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Knowledge capitalization in mechatronic collaborative design

Mouna Fradi^{1,2}, Raoudha Gaha^{2,3}, Faïda Mhenni¹,
Abdelfattah Mlika² and Jean-Yves Choley¹

Abstract

In mechatronic collaborative design, there is a synergic integration of several expert domains, where heterogeneous knowledge needs to be shared. To address this challenge, ontology-based approaches are proposed as a solution to overtake this heterogeneity. However, dynamic exchange between design teams is overlooked. Consequently, parametric-based approaches are developed to use constraints and parameters consistently during collaborative design. The most valuable knowledge that needs to be capitalized, which we call crucial knowledge, is identified with informal solutions. Thus, a formal identification and extraction is required. In this paper, we propose a new methodology to formalize the in-terconnection between stakeholders and facilitate the extraction and capitalization of crucial knowledge during the collaboration, based on the mathematical theory ‘Category Theory’ (CT). Firstly, we present an overview of most used methods for crucial knowledge identification in the context of collaborative design as well as a brief review of CT basic concepts. Secondly, we propose a methodology to formally extract crucial knowledge based on some fundamental concepts of category theory. Finally, a case study is considered to validate the proposed methodology.

Keywords: knowledge capitalization, mechatronic systems, collaboration, crucial knowledge, knowledge sharing, category theory

Introduction

Within the current industrial and economical context, reaching the famous cost, delay and quality objectives is becoming an important challenge for companies (Penas et al., 2017; Zheng et al., 2016). In order to obtain this goal, the design process has evolved from sequential design, in which a system design is generated following a particular order of steps, towards collaborative design (Monticolo et al., 2015). Since mechatronic system involves a variety of disciplines including mechanics, electrical, software and control, an efficient collaboration is needed to accomplish the design goals (Ammar et al., 2019; Zheng et al., 2014). During this collaboration, the major difficulty remains in sharing and capitalizing the right knowledge at the right moment (Belkadi et al., 2012). Parametric-based solutions have been subject to considerable interest in knowledge sharing. These approaches make use of fine granularity data (i.e. constraints and parameters) in a consistent way during collaborative design in order to facilitate dynamic collaboration as well as reuse phases (Mcharek et al., 2019; Zheng et al., 2018). However, these approaches are limited in term of crucial knowledge identification as they are based on informal solutions.

Hence, identifying the most valuable knowledge to be capitalized is becoming increasingly complex (Brigui-Chtioui and Saad, 2011; Saad and Chakhar, 2009). This knowledge is called crucial since it is used in more than one specific domain and its contribution to the project success is important (Grundstein, 2000; Saad and Chakhar, 2009).

Therefore, relying on formal methods and mathematical techniques to extract the most valuable knowledge is recommended (Ghrab et al., 2014). According to Fisher et al. (2014), a model can be considered as a set of elements and relations. For this reason, it is natural to consider models as graphs. Hence, instead of working directly on the heterogeneous model languages, a unifying and comprehensive

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formalism is used. In order to keep the right meaning of the different models, graphs should illustrate all the insights of these models. Thus, CT, the mathematical theory, is considered as a powerful tool to provide a unified and formal framework to illustrate the interconnections between the different stakeholders while keeping their right content. This theory was introduced by Samuel Eilenberg and Saunders Mac Lane in the early 1940s (Mabrok and Ryan, 2017) to bridge two distinct fields: algebra and topology. It aims at describing the relation between objects instead of the objects themselves. With such theory, it is possible to formalize an idea, a concept or a field, using a category and connecting this category with another one through functors (Spivak, 2013). Using this technique, engineers can identify the crucial knowledge that will be considered as a richness for the companies. In this context, we propose a new methodology based on CT to support crucial knowledge identification in parametric-based approaches during mechatronic system design. Our main goal is to extract the most important knowledge for collaboration in a formal way and, consequently, reduce this task execution delay.

The paper is organized as follows. A summary of the most used methods for crucial knowledge identification in the context of collaborative design as well as a brief overview of CT basic concepts are given in the State of the Art section. The Proposed Approach section presents the proposed methodology to formally extract crucial knowledge based on some fundamental concepts of category theory. The validation of our proposal is illustrated through the EMA case study in the Case Study section. The discussion is given in the Comparison with Related Works and Discussion section. Finally, the Conclusion and Future Works section concludes this article and addresses our future works.

State of the art

In this section, the most widely used methodologies to extract crucial knowledge are summarized. Furthermore, an overview of the fundamental concepts of category theory as well as the related works done in the context of collaborative design are presented hereafter.

Crucial knowledge identification approaches

During mechatronic system design, the different stakeholders use their knowledge specific to their expert domains. Knowledge is obtained from information, which is the result of structured and organized data (Bouazid et al., 2017). Unlike data, information has a meaning and is not objective (Grundstein, 2000). Thus, knowledge is considered as the use of information in a particular context, requiring the interpretation of a stakeholder (Arduin et al., 2013). Nonaka and Takeuchi distinguished between tacit and explicit knowledge (Nonaka and Takeuchi, 1995). Tacit

knowledge is personal and cannot be written or transferred. It consists of experiences and know-how and can be acquired through practice (Grundstein et al., 2003). However, explicit knowledge is transferred using formal languages. It can be captured in libraries and databases. Hence, capitalizing on knowledge is a fundamental task for collaborative project's success. Nevertheless, capitalizing on all project's knowledge requires an important time and human investment. Therefore, only crucial knowledge (i.e. the most valuable ones) needs to be capitalized (Brigui-Chtioui and Saad, 2011; Grundstein, 2000). For this purpose, some efforts have been elaborated. Grundstein proposed a guiding framework called Global Analysis METHodology (GAMETH) in order to identify crucial knowledge to be capitalized (Grundstein, 1995; Grundstein and Rosenthal-Sabroux, 2004). GAMETH framework consists of three steps. The first step provides the specification of the problem space and operation context. The second step aims at locating and characterizing crucial knowledge. The last step remains in assessing the value of crucial knowledge and determining the knowledge management objectives. In this approach, knowledge analysis is based on the decision-maker experiences. Additionally, Pomian and Roche (2002) suggested that crucial knowledge can be identified through interviews with the project manager. In similar way, Ermine (2005) proposed a series of interviews with the manager as well as strategic document studies in order to extract the most valuable knowledge. The same concept was used by Ammar-Khodja in their research work (Ammar-Khodja et al., 2008). The authors proposed a knowledge engineering process in order to structure knowledge. This process is based on The Methodology and tools Oriented to Knowledge-based engineering Applications (MOKA) methodology. The proposed approach helps to capture crucial knowledge through interviews and close communication among all design teams. Moreover, Badin et al. (2011), Monticolo et al. (2015) and Mcharek et al. (2019) recommended a meeting between the different stakeholders to identify the needed knowledge in parametric models. These approaches are based on the decision-maker intuition, which may influence their reliability. In addition, meetings between all the project members can be difficult to organize in a distributed environment and can be a time-consuming task.

