rules

captured by the deep structure of the *Random Forest* was not fully extracted into the simplified rule set. We emphasize that this is a context-specific limitation: in scenarios where models composed of shallow trees are sufficient, the SIRUS approach would be appropriate. Nevertheless, since our objectives are to extract a rule set that represents a maximum of the learned knowledge, such rules were considered insufficient.

Consequently, a second iteration loop is necessary in order to extract a set of rules capable of describing workload estimation more accurately. The analysis of the hyperparameter heatmap (Figure 27) indicated that, while the maximum tree depth was an important factor, the number of trees was relatively less critical for optimal performance. Based on this evidence, we attempted a second loop of the data-driven knowledge extraction by exploiting a single *Decision Tree* model.

Model training (E4, loop 2): Then we conducted another Grid Search analysis on the hyperparameters of the *Decision Tree Regressor*. The resulting hyperparameters are detailed in Table 6

Hyperparameter name		Hyperparameter value
max_depth	=	12
criterion	=	"*squared_error*"
splitter	=	"*best*"

Table 6: Decision Tree hyperparameter values

Model evaluation (loop 2): As demonstrated in Figure 29, the performance metrics for the single *Decision Tree* model, while slightly lower than those achieved by the *Random Forest*, still achieved adequate metric results. Specifically, the model yielded an R^2 of 89% and a RMSE of 184 IM. Satisfying the minimum requirements established for the project ($R^2 > 70\%$ and RMSE < 300 IM) it confirms the model's prediction capability for early workload estimation. Nevertheless, we can notice stronger errors than with the *Random Forest*.

Rules extraction (E6, loop 2): Once the successful training of the DT model for workload estimation has been confirmed, the process of extracting an explicit rule set mimicking its

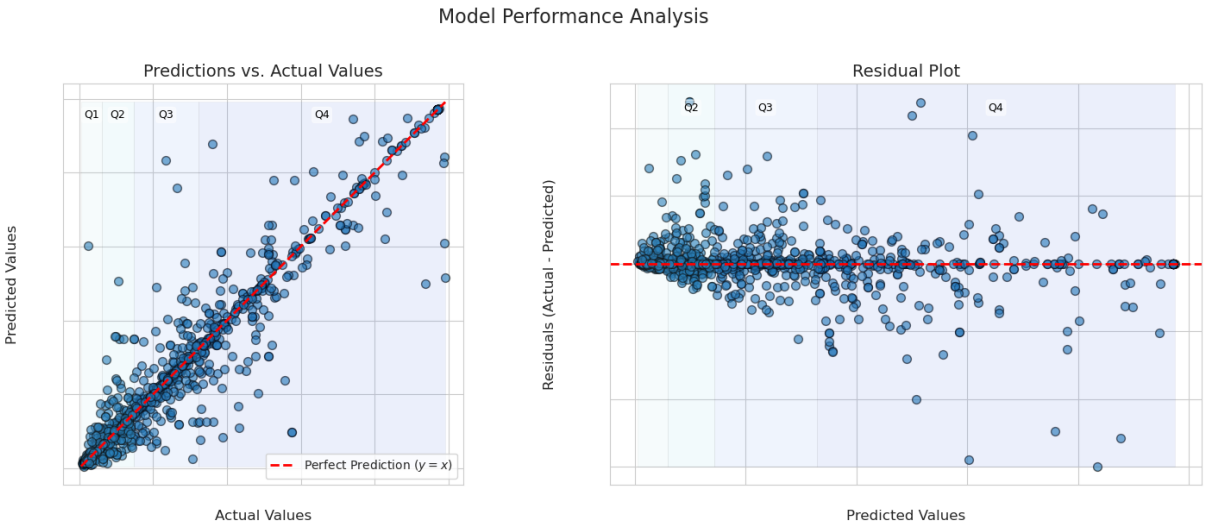


Figure 29: Single Decision Tree - performance analysis

behavior is quite straightforward.

The inner structure of a DT model is a rule set itself. Thus, we systematically collect all paths from the root to leaf nodes. These unique paths constitute precise *if-then* rules that describe the model's predictive behavior. A subset of the extracted rules are detailed in Table 7.

The major drawback of this direct extraction method is the resulting large volume of rules compared to the SIRUS algorithm. While the magnitude of the rule set can be managed by limiting the maximum tree depth, the number of rules will inevitably generate a considerable complexity.

The core motivation for this rule extraction step was primarily to demonstrate the principles of interpretable machine learning and to enhance the trust placed in predictive models.

Rule body	Rule head	Sample basis
IF *size_z* $> 6{,}501.4\ mm^3$ **AND** *weight* > 4.3 kg **AND** *category* $\neq$ "Electrical assembly" **AND** *material* = "ALUMINIUM"	**THEN** *workload* = 4,667.7 *IM*	Based on 1,271 samples
IF *size_z* $\leq 2,566.8\ mm^3$ **AND** *volume* $\leq 3,309,015,256.6\ mm^3$ **AND** *category* = "Electrical assembly" **AND** *volume* $> 654{,}746{,}152.5\ mm^3$ **AND** *weight* > 1.4 kg **AND** *size_y* $\leq 3{,}006.1\ mm^3$ **AND** (*ata* $\neq$ "57" & subata $\neq$ "5") **AND** (*ata* $\neq$ "92" & subata $\neq$ "8") **AND** (*ata* $\neq$ "54" & subata $\neq$ "5")	**THEN** *workload* = 450.4 *IM*	Based on 71 samples
IF *size_z* $\leq 10,277.0\ mm^3$ **AND** *volume* $\leq 6,136,550,323.2\ mm^3$ **AND** *composition* $\neq$ "STAINLESS_STEEL" **AND** *weight* ≤ 10.4 kg **AND** *weight* > 0.351 kg **AND** *size_y* $\leq 2{,}273.6\ mm^3$ **AND** *size_x* $\leq 5,456.7\ mm^3$ **AND** *ata* $\neq$ "38" **AND** (*ata* $\neq$ "53" & subata $\neq$ "3")	**THEN** *workload* = 89.6 *IM*	Based on 56 samples
IF *size_z* $\leq 8,754.0\ mm^3$ **AND** *volume* $\leq 6,307,480,845.7\ mm^3$ **AND** *composition* $\neq$ "ALUMINIUM" **AND** *weight* ≤ 3.3 kg **AND** *weight* > 1.1 kg **AND** *size_y* $\leq 1{,}936.8\ mm^3$ **AND** *size_x* $\leq 4,648.3\ mm^3$ **AND** (*ata* = "54" & subata = "1") **AND** *volume* $> 5,227,431,757.5\ mm^3$	**THEN** *workload* = 1,871.5 *IM*	Based on 52 samples
...		

Table 7: Decision Tree rules subset

Validation (F5) The validation step has been conducted on both extracted rule sets: the concise, yet imprecise, set obtained through the SIRUS algorithm, and the precise, yet lengthy, set constituting the *Decision Tree* model.

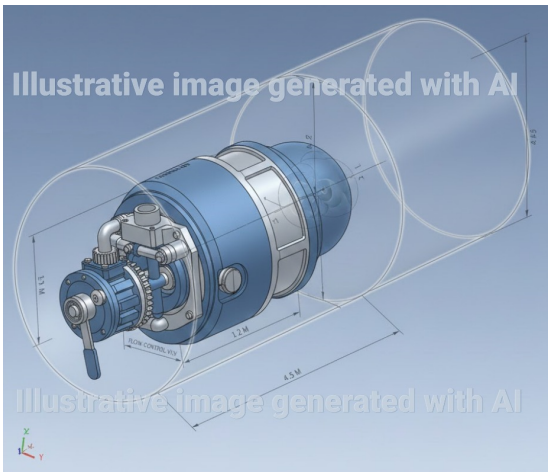
It has already been established that the SIRUS rule set did not capture all the complexity of the knowledge involved for workload estimation. However, after discussion with experts, it appears that these few rules remain coherent and could be used at a very high degree of abstraction. This qualitative validation allows architects to obtain an estimation when the complete context is still undefined. Furthermore, its concise format facilitates its integration for human interpretation.

On the other hand, the rule set constituting the DT model was quantitatively evaluated during the learning process with RMSE and R^2 metrics. While these rules represent a more accurate version of the captured knowledge, their large numbers make them more cumbersome to integrate and reuse in a KBE system.

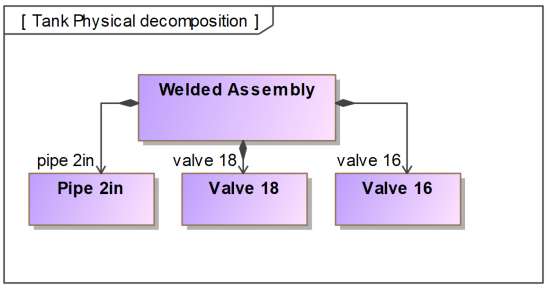
3 Ontology instantiation

Through ontology-based approaches, this section intends to demonstrate how our contributions address the scientific and industrial needs in a real-world application. This study was conducted in a context of new generation hydrogen fuel tanks architectures, which are a key enabler for innovative new designs of sustainable commercial aircraft.

