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Ontology-augmented Prognostics and Health Management for shopfloor-synchronised joint maintenance and production management decisions

In smart factories, guaranteeing shopfloor-synchronised and real-time decision-making is essential to be responsive to the ever-changing internal environment, namely the shopfloor of the production system and assets. At operational level, decisions should balance counter acting objectives of maintenance and production; therefore, their decision-making processes should be joint and coordinated, to fulfil production requirements considering the health state of the assets. The knowledge of the current state is promoted by the application of Prognostics and Health Management (PHM) as an aid to support informed decision-making. Nevertheless, PHM-purposed information is usually not complete in terms of production requirements. To support joint maintenance and production management decisions, an ontological approach is proposed. The ontology, called ORMA (Ontology for Reliability-centred MAintenance), has a modular structure, including formalisation of asset, process, and product knowledge. Via suitable relationships, rules, and axioms, ORMA can infer product feasibility based on the current health state of the assets and their functional units. ORMA is implemented in a Flexible Manufacturing Line at a laboratory scale. Therein, an integrated solution, involving a health state detection algorithm that interacts with the ontology, supports human decision-making via a web-based dashboard; joint maintenance and production management decisions can be then taken, relying on diversified information provided by the PHM algorithm as well as the augmentation via ontology reasoning. The proposed ontology-based solution represents a step towards reconfigurability of smart factories where human and automated decision-making processes work in synergy.

Keywords: ontology, reasoning, Prognostics and Health Management, PHM, maintenance, production

Highlights

1. Maintenance and production information to be shared for joint decisions
2. Maintenance-related ontologies need to consider process and product knowledge
3. Joint decisions are favoured by cross-functional knowledge management
4. As information integrators, ontologies support multiple decision-making processes
5. Ontologies serve to augment and dispatch information in smart factories

1. Introduction

The market turbulence and the digitalisation that are characterising these days are challenging companies in maintaining their competitiveness. Whilst on one side they have to cope with external changes, like demand volatility [1], companies have to face ever-changing internal environment [2], too. In this regard, production systems and assets are influenced by several sources of uncertainty at shopfloor level, and the decision-making process should be robust [3]. To cope with uncertainty, characteristics like predictability and reconfigurability are needed [4], and exploited in production systems by implementing CPS (Cyber Physical Systems) as key constructs to move towards smart factories [5], [6]. Indeed, reconfigurability in smart factories may be tackled at various production levels, from machine to network [7], and control levels, from operational to strategic [8]. At operational level, performing maintenance in a suitable manner while optimising the system throughput is amongst the objectives residing under reconfigurability [9]. Therefore, maintenance is central [10,11], relying on the possibility to have insights on the current assets and system states to synchronise the decision-making process with the actual situation of the shopfloor [12].

Maintenance-focused analytics allows to cope with the uncertain behaviour of the assets [13], preventing from stoppages or underperformance of the production. Indeed, assets experience faults or, in general, abnormal states that may impact on product quality, preventing to keep the highest standard. Deviations from the normal operating conditions are needed to be identified to guarantee product quality above acceptable thresholds. To this end, it is the goal of Prognostics and Health Management (PHM) to determine the system/asset health state and predict future behaviours [14,15]. Hence, this shopfloor-related knowledge, in terms of the health state, allows avoiding production losses, if suitable decisions are promptly triggered [16]. Nevertheless, at the state-of-the-art the PHM-purposed information is traditionally useful for maintenance only [14]. On the other hand, PHM has potentialities to be exploited to support joint decision-making [17], namely by integrating and elaborating maintenance-related data/information with data/information coming from other sources/processes, like production. Indeed, a concurrent evaluation of the asset health state and the production requirements could empower the decision-making, considering multiple and diversified objectives of the different organisational functions in a systematic way [18]. The need to integrate data and information in this context embraces the wider Industrial Information Integration, which is a growing field in almost all sectors [19] and is a broader system that is on top of various domains, including those of industrial engineering and operations management, particularly addressed by the present work. Indeed, manufacturing represents one of sectors in which Industrial Information Integration is spreading the most [20,21] and several technologies are adopted, like ontologies, which allow to improve management systems performance for various business objectives [22].