Additionally, interesting approaches based on decision-making methods have been proposed. Tseng and Huang (2005) proposed to compute the average score of each knowledge. Then, the analyst evaluates the importance of knowledge. Moreover, Saad proposed to extend GAMETH framework by constructing a learning set (Saad et al., 2009). This approach consists of two main steps. The development of a decision makers' preferences model is presented in the first step. This model aims at determining decision rules based on decision makers' preferences. The second step of the proposed approach remains in the classification of

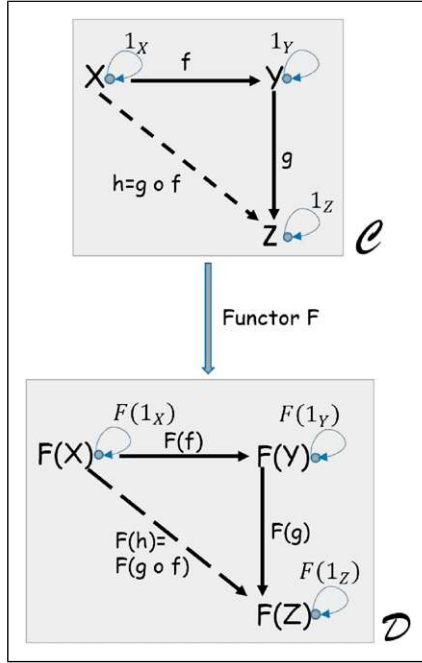


Figure 1. A mapping from a category 'C' to 'D' through a functor 'F' (Roman, 2017).

knowledge. A multi-criteria decision-making method is used in this research in order to take into consideration the preferences of the decision maker. This research work was extended by Brigui-Chtioui and Saad (2011) and Ghrab et al. (2014) where new knowledge classifications were presented to choose crucial knowledge while using decision-making methods. Similarly, Hassan presented a multi-criteria evaluation framework that supports the identification and localization of crucial knowledge (Ben Hassen et al., 2019; Hassen et al., 2016). The authors make use of multi-criteria decision-making in order to improve the localization of crucial knowledge created and mobilized by the sensitive business processes. Nevertheless, such approaches require an important time for implementation and a large number of stakeholders, which may further complicate the collaborative process.

In summary, several propositions are presented to identify crucial knowledge. These research works are based either on organizing meetings between all the stakeholders involved in the design process or on integrating some decision-making methods. As aforementioned, identifying crucial knowledge based on meetings organization between all the project actors in parametric models might be difficult to organize due to the complexity of mechatronic systems. Moreover, integrating decision-making methods may need numerous stakeholders that will make the design process more complex. Hence, a formal solution to extract the most important knowledge becomes necessary. The formalization of crucial knowledge is highly valuable in the context of mechatronic design since it makes the extraction of

knowledge more formal and easier. CT can be used as an efficient tool to formalize crucial knowledge identification thanks to its mathematical constructions. Thus, the fundamental concepts and related works to this theory are presented in the following section.

Category theory related works

The basic concepts of CT are illustrated as follows:

A category consists of the following elements (see Figure 1) (Mabrok and Ryan, 2017; Roman, 2017): (1) a set of objects X, Y, Z , etc. (2) a set of arrows or morphisms f, g, h , etc. (3) each morphism f has a domain (dom) and a co-domain (cod): $f: X \rightarrow Y$, where $X = \text{dom}(f)$ and $Y = \text{cod}(f)$, (4) given two morphisms $f: X \rightarrow Y$ and $g: Y \rightarrow Z$, there is a given morphism $g \circ f: X \rightarrow Z$ called the composition of g with f , (5) for each object X , there is a morphism $1_X: X \rightarrow X$, called the identity morphism with the property $f \circ 1_X = f = 1_Y \circ f$, (6) whenever the composition is defined, it is associative: $h \circ (g \circ f) = (h \circ g) \circ f$, for all $f: X \rightarrow Y, g: Y \rightarrow Z$ and $h: X \rightarrow Z$.

A functor $F: C \Rightarrow D$ between two categories C and D is a mapping of objects to objects and morphisms to morphisms.

A discrete category is a category where all morphisms are identity morphisms. The composition and the identity are vacuously satisfied since there exists only identity arrows (Roman, 2017).

An object is called Initial object I if for any object X in a category C there is exactly one morphism from I to X .

An object is called Terminal object T if for any object X in a category C there is exactly one morphism from X to T .

Due to its generality, CT has found wide applications in recent years in several areas such as computer science (Guo, 2002), artificial intelligence (Phillips, 2017), Systems Engineering (SE) (Mabrok and Ryan, 2017) and collaborative design (Suto and Patitad, 2015). In the context of collaborative design, Rutle et al. (2009) described an approach to three-way merging of models represented as graphs based on CT. Using pushout structures, a union graph containing all model elements is constructed. This common graph allows the identification of element differences. Moreover, Ormandjieva et al. (2015) proposed an approach based on CT to construct a unified multi-agent systems model and represent the communication between the different agents using CT. This proposition aims at checking the system properties by construction of categories and functors. Another research work using CT was presented by Mabrok and Ryan (2017). The authors applied CT in order to verify and validate the modelled system design. The researchers have introduced CT as a formal foundation for Model-Based Systems Engineering (MBSE). The global system is considered as a category and its components and elements are presented as objects. The relationship between these objects is presented through morphisms and the system alternatives

are introduced as categories. The solution category is related to the system category using functors where every alternative is a result of a different functor. Similarly, Zhu and Li (2018) proposed a categorical framework to formally design and implement concurrent systems as well as to verify communication consistency among design and implementation. The presented framework is based on the use of functors in order to verify design categorical models against implementation categorical models. Additionally, Zhu et al. (2018) suggested the use of CT to formally specify Reactive Autonomic Systems (RAS) and its configuration workflows. The proposed categorical approach can help to check errors in RAS. Furthermore, Kibret et al. (2019) proposed to formalize the Verifiable Design Process (VDP) using CT. In this approach, the system models or representations are presented through categories and their constituent parts are defined using objects and morphisms. Categorical structures such as pushout and pullback are used in order to analyse the different representations and functors are applied to define an abstraction layer of the VDP.