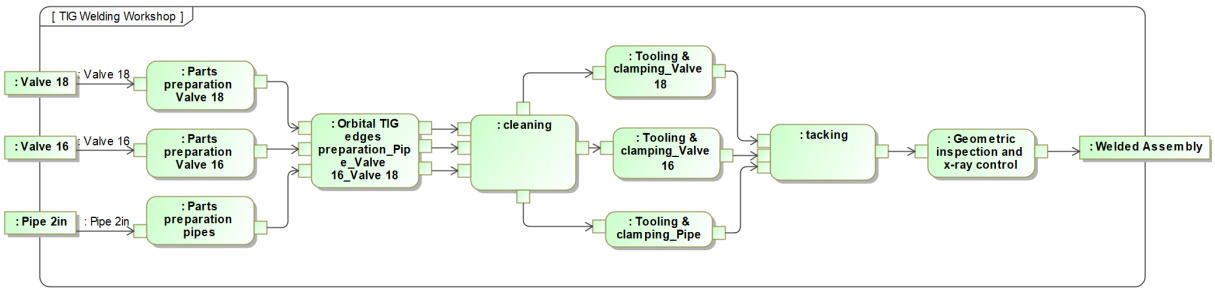
Because such on-going studies are strictly confidential, the following paragraphs are illustrated by edited models which do not disclose sensitive information. In order to provide a concrete example to the reader, a generative AI model has even been used to depict a shareable illustration in Figure 30a.



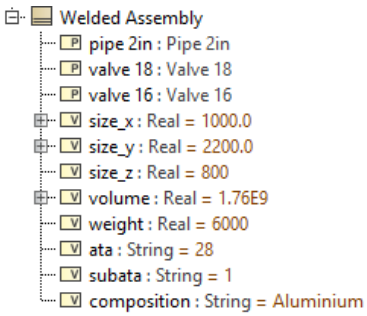
(a) CAD of the tank assembly



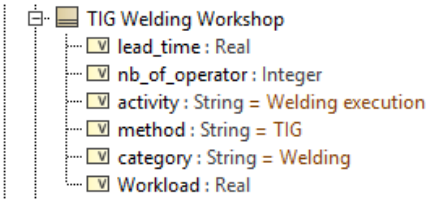
(b) SysML product model - Physical layer



(c) SysML manufacturing model - Functional layer



(d) Welded assembly properties



(e) TIG welding process properties

Figure 30: Illustrative digital models

For clarity sake, the demonstration of the ontology instantiation will focus on the specific assembly illustrated in Figure 30. Nevertheless, the ontology instantiation is applied to the whole use-case context with its numerous MBSE models.

Within this case study, the product and manufacturing architectures were developed as SysML models with RFLP structure. Figure 30b shows the *Physical layer* of the product welded assembly and Figure 30c illustrates the manufacturing operations required for its assembly through the *Functional layer*. Furthermore, each MBSE artifact is described with diverse properties as shown in Figure 30d and Figure 30e.

The next section addresses the ontology instantiation that follows the ontology development phase as described in Figure 17. This instantiation relies on the *Semantic model* that acts as a dynamic link between the MBSE architectures and the ontology.

3.1 Semantic model

The *Semantic model* serves as the interface between the *Data model* and the MBSE environments. It ensures the seamless integration of product and manufacturing architectures following the ontology agnostic structure into the digital thread. By defining easily maintainable links in a collaborative manner, this model allows for interoperability between MBSE models and the rest of the digital ecosystem.

In the context of this case study, the specialization of the *Semantic Model* (derived from Figure 20) focuses on integrating the product architecture's *physical layer* and the manufacturing architecture's *functional layer*. Thus, the digital thread's ontological core (4b in Figure 16), shall be populated with MBSE instances in the digital thread's knowledge base (4a in Figure 16).

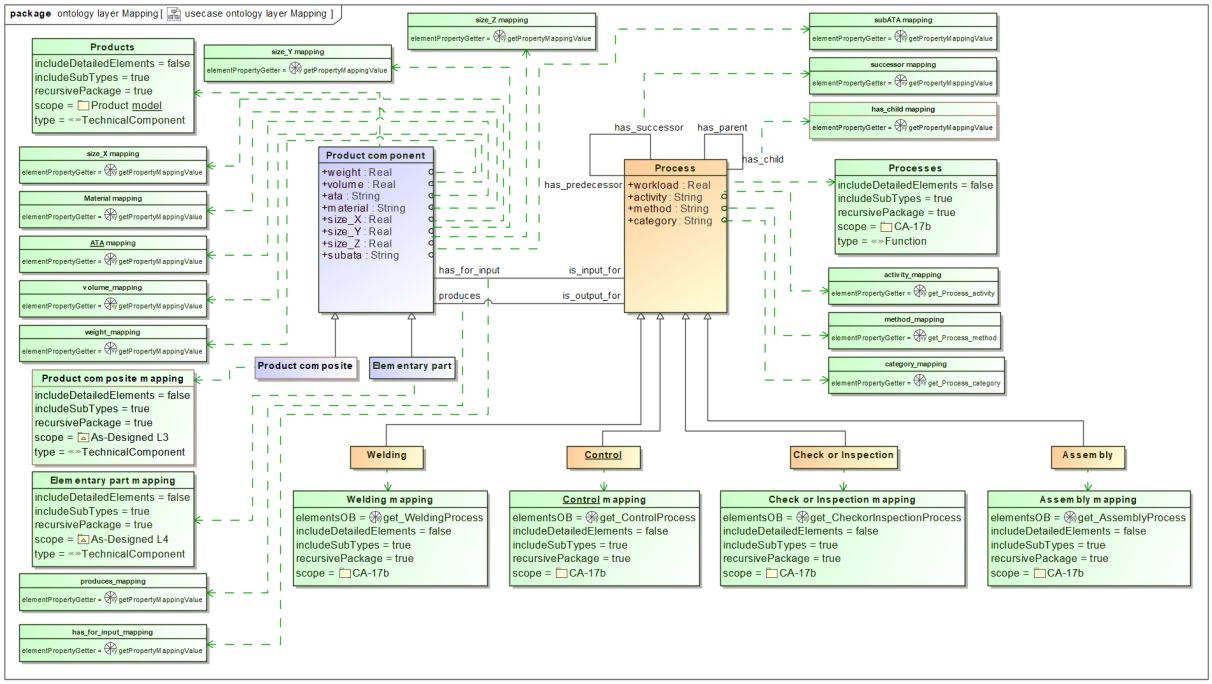


Figure 31: Semantic model

Each element from the specialized *Data model* is mapped to its related MBSE artifact as illustrated in Figure 31. Classes are mapped with *scope* and *type* information while their properties

rely on *Opaque Behaviors* to retrieve the right information.

Opaque Behaviors operates functions from the *Cameo Systems Modeler* software. They can range from simple value retrieval to more complex navigation through the MBSE framework. The functions employed within this case study were mainly *Find, Simple navigation and Metachain navigation.*

Metachain Navigation is a feature designed to create dynamic and complex queries. This functionality allows to systematically navigate within relationships between various model artifacts based on specified conditions. As an example, Figure 32 shows the inner structure of an *Opaque Behavior* used to retrieve the *material* value of a product component.

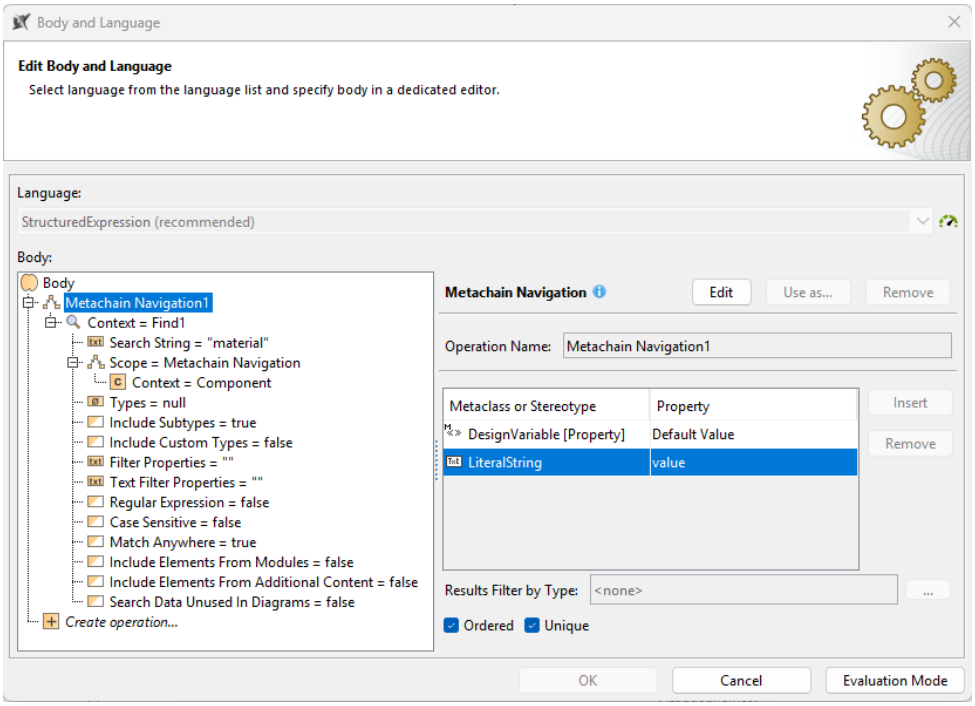


Figure 32: Opaque Behavior inner structure

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

3.2 Digital Thread deployment

Until this moment, the ontology models were collaboratively elaborated within a MBSE environment for enhanced linking capability toward the architecture models.