Given these premises, an ontological approach fits with the current industrial challenges [23]. Firstly, being smart factory knowledge-intensive, ontologies allow to properly retrieve and dispatch data/information between interested parties for cross-functional decision-making [24]. Secondly, but connected, ontologies provide a unique and standardised vocabulary to guarantee consistent meaning, avoiding misinterpretations between stakeholders [25]. Thirdly, ontologies guarantee reasoning and inferencing capabilities, pointing towards augmenting the information content [26]. All in all, ontologies serve as a mean to guarantee technical and semantic interoperability [27,28] that is essential to exploit current CPS-based smart factories [29].

Nevertheless, ontologies for PHM experience an important gap regarding the exploitation of knowledge belonging to domains but maintenance. As the systematic literature review in this work demonstrates, PHM-related ontologies are asset-centric and does not introduce process and product-related knowledge to augment the information to go beyond the traditional scope, towards joint maintenance and production management decisions. Anyway, three-module ontologies, i.e., including resource (that is, asset), process and product knowledge, are necessary to guarantee the maximum exploitation of stored knowledge [22,30].

Therefore, the goal of this research work is to overcome this gap by proposing an ontological model called ORMA (Ontology for Reliability-based MAintenance). ORMA will firstly tackle the semantic interoperability issues by establishing a common knowledge base with concepts' definitions from scientific literature and international standards, framed in standardised high-level conceptualisations. Hence, the ontology will include both maintenance and production-related concepts (thus spanning from asset, through processes, to product), properly connected to promote a shopfloor synchronised and joint decision-making process. Secondly, the ORMA ontology, after being tested through competency questions (CQs), is integrated in a solution deployed in a Flexible Manufacturing Line (FML) at laboratory scale. The implementation is complemented using algorithms for state detection proper of the PHM approach. ORMA will infer the feasibility of products in a synchronized manner with the health state of the assets. Overall, this work aims at improving the performance of the joint maintenance and production decisions through the establishment of an ontological knowledge base, which ultimately is promising for improved operation/system level of reconfigurability.

1.1 Research methodology

This research work is grounded on the Design Science Research Methodology (DSRM) [31] that has been widely used in engineering field for the development of ontological models [32,33]. The DSRM has several activities composing the nominal process sequence, which could be summarised as in the top part of Figure 1. Figure 1 also proposes a mapping between DSRM, and the methodologies specifically adopted in this research, alongside with the outputs.

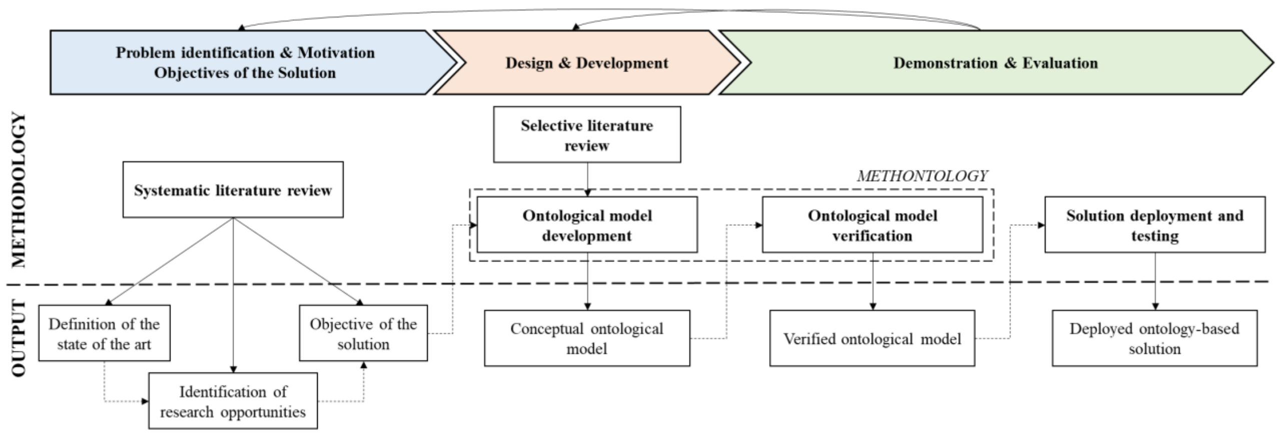

Figure 1 – Research methodology.