To sum up, a multitude of approaches using CT can be found in the context of collaborative design. Despite their diversity, there is a common point between these approaches, that is, the use of CT as a formal tool to support their systems representation and description. Similar to these aforementioned approaches, CT will be used in this paper as a common formalism to support crucial knowledge identification. However, this theory will be used to manipulate fine granularity data (in the form of parameters and constraints) in contrast to previous works where the CT is used to manipulate either system components or system agents without taking into consideration the parameters or constraints of the system. Categorical structures such as objects, morphisms, functors and discrete category will be used in our formalism, as it will be further explained in the next section.

Proposed approach

With the increasing complexity as well as the domain variety in mechatronic systems, it is necessary to adopt multi-disciplinary collaboration in the design process (Penciu et al., 2014; Törngren et al., 2014). This collaboration involves the integration of multi-disciplinary activities where each expert makes use of a set of knowledge specific to his field of expertise (Fradi et al., 2020, 2021). Determining knowledge that should make the object of capitalization in the design process is a challenging and consuming-time task. Therefore, we propose a new formal method based on CT to identify the crucial knowledge (i.e. the knowledge that their contribution to reach the project objectives is considered important). The motivation of using this theory in our methodology is that CT is considered as a powerful tool and formal modelling method for capturing the

interactions between heterogeneous components in a natural way (Herzig and Paredis, 2014). Furthermore, the mathematical theory focuses on relationships between objects instead of studying the object's representation, which is suitable for collaborative design, where, knowledge sharing and exchange between stakeholders is a first-class concept (Borchani et al., 2019). Additionally, the different engineering activities are related to specific expert models. These models are composed of a set of elements interconnected among each other and can be represented as graphs. These graphs have a formal meaning in the CT and carry all the intuitions that come from the practice. Our proposed approach, illustrated in Figure 2, is composed of two phases (1) the formalization of the different expert models involved in collaborative process and (2) the extraction of the crucial knowledge that need to be capitalized.

Based on this process, a *Crucial Knowledge Identification Problem* (CKIP) is defined as a 3-tuple: $CKIP = \langle \text{Expert Model (EM)}, \text{Categorical Graph (CG)}, \text{Knowledge Classification (KClass)} \rangle$, which contains the following elements:

- *Expert Models* refer to set of models, that are relative to different design activities and are involved in the collaborative process (EM_1, EM_2, \dots, EM_n). These disciplinary models can take different forms such as a multi-physical model using Modelica language in Dymola environment,¹ a control model with Simulink software,² a COTS (Commercial off-the-shelf) model to select the appropriate components with the properties obtained from the simulation and a 3D model with CATIA environment³ to verify the integration of the whole mechanism.
- *Categorical Graph* represents the unified graphs based on category theory, CG_1, CG_2, \dots, CG_m , which contains all parameters of the different EMs and will help to identify the crucial ones that need the capitalization. A 5-tuple $CG = \langle O, \text{id}, A_{rr}, L_o, L_{Arr} \rangle$ is an attributed, directed graph. In the context of CT, this graph represents a category where $O = (O_1, \dots, O_n)$ is a set of objects (vertices). Each object has its own identity (*id*). These objects are the different versions of parameters used by the involved experts.

Objects are related between each other through a set of arrows or morphisms A_{rr} (edges). All the objects and arrows have labels (or attributes) L_o and L_{Arr} , respectively. A sample CG, created following the previous definition, is illustrated in Figure 3.

- *Knowledge Classification* refers to a set of Knowledge classification, ($KClass_1, KClass_2$). Knowledge is considered crucial if its CG is not a discrete category. This means that there are not only identity arrows, but it exists also as different morphisms between the

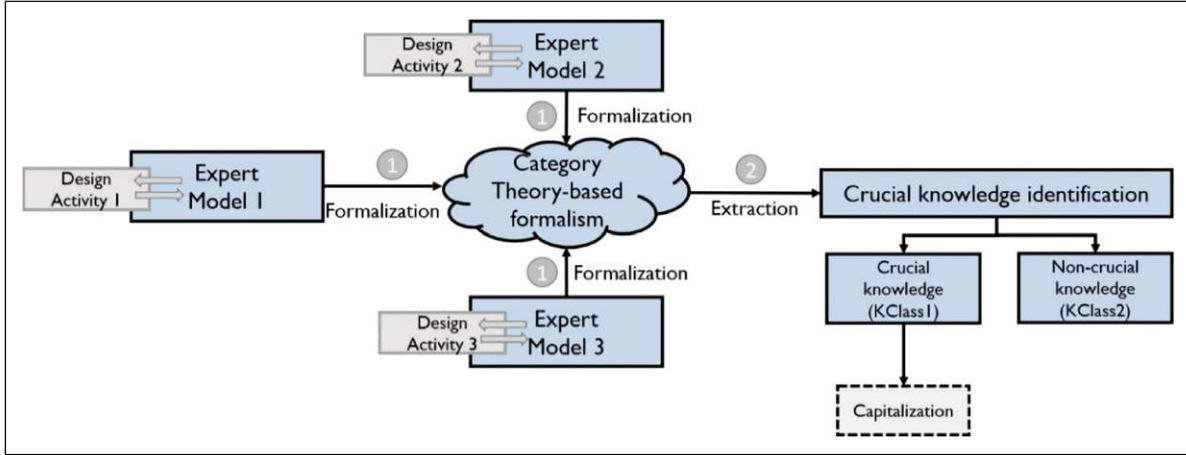


Figure 2. The proposed methodology for crucial knowledge extraction overview.

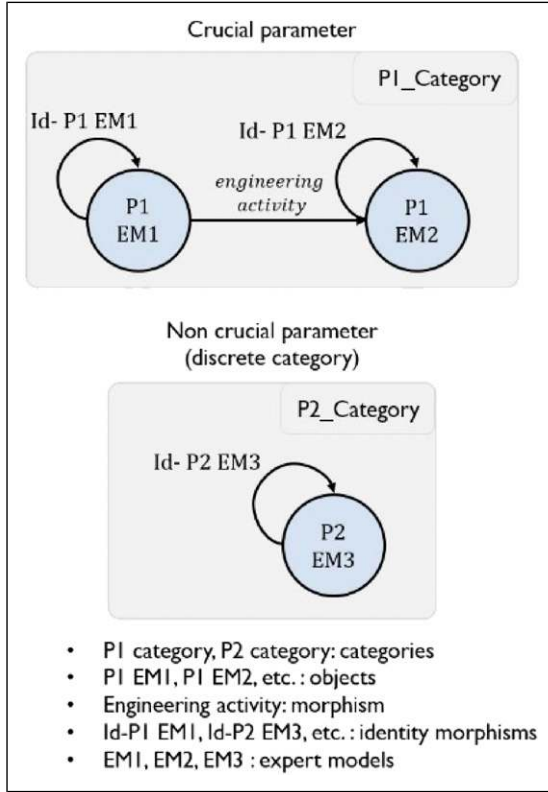


Figure 3. Categorical Graph (CG) of crucial and non-crucial parameters.

objects, which represents the dependency links between them. The $KClass_1$ contains all the crucial knowledge that will be capitalized during the collaborative process. Nevertheless, the $KClass_2$ groups the non-crucial knowledge.