In one hand, ontology models were developed to describe both architectures and their interdependencies in a tool-agnostic manner. This representation has provided a unified representation of classes and properties for a shared knowledge representation without product-specific of manufacturing-specific biases.

On the other hand, the links between the MBSE architectures and the *Data Model* were established in the *Semantic Model* using features from *Cameo Systems Modeler* allowing for easy linking maintenance.

The final step is to deploy the digital thread outside the MBSE environment. By using an Airbus internal plugin named MBSELab (Habib Essoussi et al., 2024), the *Data Model* instantiated with the MBSE architectures has been automatically exported to a Neo4J server in a .OWL format.

Thus, any stakeholder is able to access the digital thread's knowledge base by using flexible Cypher queries such as the one shown in Listing 4.1. Such queries provide the means visualize the architectures as illustrated in Figure 33 but also to connect third party simulation tools, thereby preserving the digital continuity and information flow between MBSE end the rest of the Digital Engineering suite.

```
MATCH (input:Product)<-[:Process_has_Input]-(prev_process:Process)
// prev_process consumes the input Product

-[:Process_has_Successor]->(next_process:Process)
// next_process is the direct successor of Process 1

-[:Process_has_Output]->(output:Product)
// next-process produces the output Product

RETURN prev_process, next_process, input, output
```

Listing 4.1: Cypher query: getArchitectures

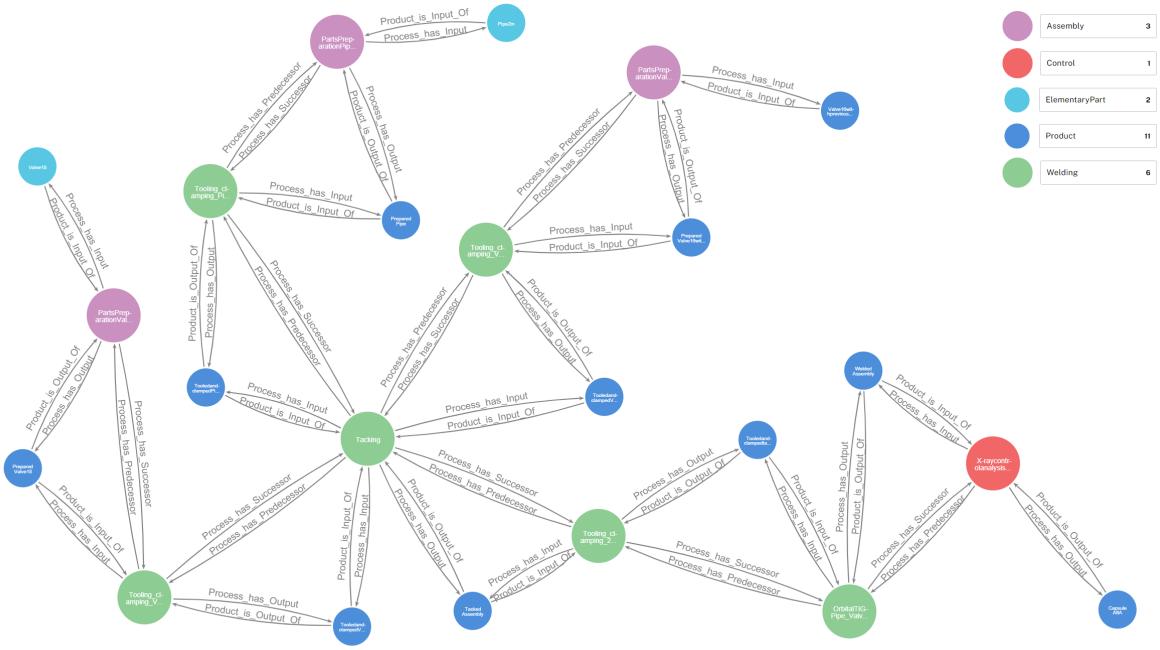


Figure 33: MBSE architecture extracted in the digital thread

This integration, described as a graph-based shared reference with agnostic data structure, also allows each stakeholder to explore the various architectures without requiring extensive knowledge of MBSE modeling framework. Thus, it enhances the models' comprehensiveness and can help reducing the discrepancies of modeling maturity.

Therefore, by integrating MBSE artifacts across domains, this knowledge base becomes a communication medium within the rest of the digital environment. Through digital continuity and information traceability it enables syntactic interoperability.

Furthermore, the shared conceptualization of the overlying ontology ensures semantic interoperability with the rest of the digital environment. Thus, the various concerns of multiple stakeholders can be addressed while conveying a mutual understanding. Moreover, its tool-agnostic format allows for flexible data exchanges between each tool of the digital ecosystem regardless of the input data format required.

Finally, acting as a common reference among engineers, this ontology-based digital thread provides the means to coordinate among various teams and disciplines in an extended enterprise context, achieving organizational interoperability.

3.2.1 Knowledge execution for workload estimation

Additionally, through the expert-centric knowledge formalization as a part of the *Behavior model* elaboration, cross-domain MBSE artifacts have been linked identifying key classes and attributes playing a fundamental role in the estimation of the workload. This formalization has acted as an additional bridge between product and manufacturing system architectures.

Such knowledge has also oriented further data-driven studies with the aim to capture its underlying design rules. From the intuition of experts, the robustness and scalability of large databases were exploited to transform a tacit knowledge into explicit *if-then* rules.

Nevertheless, while the acquisition of such knowledge is an achievement itself, its execution in the context of this case study would demonstrate the complete value of our contributions. To this extent, both extracted rule sets were integrated into the digital thread for different moments of the co-architecture process.

Firstly, the SIRUS rule set has been incorporated to the workload estimation pattern, as illustrated in Figure 34.

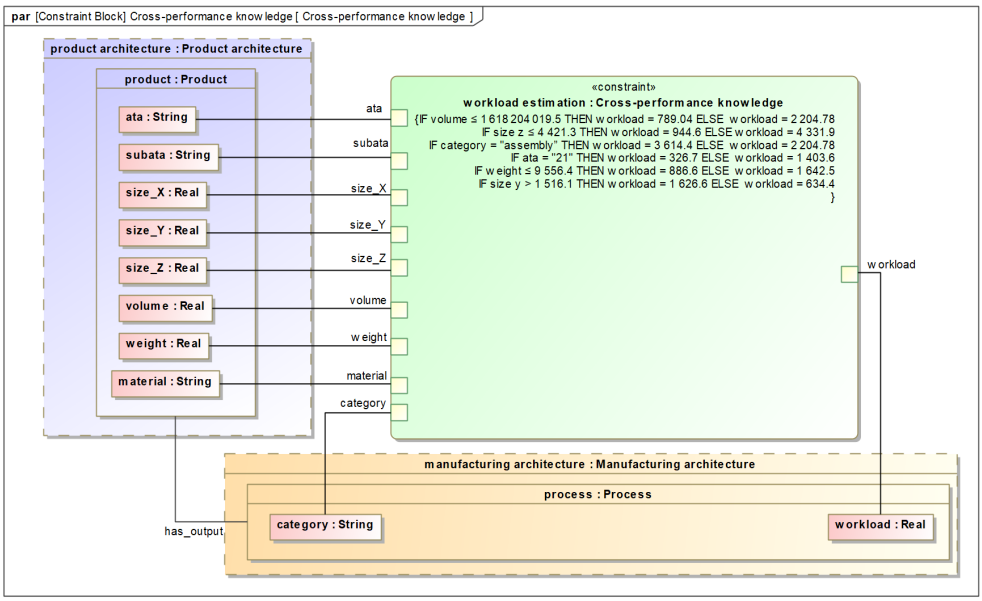


Figure 34: Extracted rules formalized in the behavior model

Thus, these rules were available to engineers, directly linked to the MBSE artifacts. While imprecise, this knowledge helped to manually estimate a first degree of magnitude during early co-architecture activities, demonstrating the capability of MBSE to represent knowledge in the form of *if-then* rules.