In the Problem Identification and Motivation, and Objectives of the Solution, a systematic literature review is adopted to define the state of the art as background to look for research opportunities and motivate the objective of the proposed solution. Secondly, the Design and Development includes the first steps of the selected ontology building methodology, that is METHONTOLOGY [34], with a selective literature review to recover relevant concepts to be formalised in the ontology; the output is a conceptual ontological model with definitions, relationships, axioms and rules. In the Demonstration and Evaluation, the last steps of the ontology building methodology are faced, where the ontology is verified; moreover, the ontology is made operative in an integrated solution working with state detection algorithms. In particular, the integrated solution is finally deployed and tested. An iterative process is generally established if model's performances are not satisfactory.

The activities are retraced also in the structure of this document. Section 2 extensively revises the literature to identify scientific contributions in the field of ontologies for PHM. Section 3 provides a brief introduction to METHONTOLOGY, which is the needed knowledge background for ontology building. Section 4 represents the ontological model development step, where the conceptual model of ORMA is proposed, which integrates extant contributions retrieved by a selective literature review. Section 5 firstly proposes the demonstration of the ontology by verifying its functioning and then describes the deployment and testing of the integrated solution in a laboratory scaled FML. Finally, Section 6 draws some conclusions and paves the way for further research.

2. Review of ontologies for Prognostics and Health Management

Ontologies are defined as the specification of a conceptualisation [35]. They formally describe a specific domain of interest by listing relevant concepts and relating them properly. The developed asserted model is general enough to be applied to more contexts and the reusability property is core in ontology engineering [36]. Computational ontologies, known as those ontologies that describe a system and could be used for computational reasons [37], found their first applications in the Semantic Web, which is an extension of the Web where [38]: i) the presentation of the information is different from the information itself, ii) the meaning of the information is well-defined, and iii) the information has a precise structure so to be processable by machine. The computational capability and the scaling up of data quantity have made ontologies appealing for industry as well. Here, interoperability is the main driver [39], put at the centre by the advent of the PLM (Product Lifecycle Management) [40] and ALM (Asset Lifecycle Management) [41], which require heavily integration of information systems to guarantee robust decision-making. Within ALM, maintenance is seeing an increase in the application of ontologies, being pushed by the advent of eMaintenance [42]. More recently, PHM is establishing itself as a core engineering discipline to gather insights on the health state of the production system at different granularity, from component, through asset, to plant as a whole [14]. This occurs thanks to its capability to define the health state, diagnose failure and predict future behaviour. As such, ontologies for PHM are arising, as the literature review in subsection 2.1 demonstrates. Nevertheless, some gaps emerge that unlock research opportunities and motivate this research.

2.1 Literature review on ontologies for PHM

A systematic literature review (SLR) is established to extrapolate relevant extant scientific literature dealing with ontologies for PHM from databases, namely Scopus, Web of Science (WoS) and IEEE Xplore. The methodology for the SLR is inspired by Sansone et al. [43]. After the definition of a proper research protocol, the adherence of the document with the engineering field is verified while retrieving documents so to avoid including works from other field, like medicine, which is flourished in ontology development. Moreover, being the scope of this work related to production systems, thus including discrete manufacturing and process industry, documents dealing with, for example, building management or transportation, are excluded. This is mainly due to the substantial difference between the "assets", and related complexity, that have to be managed. The summary of the research process is reported in Figure 2 where the screening phase oversees removing documents not aligned with the goal of this work. Only those documents describing the developed ontologies are considered, while leaving literature reviews, theoretical frameworks, architectures, and similar ones, aside.