As mentioned beforehand, CT is used in this paper to provide a formal framework to identify the most important

knowledge that need to be capitalized and shared during the collaborative process. Our methodology is composed of five main steps. The flowchart of the proposed approach is described in Figure 4.

Step 1: Creating categories for requirement parameters

As a first step, the project manager creates categories for each parameter (the knowledge in each EM) specified in the requirements. These categories are considered as the starting point for the crucial knowledge identification process. At the end of this step, we obtain a set of categories CP_i (P1 category, P2 category, for example, in Figure 3) where i is the number of all parameters identified in the requirements.

Step 2: Filling the created categories with the objects and the identity arrows

At this level, the project manager has to fill the created categories with the objects. The objects OP_{i1} ($P1_{EM1}$ and $P2_{EM3}$ as shown in Figure 3) represent the first version of the parameter which refers to the initial expert model that will make use of the concerned parameter. Moreover, as aforementioned in the state of the art section, for each object in a category, there is an identity morphism (the looped arrow in Figure 1, where its source and target are the same object). This morphism does exist as a natural representation of internal evolution of the parameter value.

Step 3: Adding new categories for each new parameter

Here, if the disciplinary engineers need another parameter that is not defined in the requirements, a new category representing the needed parameter is created. All the involved parameters in the collaborative process must be represented as categories.

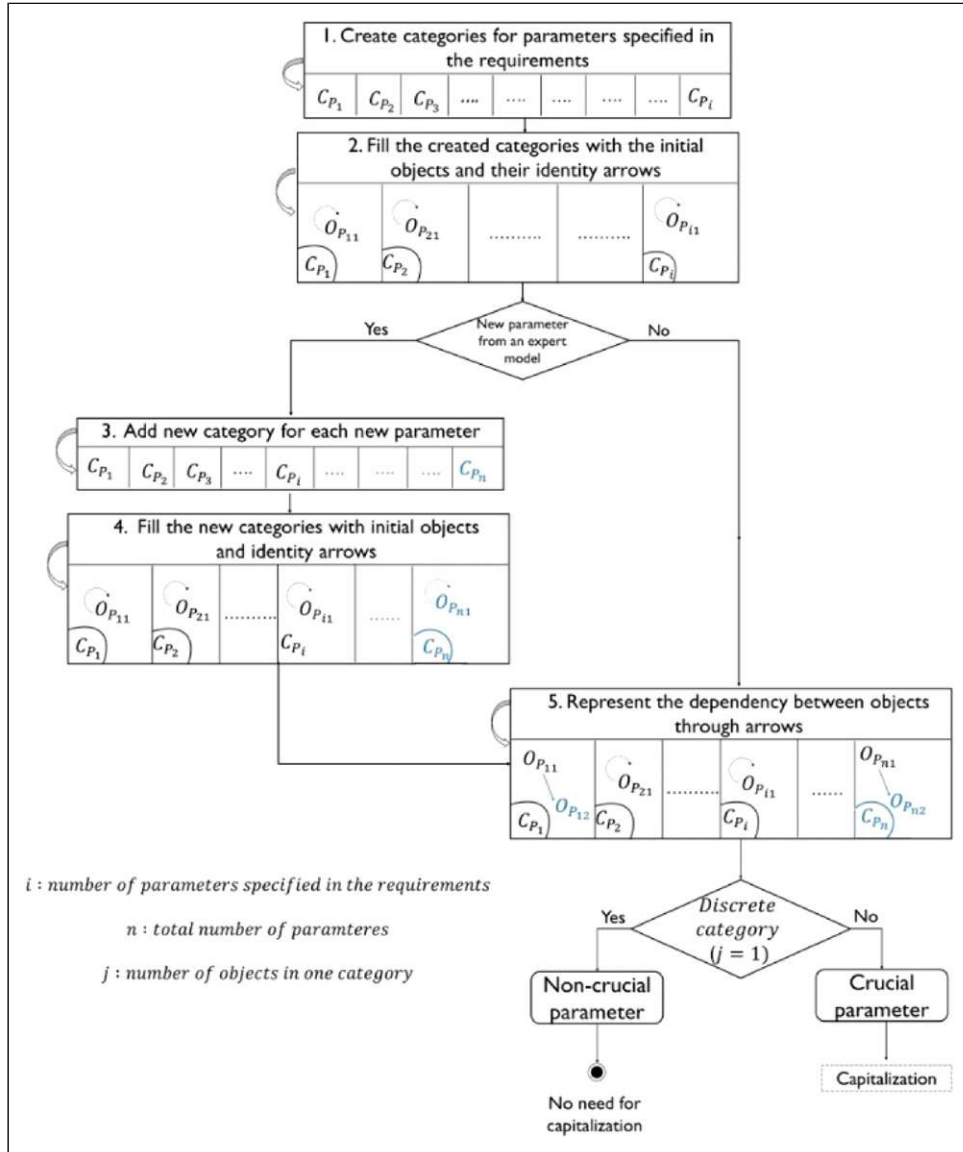


Figure 4. Flowchart of the crucial knowledge identification approach.

Step 4: Filling the new categories with the objects and identity morphisms

Similar to the second step, at this level the created categories will be filled with the corresponding objects as well as their identity arrows. Step (3) and step (4) will be repeated until obtaining categories for each parameter used by the expert models (CP_n , where n represents the total number of parameters).

Step 5: Representing the dependency between objects using the morphisms

In this final step, all the stakeholders highlight the evolution of the needed parameters by creating a new object in the

corresponding category and linking this object with the previous one through a morphism. If the category contains more than one object ($j > 1$, the parameter evolves from one expert model to another), the parameter is considered crucial and needs the capitalization. Otherwise, it will not be capitalized and remains specific to a single expert model.

Our proposed approach based on CT provides a formal framework to identify the most important knowledge that needs the capitalization during mechatronic collaborative design. This framework can reduce the execution time of the crucial knowledge extraction task and make it more formal. In order to better illustrate the capacity of our methodology, a concrete mechatronic system will be presented in the following section.