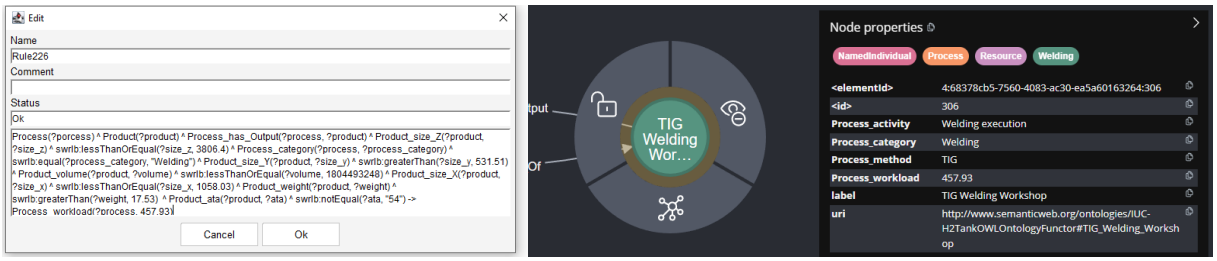
Later during the co-architecture process, as both product and manufacturing MBSE architectures were extracted in the knowledge base with greater granularity information, the lengthy rule set constituting the trained *Decisions Tree* model was systematically integrated as Semantic Web Rule Language (SWRL) rules as leveraged by Kim and Ahmed (2018). This more precise knowledge then becomes accessible to any stakeholder, with reasoning capabilities allowing for automatically executable cross-domain impact assessments.

In the context of this experiment, the workload estimation involved welding process operations was enabled by the rule n°226 as detailed below and depicted in Figure 35.

```
if (size_z <= 3806.4) and (category = ‘‘Welding’’) and (size_y > 531.51) and (volume <= 1804493248.0)
and (size_x <= 1058.03) and (weight > 17.53) and (ata notes  "54")
then response: 457.93 | based on 12 samples
```

```
MATCH (rule:Imp)-[*]->(x)
//Imp (for Implies) is the format defining if-then statements where the
    antecedents leads to the consequent
WHERE rule.label = "Rule226"
RETURN rule, x
```

Listing 4.2: Cypher query: getRule226



(a) SWRL rule example in Protégé

(b) Rule inferred

Figure 35: Knowledge incorporation in the digital thread

This knowledge incorporation allowed architects to automatically estimate the workload of a whole series of operations based on explicit *if-then* rules captured from past production records.

Instead of asking domain experts, often different people, for each independent operation, this ontology-based digital thread has provided architects the means to quickly estimate the workload at a higher degree of granularity, thus highly shortening iteration loops without necessitating deep analysis relying heavily on domain experts.

4 Chapter conclusion

This chapter demonstrates the practical value of this research through a real-world case study on early co-architecture activities. Domain experts identified two primary challenges: first, the cumbersome interface between Model-Based Systems Engineering (MBSE) architectures and the

broader digital environment, necessitating heavy link maintenance and processing steps. Second, workload estimation activity acting as the main bottleneck for impact assessments between product engineering and manufacturing systems engineering.

By applying the MfM methodology within this use-case specific context, the ontology-based digital thread framework described in the previous chapter has been successfully implemented. The specialization of *Data*, *Behavior*, and *Semantic* models have addressed concerns of both interoperability and knowledge capitalization for Collaborative and Concurrent Engineering during the conceptual design phase.

By leveraging our industrial collaboration, we met with diverse domain experts possessing unique backgrounds in order to formalize an agnostic conceptualization of the co-architecture process.

This collaborative effort defined the primary entities, their behavioral patterns, and their respective MBSE interfaces. By embedding the ontology development directly within the MBSE environment, we ensured that the formalization process remained both collaborative and easily maintainable, effectively utilizing MBSE capabilities for ontology engineering.

Consequently, the integration between MBSE architectural views and ontological models was streamlined, facilitating a seamless instantiation process.

The resulting digital thread integrated both product and manufacturing MBSE architectures within an ontology-aligned format. The underlying knowledge graph serves as a robust communication medium, bridging the MBSE environment with the broader Digital Engineering ecosystem. By utilizing flexible queries tailored to answer the diverse concerns of project stakeholders, the framework has established a foundation for syntactic, semantic, and organizational interoperability.

Furthermore, by conducting a hybrid approach for knowledge acquisition, a workload estimation knowledge pattern was formalized through expert-centric elicitation. By acting as an additional cross-domain bridge, this pattern identified concepts and attribute playing a crucial role in this complex cross-domain relationship. Through MBSE information traceability, engineers can easily highlight actionable levers for cross-domain impact assessments.

Moreover, this pattern also served as the basis of data-driven studies, resulting in the capture of design rules. Concise yet approximative, and precise yet numerous rulesets describing workload estimation knowledge were extracted. By delivering enriched insights back into the MBSE environment and enabling executable cross-domain impact assessments via automated inference reasoning, the framework empowers engineers to conduct global trade-offs across divergent perspectives with significantly shortened iteration loops.

Ultimately, by resolving persistent barriers to interoperability and knowledge reuse, this ontology-based digital thread has provided a cohesive support structure to support Collaborative and Concurrent Engineering in the context of this case study.

Chapter 5

Discussion & Conclusion

Following the Design Science Research Methodology, the previous chapters have identified the research problem, defined objectives of a solution, developed a corresponding artifact, and demonstrated its value in an industrial context. The final step of DSRM is the **communication** of this research's results.

Therefore, this chapter aims to hold discussions regarding the conducted study, summarize the key research results and open perspectives toward its generalizability to other contexts or domains.

1 Discussions

While our ontology-based digital thread framework has successfully demonstrated its value for Collaborative and Concurrent Engineering, we now have the opportunity to explore broader considerations and high-level discussions in order to address complex integration points and enhance the study's overall impact.

These discussions serve as fuel material for academic and industrial communications by highlighting axes that were not main elements of the demonstration. Such discussions bring interesting counterweights and perspectives to the proposed research.

1.1 Knowledge trust in new design context

The first discussion should be about the confidence engineers can put in the extracted rules for new, innovative design activities. While the knowledge formalized with experts tends to naturally adapt toward expected changes in new design contexts, the question can be raised regarding knowledge extracted from databases which can be seen as a frozen image from the past.

The implementation of CCE relies heavily on the trust that architects can place in the acquired knowledge. Therefore, in order to ensure that the rules extracted with data-driven approaches are reliable enough to be trusted, the sole justification of the training metrics may not be sufficient, particularly in new innovative design contexts. Thus, the question arise: How to provide enhanced trust toward such extracted rules for the development of new systems ?

We can address this question upon two axes: Similar data points comparison and Cross-Project Knowledge Transfer (CPKT) analysis.

1.1.1 Similar data points comparison

By extracting and incorporating *if-then* rules, this knowledge becomes explicitly verifiable with concrete evidence. This approach enables the identification of all historical data points that conform to specific rules. Thus, architects have access to a quantifiable measure of how often a given scenario has occurred. With this frequency, statistical weights can be assigned to individual rules, thereby establishing a formal degree of reliability.

Beyond this simple quantification, this approach also allows architects to qualitatively examine these historical instances in order to assess their similarity and relevance to current projects. This provides an enriched context that serves as a robust, empirical justification for the extracted knowledge.

Although this provides greater analytical depth, it still requires significant manual oversight.

1.1.2 Cross-Project Knowledge Transfer analysis

In a complementary manner, studies can be conducted to systematically evaluate how the rules extracted from one project perform on another project.

This Cross-Project Knowledge Transfer capability can serve as an additional indicator toward the reliability of the extracted knowledge in a context of new product design. Verifying *if-then* rules with data points from an unused project can simulate a new design context while still providing a point of comparison.

In the previous chapter, the model training relied exclusively on data from the recent programs, raising critical questions about its generalizability. To evaluate this capability, data samples from the older programs were extracted and processed using identical methodology. These older samples were then used to test the performance of both the pre-trained *Random Forest* and *Decision Tree* models.

As anticipated, the models trained specifically on the recent program data demonstrated a reduced performance when executed on the older data. Nevertheless, they still yielded acceptable metrics as summarized in Table 8.

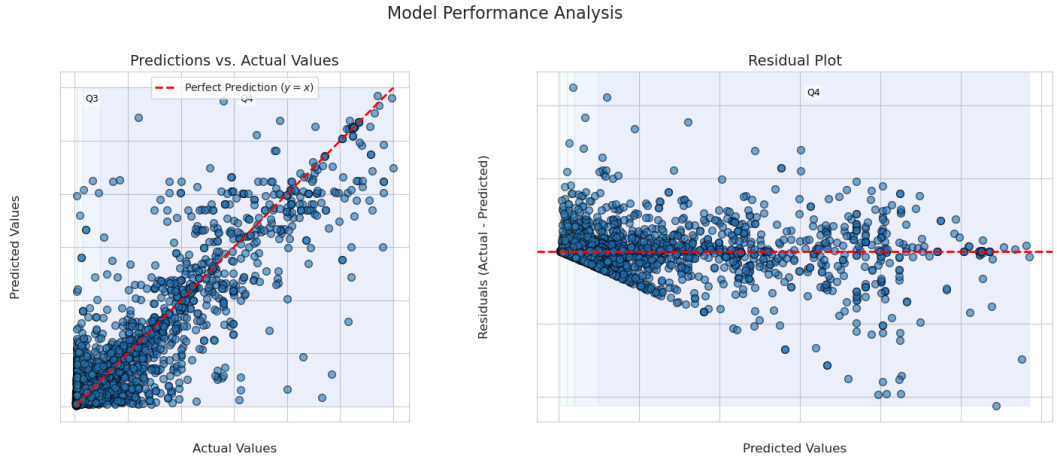
The *Random Forest* slightly outperformed the *Decision Tree*, consistent with the trend observed during the learning process. Each model evaluation, respectively illustrated in Figure 36a and Figure 36b, satisfied the specified metrics of a R^2 greater than 70% RMSE inferior to 300 IM. These results indicate that while nuances exist between the programs, the fundamental knowledge captured is relevant for early workload estimation in new design contexts.