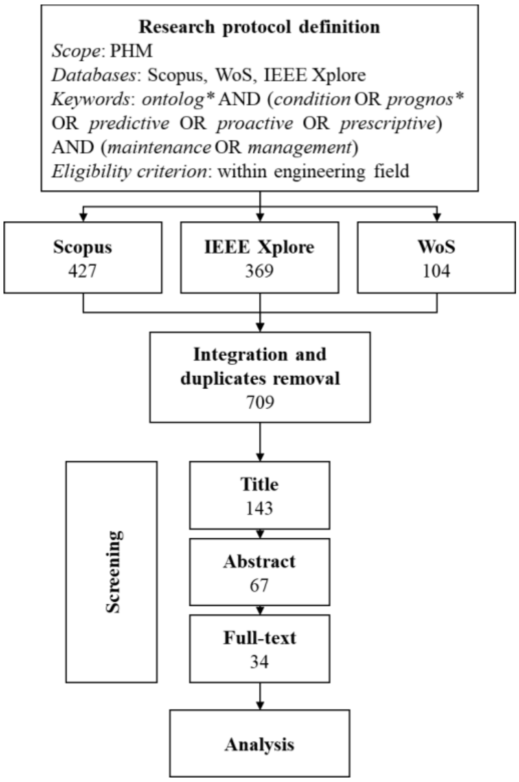

Figure 2 – Literature review process.

It is worth noting that most of the excluded documents in title and abstract screening belong to medicine or related fields of research, construction, and transportation. The identification of 67 in abstract screening is based on the exclusion of works mainly due to their application sectors, like buildings or aviation, or application, like PLM. Finally, 34 out of 67 documents are considered eligible.

2.2 Document analysis

The 34 eligible documents are concentrated in the timespan between 2005 and 2021. Table 1 provides a summary of the eligible documents by classifying them according to some meta-variables of interest. These meta-variables describe: i) the functioning of the ontology, or the system to which it belongs to, with online algorithms, ii) whether the proposed ontology considers asset-related concepts or not, iii) whether the proposed ontology considers product-related concepts or not, iv) if the reuse of semantics (based on other ontologies, international standards, etc.) is explicit or not.

Year	Reference	Online algorithm	Asset concepts	Product concepts	Reuse of semantics
2021	Roopa et al. [44]	x	x		Not explicit
2020	Shcherbakov et al. [45]	x	x		Not explicit
	Cho et al. [46]			x	Not explicit
2019	Rachman et al. [47]		x		Explicit
	Ansari et al. [48]	x	x	x	Not explicit
	Giustozzi et al. [49]	x	x	barely	Explicit
	Cho et al. [50]	x	x		Not explicit
	Cao et al. [51]	x	x		Explicit
2018	Arena et al. [52]	x	x		Explicit
	Smoker et al. [53]		x		Explicit
	Järvenpää et al. [54]		x	x	Explicit
	Hegedűs et al. [55]	x	x		Explicit
	Bunte et al. [56]	x	x		Not explicit
	Nuñez and Borsato [57]		x		Explicit
2017	Maleki et al. [58]	x	barely	barely	Not explicit
	Nuñez and Borsato [32]		x		Explicit
	Qiang et al. [59]	x	x		Explicit
2016	Saalmann et al. [60]		barely		Explicit
	Nuñez and Borsato [61]		x		Explicit
	Zhang et al. [62]	x	x	x	Not explicit
2015	Xu et al. [63]		x		Not explicit
	Mehdi et al. [64]	x	x		Not explicit
2014	Roda and Musulin [65]		x		Explicit
	Zuccolotto [66]		x		Explicit
	Abele et al. [67]	x	x		Not explicit
	Aarnio et al. [68]	x	x		Explicit
2013	Jin et al. [69]		x		Explicit
2011	Karray et al. [70]	x	x		Not explicit
2010	Akbari et al. [71]	x			Not explicit
	Németh et al. [72]	x	x		Not explicit
2009	Jin et al. [73]	x	x		Explicit
2007	Campos [74]		x		Explicit
2006	Zu et al. [75]		x		Not explicit
2005	Feng et al. [76]	x	x		Not explicit

Table 1 – Systematic literature review: meta-analysis of the eligible documents.