Case study

The case study considered in this paper refers to an Electro-Mechanical Actuator (EMA) of an aileron for a small aircraft (Jian et al., 2018; Mhenni et al., 2018). The EMA is a mechatronic system that actuates the aileron of the aircraft and replaces the usual rod, lever and cables mechanisms. Several architectures are possible to design the EMA depending on the electric machine type or the mechanism nature. In this work, only one mechanism type will be studied which is the 3-bars architecture. This architecture is illustrated in Figure 5, adopted from reference (Siala et al., 2020). The EMA is a multi-physical system since it involves mechanics, control, electrics, etc. which makes it an interesting example to validate our methodology. Each step of the proposed methodology (see Figure 4) will be demonstrated through this example. The EMA is linked to the aileron and the wing through two spherical joints. It encapsulates a DC motor controlled by a Micro Controller Unit (MCU), a gearbox and a ball screw-nut assembly, which transforms the rotation movement of the motor into

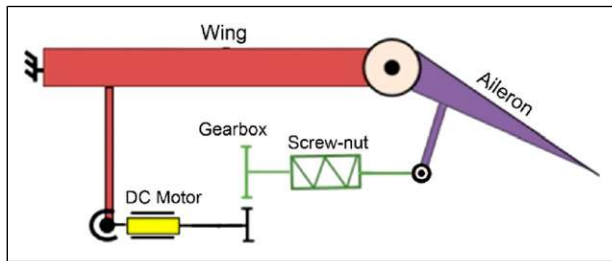


Figure 5. 3-bars architecture of the EMA adopted from (Siala et al., 2020).

the translation of the rod in order to push and pull the aileron.

During the collaborative design of the EMA system, four expert models are involved. The first expert model (EM_R) refers to a specification model where the requirements to be respected are identified. These initial requirements of the studied system are given in Figure 6 using the SysML language requirement diagram within Magic Draw environment.⁴ The response time of the EMA shall be less than 600 ms and the static error shall be less than 3°. Its mass is 3 Kg. The required power shall not exceed 500 W and the system cost must not exceed 1000 €. In order to verify the integration of the components, they shall fit in the allocation area between the aileron and the wing. The second model (EM_{MP}) is a multi-physical model using Modelica language. This model is based on differential, discrete and algebraic equations in order to describe the dynamic response of the system (Hehenberger et al., 2016). Using Modelica language, it is possible to simulate virtual prototypes and to evaluate the physical behaviour of multi-disciplinary systems which is suitable for mechatronic systems design (Mcharek et al., 2018).

The EMA system multi-physical model within Dymola environment is presented in Figure 7. Based on the previous multi-physical model and its calculated parameters, another expert model (EM_C) is established. The existing Commercial Off-The-Shelf (COTS) components⁵ are chosen conforming with the simulation results (see Table 1). The final expert model involved in the collaborative design of the studied case study is a 3D model (EM_{3D}) using CATIA environment (see Figure 8). This model is created in order to verify the integration of the whole mechanism in the aileron and the wing assembly. Each expert model is composed of

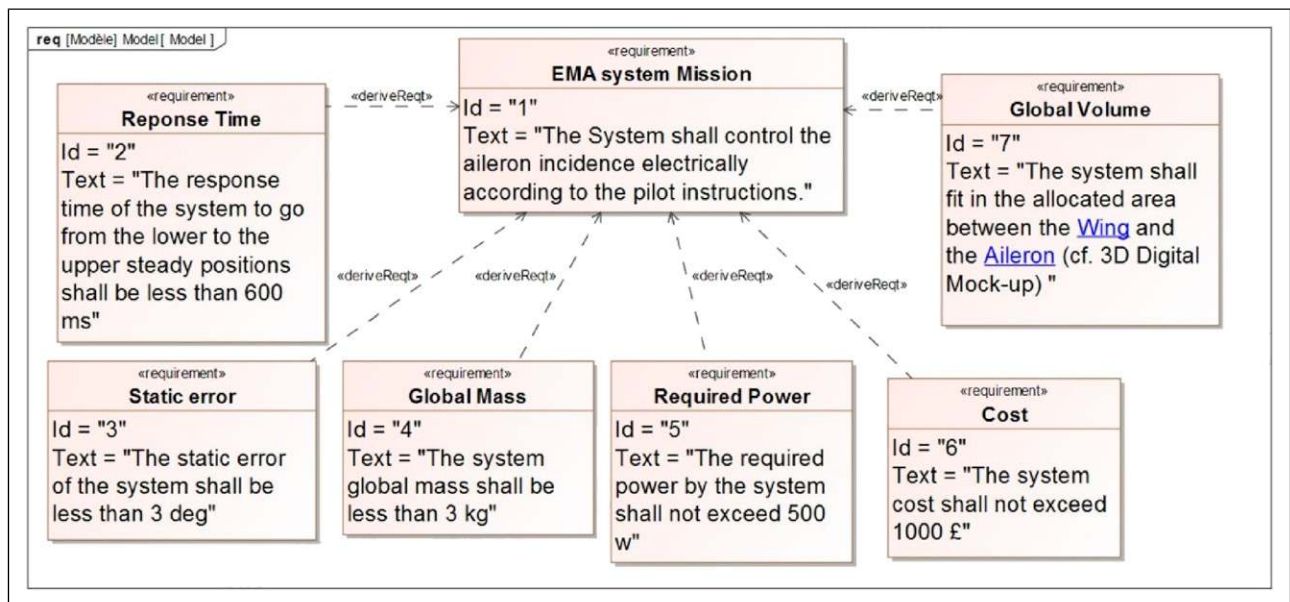


Figure 6. The initial requirements of the EMA system.