Nevertheless, the most significant and obvious issue regarding the trustful reusability of captured knowledge in new design context are technological breakthroughs. The introduction of new categorical values (such as unknown product material or innovative process category) would greatly decrease the predictive performance of our models.

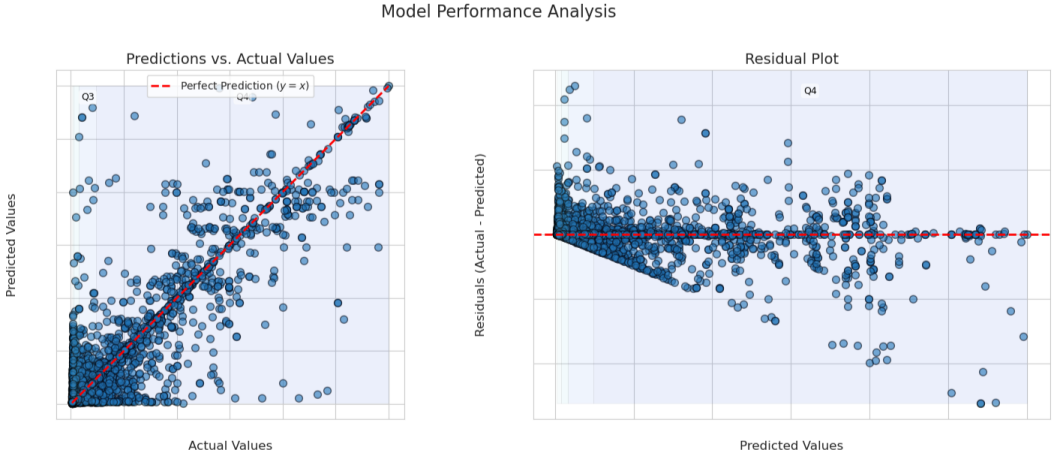
In such scenarios, the captured knowledge would certainly not be able to reliably predict the outcomes of new data points. Fortunately, such technological breakthroughs were not involved in the case study from the previous chapter as the architectures were elaborated with known technology bricks.

Model	R^2	RMSE
Random Forest	**81%**	**211 IM**
Decision Tree	78%	228 IM

Table 8: RF and DT models performance on older data



(a) Random Forest performance on older programs



(b) Decision Tree performance on older programs

1.2 Data quantity and quality

The second discussion is about the data quantity and quality. We acknowledge that the presented study was conducted on a relatively small input dataset. As the interpretable machine learning models leveraged in our approach are not specifically reliant on considerable volumes of data, we managed to successfully implement a training process despite this constraint.

Nevertheless, this highlights the critical dependency on both data quantity and quality for such approaches. To this extent, we greatly benefited from our collaboration with Airbus, which possesses several decades of aircraft design and production data. Therefore, the proposed data-driven approach would become significantly more challenging to implement within younger companies or sectors characterized by limited data accessibility.

Despite the large volume of historical data available for our study, we faced a major challenge regarding the quality of the data, which was frequently found to be unreliable or incomplete. This resulted in additional difficulties and a considerable amount of hours spent unnecessarily for data-driven studies.

These quality issues often originated from the on-going digital transformation at company level where the methods used to record, structure, and store the information are not designed to

foster future knowledge capitalization.

Among issues of incomplete, incoherent, or inconsistent information, one example illustrates well our discourse. During the Cross-Project Knowledge Transfer analysis from the previous section, a lack of homogenization was identified among manufacturing process categories between older and more recent programs. Indeed, identical or similar process categories were distinctively stored with no way of considering them from a same family. This issue, among others, has hindered the effective capture and reuse of knowledge.

This study underlines a fundamental concern toward information storage and knowledge capitalization. By considering the explosion of data volumes as part of DE, we conclude that guidelines for recording, structuring and storing data within such organizations are essential for future knowledge extraction as leveraged in our study. Such guidelines must be designed and implemented to achieve the digital transformation of the industry.

1.3 Unnecessary data-driven studies for some knowledge patterns

Among the several cross-domain knowledge patterns elaborated during this study, only the workload estimation pattern (from the *cross-performance* pattern category) has been developed and instantiated through the hybrid knowledge acquisition method. Of course, other patterns should be developed in future research through various use-case applications. However, in the authors' opinion, the hybrid knowledge acquisition method leveraged in Chapters 3 & 4 should not be blindly conducted for all patterns.

The workload estimation knowledge pattern was indeed suited to data-driven studies as it involves a complex relationship between various features. Such situation involving tacit knowledge difficult to formalize from experts' minds, while having large datasets of industrial records related to this knowledge, was extremely convenient to apply this hybrid knowledge acquisition method.

Other categories of knowledge, such as the *compatibility knowledge*, seem much more suited to traditional expert-centric formalization or technical documentation data mining.

2 Conclusion

After the enumeration of essential discussions regarding the results of this research, the following section synthesizes these achievements and outlines the strategic trajectory for future developments.

2.1 Academic and industrial communication of this research

According to the DSRM, the communication of the research advancements and results have to be presented to both academic and industrial audiences. Among international scientific conferences and industrial workshops, we had the opportunity to present our research with various scopes and degrees of description.

2.1.1 Academic communications

On the academic side, three conference proceedings and two journal reviews were published. Each conference paper has also been communicated to its related scientific community through oral presentation.

Our publications are listed below:

- Duverger et al. (2024). Early concurrent engineering in the aerospace industry supported by a digital thread framework. *IFAC-PapersOnLine*, 58(19):510–515. 18th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2024.
- Duverger et al. (2025a). An ontology-based engineering methodology to support early concurrent engineering. *IFAC-PapersOnLine*, 59(10):2838–2843. 11th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2025.
- Duverger et al. (2025c). A hybrid knowledge extraction approach to support early concurrent engineering in the aerospace industry. *Product Lifecycle Management. PLM in the Age of Model-Based Engineering in Industry*, pages 98–108, Springer Nature Switzerland.
- Duverger et al. (2025b). An ontology-based digital thread framework to support early concurrent engineering in the aerospace industry. *Journal of Industrial Information Integration*, 48:100984.
- Duverger et al. (2026). A Hybrid Knowledge Extraction Method to Support Early Concurrent Engineering in the Aerospace Industry. Aerospace, 13(4), 337.

2.1.2 Industrial communications

From an industrial perspective, our research led to the creation of a dedicated internal project. This phase involved frequent stakeholder engagements and presentations designed to transparently communicate milestones, mitigate technical challenges, and address concerns.

Beyond a simple proof-of-concept, this study was successfully integrated into a pre-industrialization workflow, providing a framework for ongoing operational studies.

2.2 Research key results

As this document is also a part of of the communication process, the next sections aim to provide a clear summary of our key research results.

2.2.1 Knowledge-driven, early concurrent engineering framework

This doctoral work presented an ontology-based digital thread framework integrating cross-domain engineering activities during the conceptual design phase of a new aerospace product.

Grounded on Model-Based Systems Engineering (MBSE), this framework leverages standardized engineering processes that provide a structured collaboration approach with specified deliverables. One of the main advantages of using MBSE is the digital model decomposition, which allows to address considerable system complexity while maintaining information traceability. By representing the systems of interest with multi-disciplinary views and various degrees of granularity, aerospace engineers can obtain the right level of information in a collaborative environment for enhanced design quality.

Additionally, this framework comprises simulation models and engineering knowledge to enrich MBSE models in order to shorten iteration loops and facilitate trade-off analysis. Engineering knowledge can be either formalized with domain experts or extracted from large scale databases through data-driven techniques.

The ontology-based digital thread is at the center of this framework, interfacing with all the other modules. Constituted of a knowledge base, it serves as a communication medium through

flexible graph-based queries, addressing tailored stakeholder concern or input data format specification. Within its knowledge base, MBSE artifacts, simulation results, and engineering knowledge are instantiated and structured by an ontological core.

The ontological core of the digital thread provides common conceptualizations and understanding for all stakeholders, enabling semantic interoperability. This unified knowledge representation structures an agnostic representation of the information without domain-specific or tool-specific biases. Furthermore, the ontological core integrates engineering knowledge, either formalized with experts or extracted from large databases, acting as an additional bridge between cross-domain MBSE models.