The meta-analysis shows the first insights herein reported.

- The ontologies are updated in their data values through algorithms working online, which retrieves data directly from the physical assets installed in the shopfloor or from other information systems.
- The ontologies dealing with PHM barely integrate both asset- and product-related knowledge (for the sake of simplicity, in Table 1 the "process" is not reported since it is highly correlated with the "product": when the product knowledge is included, then, also the process knowledge is formalised).
- A systematic adoption and reuse of semantics in various forms, like extant ontologies and international standards, is evident and applied systematically. Nonetheless, it should be highlighted that very few studies refer to foundational ontologies on which grounding their knowledge bases.

The detailed analysis of the documents allows to highlight and discuss three main criticalities in the extant scientific literature. These are the gaps that unlock research opportunities and motivate this research.

Heterogeneous terminology

The analysed documents show a significant degree of heterogeneity in the adopted terminology.

1. The terminology related to the physical decomposition of the system is varied. The same concept is expressed in multiple forms, like "component" that is labelled equivalently as "system component" and "system part". Also, "equipment", "machine", "asset", "manufacturing resource" and others are used to identify the same concept, i.e. the physical asset realising a process on a product.
2. The terminology related to condition monitoring is almost homogeneous when dealing with sensors, failure modes/effects, symptoms, etc. On the other hand, when defining the rule/s to determine the asset health state, various terms are adopted, like machine measurements or condition monitoring data, and measurement bounds or thresholds.

Missing relationships with product-/process-related knowledge

The formalised domains in almost every of the analysed works barely include relationships with product- and process-related knowledge. The ontologies could be in fact classified as "asset-centric" as they make the asset the most relevant concept. Nevertheless, ontologies dealing with PHM in a more holistic and integrated view, could be beneficial both for the maintenance function, guaranteeing high maintenance planning performance [48] and a more holistic approach to maintenance management [77], and for other business processes and organisational functions [78], given the possibility to recognise and forecast the state of the production system and assets.

Not fixed/unique reference ontology

Even though it is a best practice to select a reference foundational ontology used to frame the new ontology, it is barely used in the eligible documents. In the analysed ontologies, this causes, for example, that a "machine" is either classified as a physical entity, which exists "physically" in reality, and as a data/information useful for PHM applications. However, what is a "machine" should be clearly identified to guarantee semantic alignment, and a reference ontology is envisioned to solve this issue. Indeed, BFO is becoming the reference top-level ontology for industry (see ISO 21838 [79]): to align the ontological knowledge with an already established basis is vital to guarantee technical and semantic interoperability between systems and stakeholders, and a foundational ontology as BFO can be considered as a relevant means to this end in the industrial arena.

2.3 Concluding remarks

Taking step from the gaps resulting from the literature analysis, it is advisable to address several aspects of ontology engineering for PHM in industry:

1. **the identification of agreed-upon sources of terminologies**, especially for the new knowledge the ontology aims at formalising, will be essential to realise harmonized vocabularies;
2. **the modelling of relationships to the asset, process, and product-related knowledge**, will allow to promote the integration of ontologies, and to exploit knowledge belonging to domains but maintenance (production, logistics, product quality, etc.), thus taking advantage of the potentialities of integration and reusability;
3. **the use of BFO as foundational ontology as reference top-level ontology for industry**, will lead to establish a common knowledge basis from which to extend domain ontologies.