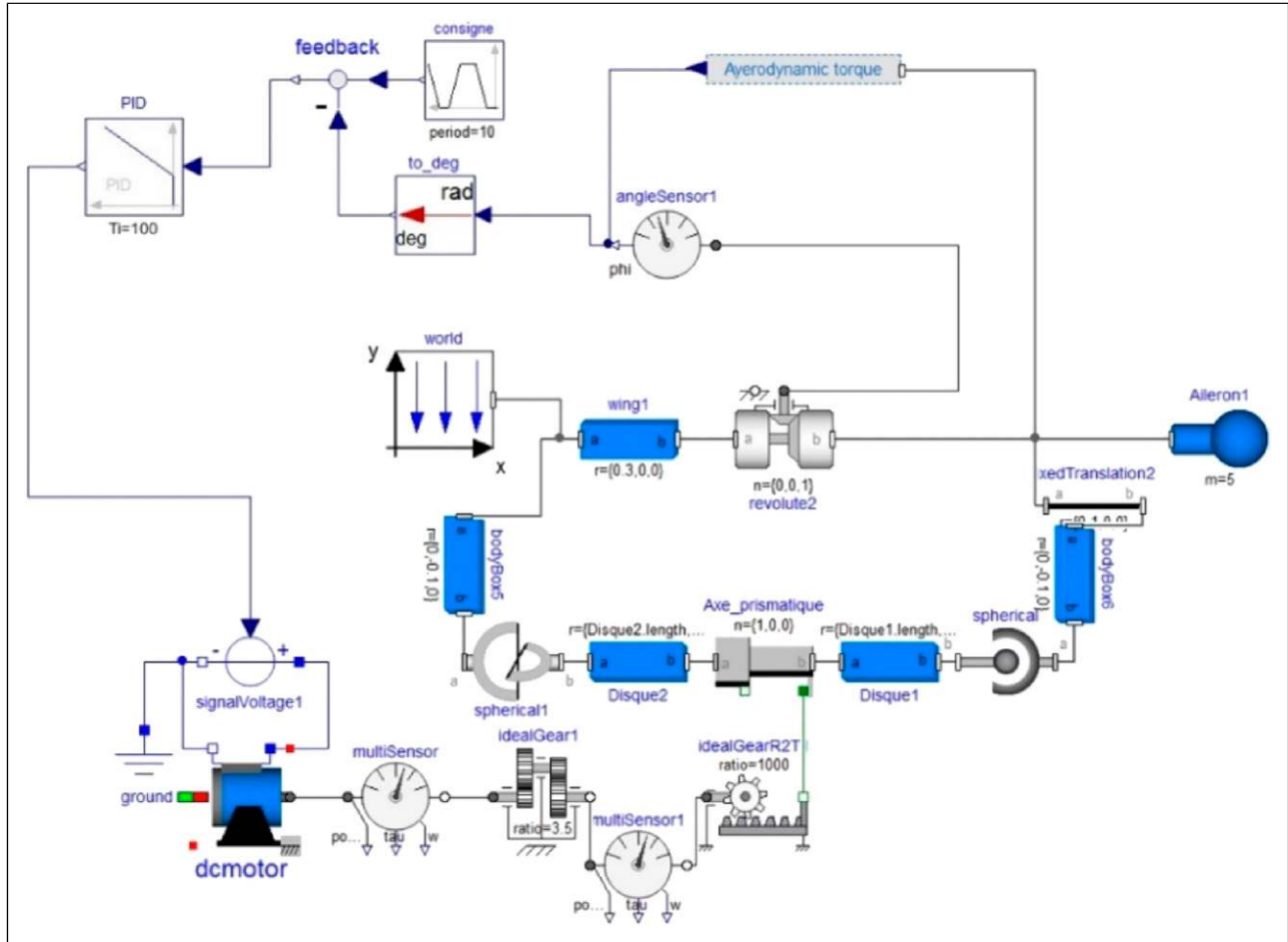


Figure 7. The multi-physical model of the EMA system using Modelica language.

Table I. Commercial Off-The-Shelf (COTS) model (EM3) (An excerpt of a DC motor characteristics⁵).

Values at nominal voltage	
Nominal voltage	48 V
No load speed	3670 rpm
No load current	289 mA
Nominal speed	3420 rpm
Stall torque	16100 mN.m
Nominal torque	800 mN.m
Max. efficiency	88%

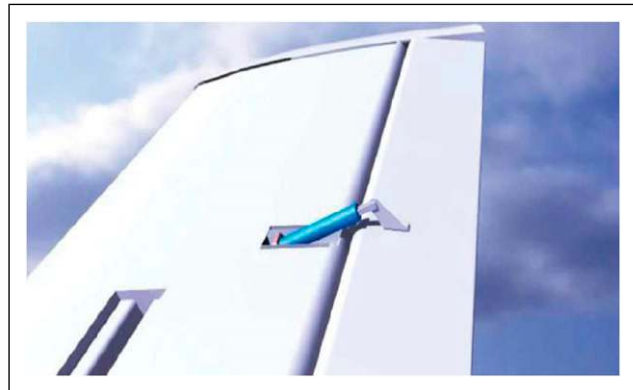


Figure 8. 3D integration within CATIA environment (EM_{3D}) (Mhenni et al., 2018).

several knowledge. Some of knowledge can be common between different expert models while others can be used by a unique expert model and their contribution to achieve the project objectives is not important. Therefore, identifying the most important knowledge that characterizes the interdependence among the expert models is challenging. In this context, after describing the different expert models of the EMA system, we will show how the category theory is used to extract the crucial knowledge for the collaborative

process. The first step in our methodology is to translate the initial requirements identified beforehand by the project manager into categorical graphs. The idea is to consider parameters as categories. The response time, the static error, the global mass, the maximal power, the cost and the

dimensions of the system will be considered as categories in our case study.

Once all the required categories have been created, the initial objects as well as their identity morphisms need to be represented in the concerned categories. These initial objects illustrate the first version of the parameter proposed by the specification model (EM_R). As aforementioned, the identity morphism of each object highlights the internal evolution of the parameter state in the same model. If a new parameter is required by the multi-physical model (EM_{MP}), the COTS model (EM_C) or the 3D model (EM_{3D}) and which was not represented by the (EM_R), a new category must be created representing the corresponding parameter. Similarly, each category will be filled in with the objects and their identity arrows. Otherwise, at this level, each created category will be modified by the different stakeholders. This modification remains in adding a new object that represents another version of the same parameter and linking this object by the previously created one through a morphism. Considering the example of the Static error defined in the (EM_R). The CG of this parameter will contain two objects where the first one is created by the engineer working on the (EM_R) and the second one is elaborated through the simulation in (EM_{MP}).

In this step, it is important to consider the order of each expert model. Although we are talking about collaboration, there is always a well-defined order while creating each expert model. In our case study, the specification model (EM_R) is provided at the beginning. Then, the multi-physical

model (EM_{MP}) of the EMA is presented to dimension the components in order to satisfy the identified requirements. Once the simulation results are obtained from the Modelica model, the existing COTS components (EM_C) have to be found. The final model (EM_{3D}) consists in verifying the 3D integration of the whole mechanism in the wing and the aileron assembly. Hence, considering this iterative collaborative process, a formal as well as understandable representation by all the projects actors is obtained. An excerpt of the CGs of some parameters is illustrated in Figure 9. The parameter Pm, \varnothing_{mot} , Mass and Km refer, respectively, to the maximal power of the system, the diameter of the motor, the mass of the system and the motor constant. The Figure 9(a) illustrates the CG of the EMA maximal power (Pm). The Pm parameter is identified, in the first place, by the specification model, then instantiated by the EM_{MP} and finally modified by the EM_C .