Furthermore, this integration of cross-domain MBSE models, simulation results, and engineering knowledge, offers the means to coordinate between teams, often in various locations and working in different time-zones. Considered as a shared reference, this ontology-based digital thread then supports organizational interoperability.

Additionally, the reasoning capabilities of ontologies permit the execution of the captured engineering knowledge and design rules. These knowledge sharing and execution capabilities support engineers for early trade-off analysis, shortening iteration loops.

This ontology-based digital thread framework enables communication, understating, and coordination between cross-domain engineering activities involving MBSE models and other tools from the extended digital enterprise environment. Therefore, this framework answers the syntactic, semantic, and organizational interoperability issues. Moreover, it provides executable knowledge with reasoning capabilities, allowing engineers to have enriched insights for their trade-off analysis during the conceptual design phase.

By integrating MBSE activities in a graph-based referential structured with an agnostic knowledge representation, this framework demonstrates its capability for global interoperability in an extended enterprise digital environment. Furthermore, by incorporating executable knowledge with reasoning capabilities, this framework intends to be the foundation of knowledge-driven, early Collaborative and Concurrent Engineering (CCE).

2.2.2 A hybrid knowledge acquisition method

The second main contribution of this work is the hybrid knowledge acquisition method proposed as a complementary approach to more traditional approaches. This method is constituted of two phase: expert-centric formalization and data-driven rules extraction.

Through human expertise and intuition, the expert-centric formalization phase intends to elicit precious knowledge buried in experts' minds. Such knowledge relies on empirical experience which is not formalized in technical documentation. Our approach is based on iterative modeling sessions with a diverse pool of experts, each with a unique background and area of expertise.

These modeling sessions aim to elaborate cross-domain *knowledge patterns*. These models describing patterns of knowledge benefit both from human interpretability and can be easily integrated in MBSE environments. Such sessions permit the identification of concepts and attributes that play a key role in cross-domain impact relationships. By formalizing diverse knowledge patterns, aircraft and manufacturing experts describe additional bridges between domains that can be extended and refined to identify actionable levers for shortening cross-domain impact assessment.

The second phase of this method is the data-driven rule extraction. Oriented by a specific

cross-domain knowledge pattern, it leverages interpretable machine learning models to extract design rules. Through the robustness and scalability of large databases, complex impact relationships can be explicitly extracted following a *if-then* rule format. After rigorous verification and validation activities such rules can be integrated in an executable manner in the ontology-based framework, allowing automatic cross-domain impact assessment.

This data-driven phase has been specifically elaborated by considering the ontology-based digital thread framework context. It aims to describe complex cross-domain impact relationships that are too difficult for humans to formalize.

By leveraging both human experts and industrial records as sources for knowledge acquisition, implicit cross-domain knowledge can thus be formalized and described in an executable manner. Described as *if-then* rules and incorporated in a knowledge base with reasoning capabilities, this executable knowledge provides enriched insights and perspectives to MBSE architects, but also to any stakeholder, supporting early impact assessment between product and manufacturing architectures for global trade-off analysis.

Furthermore, the integration of this knowledge acquisition approach into Ontology-Based Engineering methodologies, such as MfM, presents a compelling step toward the convergence between symbolic AI (ontologies) and statistical AI (machine learning).

2.2.3 Co-architecture ontology

Applied in the scope of early Collaborative and Concurrent Engineering, this research has also resulted in ontological models structuring the core of the digital thread. Although the developed ontological models could be shared and reused, the objective was to demonstrate how Ontology-Based Engineering (OBE) approaches, and more specifically MfM, could be implemented to address the concerns of early CCE rather than proposing yet another ontology as a part of the academic ontology ecosystem.

The ontological models were developed through iterative modeling sessions with key stakeholders according to MfM's protocol. This knowledge acquisition and representation provided four distinct, yet, interconnected views, articulated around *Scope*, *Data*, *Behavior*, and *Semantic* models. These views served as a basis for specialization in use-case specific contexts in an Model-Based Systems Engineering (MBSE) environment.

Such proximity with the MBSE architectures provided shared conceptualizations and a common understanding among the modelers, while enabling effective mapping, structuring, and alignment of MBSE artifacts toward their extraction into the knowledge base.

Scope model: Formalizing knowledge-driven collaborative activities for aircraft and manufacturing engineers, the *Scope model* helped to delineate global co-architecture activities on neither the product side nor the manufacturing side. These common and collaborative activities highlight the need for a common ground where the interests of product and manufacturing engineers are equally addressed without structural interference. The fundamental idea is not only to have teams of engineers working on tasks with shared resources (as in coordination) and distributed deliveries (as in cooperation), but, most importantly, with a shared common goal (as in collaboration).

In the authors' opinion, the conduct of truly collaborative activities is key in order to break the silos and design together complex systems during the conceptual design phase.

Data model: Following the Product-Process-Resource (PPR) decomposition, the *Data model* provided an agnostic knowledge representation, structuring the information within the digital thread. Although this conceptualization remains simple, the emergence of cross-domain constraints between product and manufacturing artifacts has oriented the *Behavior model*'s development. Such constraints act as an additional bridge between product and manufacturing engineering for traceable impact assessment drivers.

Behavior model: Developed with the aforementioned hybrid knowledge acquisition method, the *Behavior model* relies on the concept of cross-domain knowledge patterns. In our approach to extend MfM with this notion, knowledge patterns can be viewed as components of the *Behavior Model*, formalizing impact relationships between concepts and attributes from the *Data Model*.

In a first time, this provides additional links between product and manufacturing artifacts. With the digital traceability enabled by the MBSE environment, these links can be used to identify levers for cross-domain impact more effectively within the solution space.

Secondly, by incorporating the *if-then* rules resulting from the hybrid knowledge acquisition method, these patterns permit to execute the captured knowledge, providing instantaneous cross-domain impact assessment capability.

Moreover, the notion of knowledge patterns categories allows for descriptions with various degrees of granularity of impact relationships. We consider such patterns as an interesting manner to develop MfM's *Behavior model*.

Semantic model: Interfacing between the MBSE architectures and the ontology the *Semantic model* plays a crucial role in the integration and instantiation of artifacts from product and manufacturing domains. As previously stated, the ontology modeling has been conducted in the same environment as the MBSE architectures. Thus, the *Semantic Model* allows to define these connections through models in a collaborative manner while allowing the *Data model*'s automatic instantiation in the knowledge base. The maintenance of the links between MBSE and the rest of the digital environment is therefore highly facilitated.

2.2.4 Research questions

These key research results provide the necessary material to answer the research questions defined in chapter 2.

- **RQ1:** How collaborative and concurrent engineering activities can be supported through the integration of MBSE and ontology-based approaches?

  Through the implementation of MfM methodology in a co-architecture context, ontological models were elaborated in MBSE environment. These models have defined interdependencies between engineering activities, common conceptualizations of the involved artifacts, a mapping interface for interoperability, and descriptions of cross-domain interactions

  Thus, the integration of MBSE and OBE methodologies provided a structured approach for the systematic and multi-disciplinary design of complex systems while considering all lifecycle issues simultaneously. By enabling concurrent workflows through cross-domain communication, understanding, coordination, knowledge sharing, and reasoning capabilities, it supported the convergence toward a single, integrated global design.

- **RQ2:** How to combine human experts and industrial databases for hybrid knowledge acquisition approaches?

  The proposed method for hybrid knowledge acquisition has employed modeling sessions in order to formalize cross-domain interactions, articulated as knowledge patterns. The experience and intuition of human domain experts has facilitated the identification of key drivers for cross-domain impact assessment.

  Further, these patterns were exploited as the entry point of interpretable machine learning studies. Benefiting from the scalability and robustness of large-scale datasets, *if-then* engineering rules describing the targeted cross-domain interactions were extracted.

- **RQ3:** How to incorporate the acquired knowledge to support the collaborative and concurrent engineering activities?

  With the integration of OBE and MBSE methodologies, cross-domain knowledge patterns were formalized as SysML models. Such models linked MBSE artifacts from product and manufacturing architectures, allowing for traceable impact assessment drivers.

  Moreover, the engineering rules extracted during the data-driven studies were incorporated as SWRL rules, providing knowledge reasoning capability for automatic cross-domain impact assessment execution.

- **RQ4:** To which point the incorporated knowledge if relevant in new product development context?

  This question have been a major discussion in this chapter. We demonstrated that, through Cross-Project Knowledge Transfer analysis, the incorporated knowledge kept a satisfactory degree of relevance for new product design. However, this remains valid as long as no huge technological breakthrough is involved.

2.2.5 Synthesis

This research has leveraged Ontology-Based Engineering as a central part of the MBSE methodology. Various opportunities were combined:

- The ontology modeling within a MBSE environment allowed for a collaborative and illustrative manner to formalize knowledge with diverse domain experts that were not specifically familiar with ontology, nor MBSE modeling.
- As the ontology models were developed in the same environment than MBSE architectures, the links between ontology and MBSE artifacts were established with enhanced maintenance capability allowing for a seamless integration and instantiation.
- The elaboration of cross-domain knowledge patterns acted as an additional bridge between aircraft and manufacturing domains. This permitted enriched insights toward actionable levers of cross-domain impact to explore the solution space.
- The automatic extraction of the ontological core and its knowledge base through the MBSELab plugin has permitted the deployment of the digital thread on a Neo4J server which became the shared source of truth. Through flexible queries, any stakeholder concern or input data format could be answered by exploiting the graph-based, agnostic knowledge representation. Thus enabling syntactic, semantic, and organizational interoperability.

- The utilization of interpretable machine learning models allowed to capture complex knowledge articulated in *if-then* rules. Such rule were ultimately incorporated in the ontology with reasoning capabilities, permitting automatic cross-domain impact assessment.

The implementation of an OBE methodology has permitted interoperability between MBSE and the rest of the digital environment by elaborating easily maintainable ontological models collaboratively. By fostering collaboration between engineers and by providing knowledge sharing and execution capabilities, early Collaborative and Concurrent Engineering was supported.

As illustrated in Figure 37, short iterations of engineering activities were assisted during the conceptual design phase through syntactic, semantic, and organizational interoperability, combined with enriched engineering knowledge powered with reasoning capabilities.

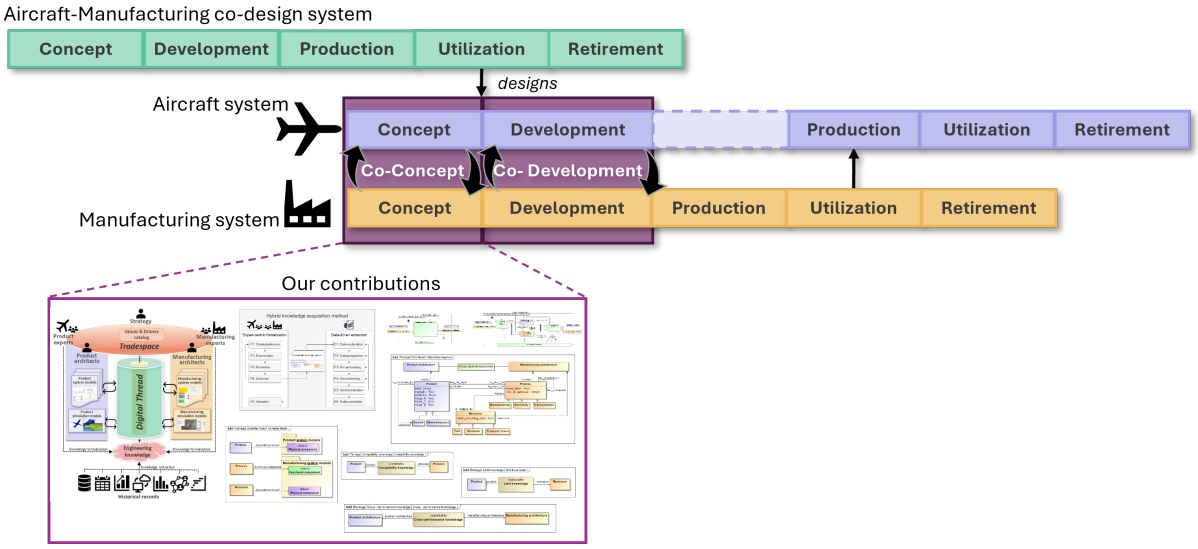


Figure 37: Aircraft-Manufacturing co-engineering process supported by this study

Grounded in the industrial chair named ACTE MBSE, the proposed approach, framework, methods, and models are:

- **Actionable**
  The results of this research can be directly acted on as they are envisioned to be industrialized. The framework, methods, and models can be implementable in the current state of the organization but are also designed to address the digital engineering transformation perspective of future engineering processes.
- **Collaborative**
  The essence of this work is to facilitate collaboration between product and manufacturing engineers. Through enhanced communication, understanding, and coordination, engineers share common resources and outcomes toward balanced system design.
- **Trustworthy**
  The deployment of a digital thread supports the trustworthiness in complex designs by providing access to a single source of truth that prevents the use of deprecated models. Moreover, the hybrid knowledge acquisition method combining human expertise and AI's robustness, scalability, and explainability, provides additional trust support concerning the knowledge employed in decision-making activities.

- **Executable**
  This study discussed notions of semi-automatic cross-domain knowledge pattern execution. While the execution of SWRL rules and ShaCL constraints has been addressed, these do not represent the core focus of the study.

2.3 Perspectives

Finally, we will end this chapter with perspectives toward future research relative to this thesis. While the preceding analysis has offered a comprehensive resolution to the research questions initially posed, it also unveiled new research scopes and axes.

The aforementioned conclusions provide a robust foundation to address early Collaborative and Concurrent Engineering. Yet they also expose inherent limitations and emerging variables that advocate for further academic research. Consequently, the following sections delineate several prospectives for future work, shifting focus from the achievements of this study toward unexplored investigations in the field.

2.3.1 Knowledge acquisition diversification

Several cross-domain knowledge categories were identified during this study. However, only the *cross-performance* knowledge has been instantiated as a *workload estimation* pattern, captured through the hybrid knowledge acquisition method. This knowledge was identified as the main bottleneck for co-architectures activities and was consequently the focus of our study.

Nevertheless, numerous other studies could be conducted with the same approach. Other *cross-performance* knowledge such as *cost estimation*, *energy consumption*, or *waste emission* could extend the knowledge base to support early CCE.

Furthermore, other categories than *cross-performance* may be relevant to describe knowledge related to *disruptions prediction* or *quality checks*. Ultimately, any additional knowledge acquisition study could be integrated in the ontology, and therefore, enhance engineers' capacity for cross-domain impact assessment.

The authors want to emphasize that not all knowledge patterns benefit from the proposed hybrid knowledge acquisition method. Categories such as *Compatibility knowledge* or *Limit knowledge* (shown respectively in Figure 22b and Figure 22a) might be found much more easily and explicitly in technical documentation rather than through machine learning models.

Moreover, the explosion of Large Language Models (LLM), Retrieval Augmented Generation (RAG), and more generally, the revolution of Generative AI that happened during the past years, also provides new means to capture knowledge from large unstructured text-based sources. Therefore, the inclusion of such approaches for knowledge acquisition offers other compelling perspectives to our work.

2.3.2 Complete framework implementation

This study has proposed a comprehensive framework, specifically validating the ontological core development and the mechanisms for engineering knowledge acquisition.

Although certain modules, such as the *Tradespace (6)*, remain at the conceptual stage, this framework remains a significant point of convergence for several research axes. By bridging requirement engineering, decision-making, MBSE adoption, and the development of OBE approaches, this doctoral work serves as a robust integrative structure for integration of other research studies.

2.3.3 As-Designed - As-Planned derivation

While this research has been developed toward a different axis, we estimate that the derivation from the *As-Designed* to the *As-Planned* product breakdown structure is essential for future work supporting Collaborative and Concurrent Engineering. This derivation has not been mentioned in this work for clarity purposes and because our reflection still needs some maturity.

However, we envision that, as illustrated in Figure 38, the precise step of deriving the *As-Designed* product breakdown structure (under the responsibility of the product engineers) into the *As-Planned* product breakdown structure (used by the manufacturing engineers) would provide a concrete common ground for collaborative work. Neither rooted in pure product design nor manufacturing engineering, this derivation process could serve as the initial point for unbiased co-conception and co-development activities toward satisfactory global trade-offs.

Nevertheless, this implementation in early design phase of this derivation process necessitates extensive knowledge and collaborative technologies. In this sense, the contributions of this study support further research regarding this axis.

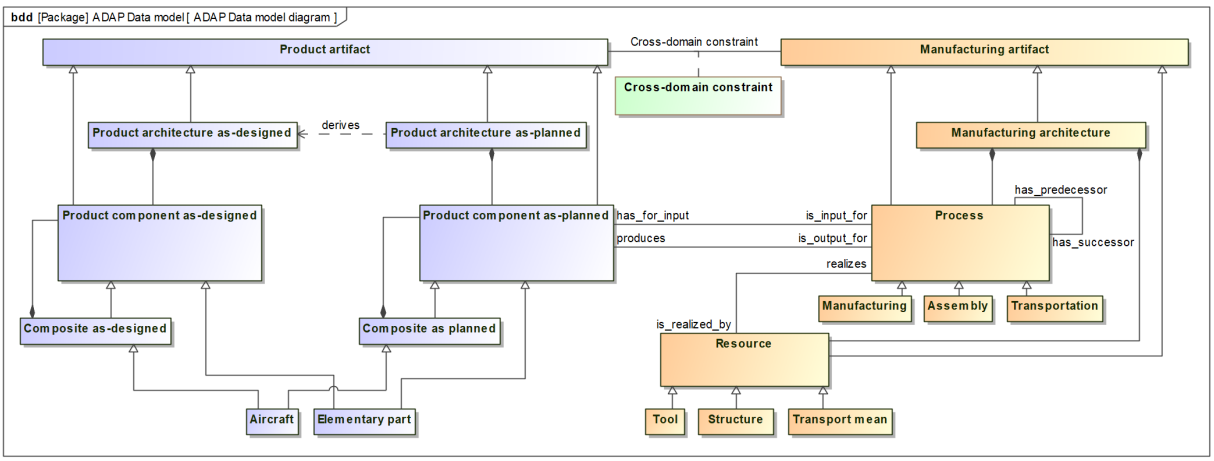


Figure 38: As-Design As-Planned Data model

2.3.4 Whole lifecycle considerations

This whole thesis has been dedicated to Collaborative and Concurrent Engineering during the conceptual design between aircraft and manufacturing engineers. Efforts were focused toward this phase for its low total committed costs and high design freedom, allowing for both system architectures to converge toward reduced overall development time, costs, and enhanced quality.