All what we need to ensure that the created category respects the mathematical definitions in the context of CT is to prove the existence of composition, identity as well as associativity. Let Pm_{EM_R} , $Pm_{EM_{MP}}$ and Pm_{EM_C} three different versions of the maximal power such that EM_R interacts with EM_{MP} , which in turn interacts with EM_C . Then, EM_R can interact with EM_C indirectly through EM_{MP} , which highlights the existence of a composition of morphisms between EM_R and EM_C . The identity arrow exists to represent the internal evolution of the Pm parameter. It is assumed to be present for each object. However, it is seldom shown in order to avoid cluttering the category with an

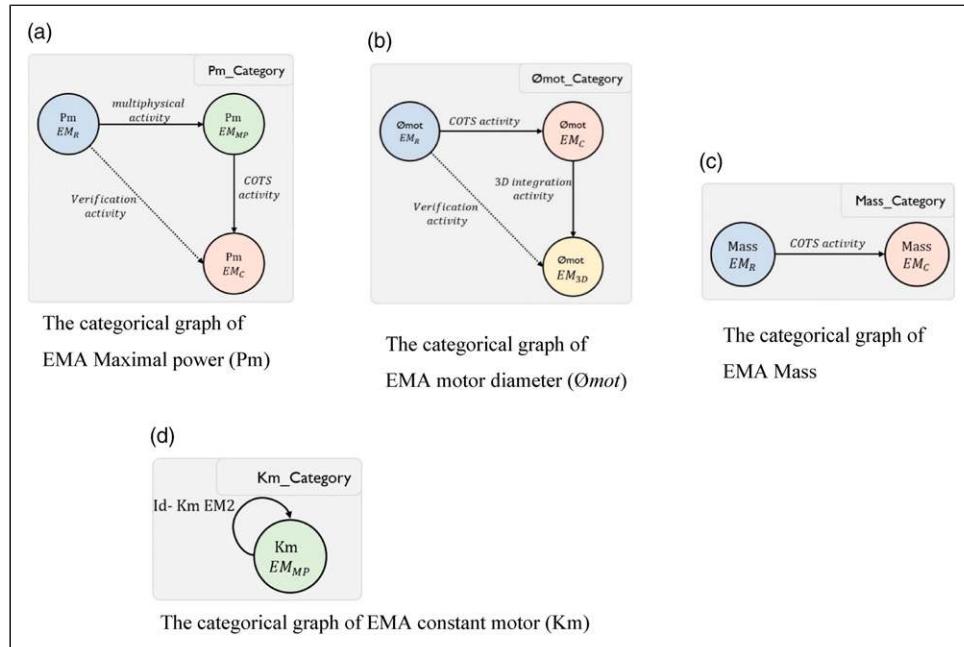


Figure 9. An excerpt of the categorical graphs of some parameters used in the design of the EMA system. (a) The categorical graph of EMA Maximal power (Pm). (b) The categorical graph of EMA motor diameter (\varnothing_{mot}). (c) The categorical graph of EMA Mass. (d) The categorical graph of EMA constant motor (Km).

identity morphism for each object. This morphism will be represented in discrete categories since they contain only identity arrows. Let evolution 1, evolution 2 and evolution 3 be the morphisms such that evolution 1: $Pm_{EMR} \rightarrow Pm_{EMMP}$, evolution 2: $Pm_{EMMP} \rightarrow Pm_{EMC}$ and evolution 3: $Pm_{EMR} \rightarrow Pm_{EMC}$. It is clear that evolution1 \circ (evolution2 \circ evolution3) = (evolution1 \circ evolution2) \circ evolution3. Similarly, the composition, identity and associativity properties are demonstrated for the motor diameter (\emptyset_{mot}) as shown in Figure 9(b). This parameter is defined first by the specification model (EM_R), modified in the second place by the COTS model (EM_C) and finally modified by the 3D model (EM_{3D}). Nonetheless, the Mass and constant motor (Km) of the system represented through Figures 9(c) and (d), respectively, are considered as particular categories. Therefore, the properties of composition as well as associativity are vacuously satisfied. In Figure 9(c), the categorical graph shows that the Mass will be used by both the EM_R and EM_C . The two versions of the Mass are linked through a morphism in order to represent the evolution of the parameter from an expert model towards another one. In this category, the composition of morphisms as well as their associativity do not exist. Moreover, Figure 9(d) highlights the CG of the constant motor Km parameter. This category is considered discrete in term of CT concept since the only existing arrow is the identity morphism of Km . In such category, the composition and associativity properties cannot be satisfied.

After creating all the necessary categories, the project manager has to identify the crucial parameters. As mentioned beforehand, the parameters in which their corresponding categories have the form of discrete categories will be considered as non-crucial for the collaborative process and do not need the capitalization. The idea is to consider the contribution of these parameters as non-crucial to attain the project objectives since they are used or created by a unique expert model. Thus, the other models will not use it in their engineering activities. However, the remaining categories, which contain at least two objects (i.e. two versions of the same parameter), will be considered and the corresponding parameters will be defined as crucial for the collaboration. In fact, capitalization is considered as important issue during collaborative design since capitalizing on previous knowledge and results will prevent the loss of time while repeating the same actions as well as errors. All the parameters generated by the four expert models involved in the EMA system design are grouped in Table 2.

The related expert models to each parameter are also illustrated in this table. The parameters identified in the requirement model (EM_R) are considered important for the collaboration. These parameters are used to verify the requirement satisfaction by the remaining models. The response time parameter presents an example of a crucial parameter since it is defined on one hand by the EM_R and on the other hand by the EM_{MP} . The value of this parameter obtained in EM_{MP} has to be compared with the required

Table 2. The different parameters found by the expert models involved in the design process.

Parameter name	EM_R	EM_{MP}	EM_C	EM_{3D}
Response time (Rt)	X	X	—	—
Static error (Se)	x	X	—	—
Global mass (Mass)	x	—	X	—
Maximal power (Pm)	x	X	X	—
Cost (Ct)	x	—	X	—
Motor diameter (\emptyset_{mot})	x	—	X	X
Motor length (Lgth _{mot})	x	—	X	X
Motor resistance (Rm)	—	X	X	—
Motor Inductance (Lm)	—	X	X	—
Motor efficiency (Eff _{mot})	—	—	X	—
Motor Inertia (Jm)	—	X	X	—
Motor constant (Km)	—	X	—	—
Reducer diameter (\emptyset_{red})	X	—	X	X
Reducer length (Lgth _{red})	X	—	X	X
Reducer ratio (r _{red})	—	X	x	—
Reducer efficiency (Eff _{red})	—	—	x	—
Screw-nut diameter (\emptyset_{sn})	X	—	x	X
Screw-nut length (Lgth _{sn})	X	—	x	X
Screw-nut ratio (r _{sn})	—	x	x	—
Axis of rotation (A _{rot})	—	x	—	—

value in order to check the requirement satisfaction. Figure 10 shows the simulation results using Dymola environment. It is clear that the EMA reached the upper position (30°) starting from the lower position (-30°) within less than 600 ms which satisfies the requirement ‘Response Time’ see (Figure 6). Consequently, this parameter will be considered as crucial since it illustrates the inter-dependency between two different expert models. The highlighted rows in Table 2 represent the non-crucial parameters for the EMA system design. Only one expert model makes use of this parameter. Thus, their CGs have the form of discrete categories. These parameters will be grouped in the $KClass2$, whereas the $KClass1$ will contain the remaining parameters that should make the object of capitalization in the collaborative process.