While this scope was sufficiently complex for this research, natural perspectives shall consider the complete development phase (i.e. conceptual, preliminary, and detailed design phases). The authors do not identify any particular issue for the adaptation of our proposed framework, methods, and models to this extended scope.

For sure, the inclusion of additional stakeholders, tools, and processes would inevitably increase the overall complexity with considerably more functions and interfaces. However, the ontology-based digital thread is designed to ensure digital continuity and interoperability for the seamless integration of product and manufacturing engineering during the complete development phase.

Moreover, a major blind spot remains to the complete integration of product and manufacturing engineering. While the aircraft is the developed product and the manufacturing system is in charge of its production phase, it is the support system that operates during the entire utilization phase of the aircraft. Therefore, the integration of the support system design is also of considerable importance for co-conception and co-development activities.

As stated above, the proposed framework, methods, and models are sufficiently generic to integrate support system engineering. Similarly to the aforementioned elements, this would result in substantially more complexity, although no inherent characteristic would cause critical incompatibility.

It is clear that adding a third system makes global trade-off analysis more challenging. Indeed, while reconciling two diverging views is challenging enough, mitigating between three sets of requirements and objectives introduces another level of complexity.

Ultimately, concerns toward reconfigurable manufacturing and service systems, combined with considerations for the disposal of retired aircraft, mean that the approach at the core of this research could address integral Collaborative and Concurrent Engineering, from the very first idea to the last decommissioned aircraft.

2.3.5 Multi-industry applications

This research was initiated and conducted within an aerospace project. Therefore, it has addressed concerns of Collaborative and Concurrent Engineering for the aerospace industry. Research toward the enhancement of CCE practices was specifically suited to this industry as it involves one of the longest development times of all industries while also delivering a significant volume of delivered products.

However, enhanced CCE ways of working would benefit other industries. While the results of this thesis have been accomplished through the perspective of the aerospace industry, the proposed framework, methods, and models have intentionally been developed to be highly generic.

In the author's opinion, it would require minimal effort to transpose the contributions of this research to other industries dealing with complex system development (e.g. the naval industry, railway, and even automotive industries).

2.3.6 Digital Twin evolution

Finally, this research could also be considered as a fundamental brick of other, larger, concepts of Digital Engineering. Through its early development scope, model-centric approaches, and information traceability and interoperability, our contributions could be incorporated to complex systems' Digital Twin development as a modeling and simulation core.

Furthermore, with their enhanced knowledge representation and reasoning capabilities, our Ontology-Based Engineering approaches would offer a compelling basis for Cognitive Twin development.

3 Special thanks

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Résumé

Le processus traditionnel de conception des avions et de leur système de production de manière séquentielle atteint ses limites avec une industrie de plus en plus complexe. À mesure que les disciplines d'ingénierie s'approfondissent et s'élargissent, une transformation radicale est devenue une nécessité industrielle pour répondre aux impératifs de compétitivité. Si la transformation digitale offre de nouvelles capacités de développement collaboratif et concourant, la partie amont de la phase de conception reste le levier principal pour réduire les cycles de développement, maîtriser les coûts et améliorer la qualité tout au long du cycle de vie des systèmes. En utilisant des approches d'Ingénierie des Systèmes Basée sur les Modèles (MBSE) et d'Ingénierie Basée sur les Ontologies (OBE), cette thèse répond au défi de la conception de produits complexes et de leur systèmes de production dans le cadre de la transformation digitale de l'industrie aérospatiale. D'une part, les processus d'ingénierie standardisés, les vues multidisciplinaires et la traçabilité de l'information du MBSE permettent aux ingénieurs de collaborer avec des degrés de granularité ajustables. D'autre part, les capacités de représentation des connaissances et de raisonnement des méthodologies OBE assurent l'interopérabilité syntaxique, sémantique et organisationnelle, tout en enrichissant les ingénieurs de perspectives supplémentaires permettant d'effectuer des compromis globaux dès les premières phases de conception. Le cœur de cette recherche présente une architecture centrée autour d'un "fil digital" à base d'ontologies, intégrant les artefacts MBSE des domaines du produit et de la production. Au cœur de ce fil digital, des modèles ontologiques définissent différent type de connaissance tels que des processus d'ingénierie collaborative, une taxonomie agnostique à quelconque outil, langage ou domaine, des interactions inter-domaines et, enfin, des correspondances spécialisées avec le MBSE. Ces modèles servent de moyen de communication avec une compréhension partagée, tout en permettant aux différentes équipes d'ingénieurs de se coordonner. Concernant le développement de l'ontologie, cette thèse enrichit l'acquisition traditionnelle de connaissances centrée sur l'expert avec une méthode hybride combinant l'expertise humaine et des techniques d'apprentissage automatique interprétables. En extrayant des règles d'ingénierie explicites à partir de vastes bases de données industrielles, cette méthode profite de la scalabilité et de la robustesse d'approches statistiques pour transformer l'intuition des experts en règles vérifiables de type "si-alors". Ces connaissances, intégrées dans l'ontologie, aident à la conception de systèmes complexes, facilitent l'analyse d'impact inter-domaines et raccourcissent les boucles d'itération entre les ingénieurs des domaines du produit et de la production. Enfin, cette recherche fait le pont entre le MBSE et l'environnement plus large de l'ingénierie digitale. Elle fournit une base de connaissances agnostique, flexible et facile à maintenir qui répond aux préoccupations des diverses parties prenantes, sert de base pour les processus d'ingénierie collaborative et facilite les compromis globaux pour une conception unique et intégrée dès la phase amont de conception d'un nouvel avion.

Mots-clés: Ingénierie concourante, Dévelopement intégré, Ingénierie des système basée sur les modèles, Ingénierie basée sur les ontologies, Fil digital, Acquisition de la connaissance, Représentation de la connaissance

Abstract

The traditional sequential aircraft design process is reaching its limits in an increasingly complex industrial landscape. As engineering disciplines grow deeper and wider, radical transformation has become an industrial necessity to meet the demands of competitiveness. While digital transformation offers new capabilities for collaborative and concurrent development, the conceptual design phase remains the most critical lever for reducing development times, controlling costs, and enhancing design quality across all systems life cycles. Through Model-Based Systems Engineering (MBSE) and Ontology-Based Engineering (OBE) approaches, this thesis addresses the challenge of complex product and manufacturing systems design within digital organizations. On one hand, the standardized engineering processes, multi-disciplinary views, and information traceability provided by the MBSE methodology, allow engineers to collaborate with adjustable degrees of granularity. On the other hand, the knowledge representation and reasoning capabilities of OBE approaches ensures syntactic, semantic, and organizational interoperability while enriching engineers with additional knowledge supporting global trade-offs in early design phase. The core of this research presents an ontology-based digital thread framework integrating MBSE artifacts from product and manufacturing domains. At the center of this digital thread, ontological models define collaborative engineering processes, an agnostic taxonomic data structure, description of cross-domain interactions and specialized mappings toward MBSE. These models act as a communication medium with a shared understanding while providing the means to coordinate among engineering teams. Regarding ontology development, this study complements traditional expert-centric knowledge acquisition with a hybrid method blending human expertise with interpretable machine learning techniques. By extracting explicit engineering rules from large industrial datasets, the method exploits the scalability and robustness capabilities of data-driven approaches to transform expert intuition into verifiable if-then rules. Such knowledge is incorporated in the ontology to support complex system design, facilitate cross-domain impact assessment and shorten iteration loops between product and manufacturing engineers. Ultimately, this research bridges the gap between MBSE and the broader Digital Engineering environment. It provides an agnostic, flexible, and easily maintainable knowledge base that addresses multi-stakeholder concerns, supports collaborative engineering processes, and assists global trade-offs decisions toward a single and integrated design during the conceptual phase of aircraft development.

Keywords: Concurrent Engineering, Integrated Product Development, Model-Based Systems Engineering, Ontology-Based Engineering, Digital Thread, Knowledge acquisition, Knowledge representation