Table 3 presents the final classification of the parameters used during the EMA design. Hence, the crucial knowledge as well as the non-crucial ones are identified in a simple and formal way.

Comparison with related works and discussion

Capitalizing on knowledge is an important operation for company’s success. In order to optimize this operation, a focus on crucial knowledge is required. For this reason, several research works are proposed in the literature to deal with crucial knowledge identification. In the work presented by Pomian and Roche (2002), the extraction of the most

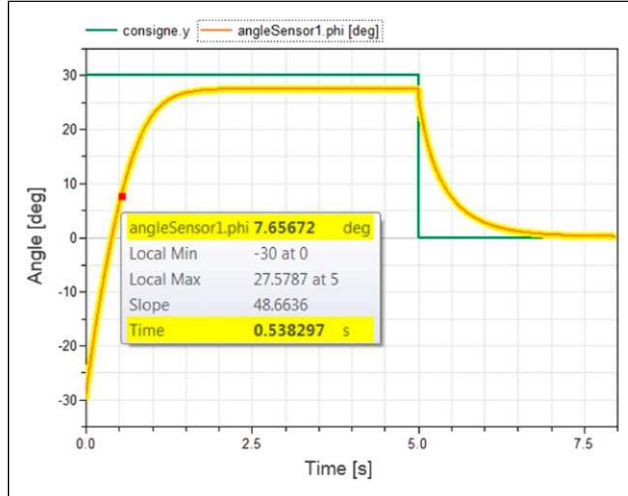


Figure 10. The EMA system response within Dymola environment.

Table 3. The final classification of EMA system parameters.

Crucial parameter (KClass _i)	Non-crucial parameter (KClass _i)
Rt, Se, Mass, P _m , Ct, Ø _{mot}	Eff _{mob} , K _m , Eff _{red} , A _{rot}
Lgth _{mot} , R _m , L _m , J _m , Ø _{red}	
Lgth _{red} , r _{red} , Ø _{sn} , Lgth _{sn} , r _{sn}	

valuable knowledge is achieved through interviews and meeting between the design teams involved in the collaboration. The same concept is used by Mcharek et al. (2019). In their research work, the authors argued that a meeting between the different design teams can be organized to extract crucial knowledge. This informal solution requires a considerable time to be achieved. The main difference between these solutions and our proposed approach is that in this later, the crucial identification process is based on the formal foundation of CT. On the one hand, this formal mathematical framework unifies the heterogeneous stakeholders involved in the design process, which is suitable for mechatronic collaborative design where a homogeneous environment is necessary. On the other hand, this knowledge formalization avoids the necessity of direct exchange between the stakeholders, which can be difficult to organize in complex environment such as mechatronic design environment where a large number of knowledge is used. Using CT as a formalization tool provides not only a formal foundation of knowledge but also a comprehensive framework by all design teams, using categories and morphisms to represent knowledge. In addition, the benefits of knowledge formalization through CT can be proven in the long term. Saving crucial knowledge in structured and organized forms (i.e. the categorical graphs of our approach) will facilitate the traceability of collaboration, which is a

challenging task in mechatronic systems design. Ensuring this traceability will identify that a given knowledge was used or modified by a given expert at a given time, which will in turn help in conflicts detection. Moreover, the traceability of collaboration evolution facilitates reuse phases in future design projects. The proposed methodology was validated using a collaborative design scenario of a mechatronic system. This validation shows that using the formal concepts of CT, crucial knowledge can be identified in an easy and simple way without the need to organize a close exchange between stakeholders, which are often geographically and disciplinarily dispersed. The motivation behind using the EMA system design as a case study refers not only to the simplicity of developing its expert models but also to its multi-disciplinary nature, which is interesting to illustrate the capacity of our approach dedicated to complex systems design. A similar example to the EMA system is used by Mcharek to validate their methodology. The authors used as a validation example, an Electronic Throttle Body (ETB) from the automotive industry, to regulate the airflow entering to the engine. Even though the EMA and ETB systems belong to different engineering fields, their structures are kinematically similar. Crucial knowledge used in the collaborative scenario of the ETB design is identified based on the project manager's previous experiences. This makes the identification process centralized on the manager decisions as we mentioned beforehand. Conversely to this approach, our validation methodology, based on the EMA system scenario, makes use of the mathematical foundation of CT, which helps to provide rational extraction of knowledge.

Although the mentioned advantages of the CT-based approach, it needs, on the one hand, to be illustrated through a software prototype to demonstrate its efficiency. Mordecai et al. argued that programming languages can be considered as categories and most of software programs are an instantiation of these languages (Mordecai et al., 2021). Thus, CT will facilitate the development of our software demonstrator. Moreover, an attempt to adapt our research methodology for autonomous systems and Cyber-Physical Systems (CPS) will be presented in our future works.

On the other hand, the created CGs require further refinement to highlight the value evolution of each parameter in each expert model. Ensuring the value parameters traceability is also an important issue in collaborative design. The CGs can contain the different values of the same parameter, which will allow conflicts detection and make it a simple task since the concerned expert models with the conflicting parameter can be identified easily using category theory constructions.

Conclusion and future works

Considering the increased level of complexity of mechatronic systems, collaborative, formal and reliable design has

to be adapted. For collaboration success, only the knowledge that their contribution to attain the project objectives need to be capitalized. The formal framework proposed in this paper enabled crucial knowledge identification during a mechatronic collaborative design process. This framework was based on the mathematical theory called ‘Category Theory’. The used concept provided a formal as well as unified representation of the involved knowledge in the collaboration. This representation gave a formal meaning to the dependencies occurred among the different stakeholders. The CT-based methodology was applied to the Electro-Mechanical Actuator of the aileron by considering several expert models that had exchanged different knowledge. This approach had proven its efficiency with the EMA system and can be adapted for other mechatronic systems.

Our future work will focus on implementing our approach in a software demonstrator in order to better illustrate and validate it in an industrial environment. The categorical graphs used in this approach will be further refined to be used in the conflict detection and resolution process during the collaborative design.

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Notes

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