Overall, this research work aims at coping with the identified gaps by proposing an ontology grounded on extant scientific and industrial literature. The objective of the proposed solution is to realise an ontology, called ORMA, which includes asset, product, and process-related knowledge in correspondent modules. It is shown that, by leveraging upon few relationships and rules between the modules, the efficacy of ontology-augmented

PHM is improved. Indeed, ORMA does not only support maintenance, but also production by evaluating the feasibility of products to favour shopfloor-synchronised and joint decision-making.

3. Ontology development methodology

To address the objective previously defined, the next steps of DSRM include ontological model development and verification. These two steps are generally the core of already available methodologies, which aim at standardising and systematising the ontology building activity. Relevant methodologies to be cited and that are used in the scientific literature are, in chronological order from 1995: Uschold and King [80], Grüninger and Fox [81], METHONTOLOGY [34], Ontology Development 101 [82], OntoClean [83], DILIGENT [84], DOGMA [85] and NeOn [86]. Some of them does not cover only the ontology building phase, which generally goes from specification to implementation, but include the entire ontology lifecycle, thus also including maintenance and update interventions. In this work, METHONTOLOGY is adopted as it represents the very basic structure also of the most advanced methodologies [87]. Figure 3 reports the phases included in METHONTOLOGY, with highlights on the main content of each phase.

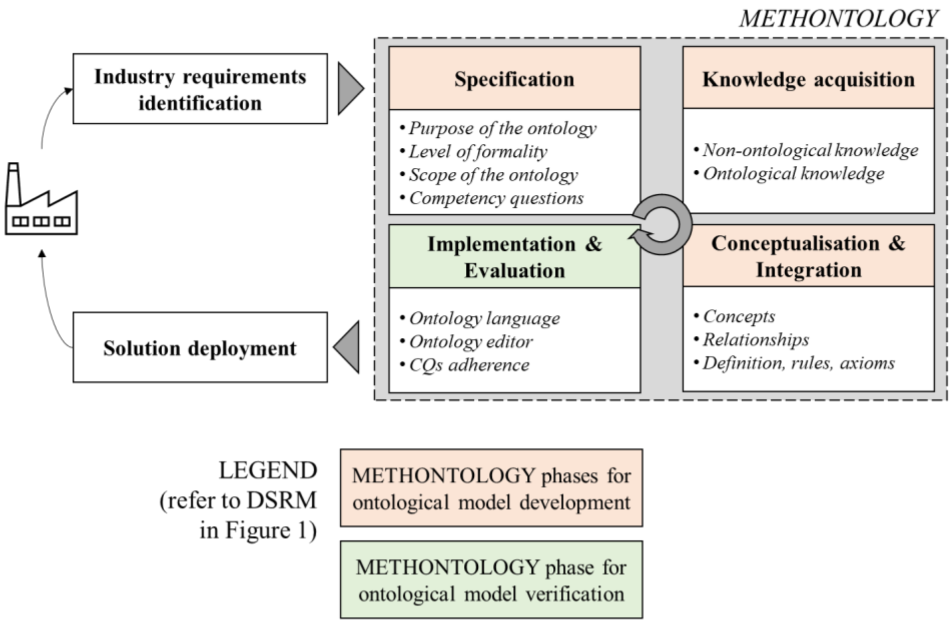

Figure 3 – Adopted ontology development methodology.

A preliminary phase is inserted, that aims at identifying the industrial requirements, as stressed by DOGMA (see “preparation and scope” therein). Furthermore, once the ontology is implemented and verified, then it should be inserted in a wider solution, and deployed to support industry decision-making. In Figure 3, the inner loop (grey arrow) of METHONTOLOGY refers to the iterative process of ontology building that allows to refine the model up to its desired performance. The outer loop (involving the company, the requirements identification, METHONTOLOGY, and the solution deployment) refers to the continuous exchange and adjustment of the ontology in the short and medium term to satisfy company requirements and, in general, of the interested stakeholders [88]. These iterative loops are consistent with the DSRM approach framing the overall research work (see Figure 1).

This methodology is retraced in the remainder of this work to develop ORMA.

4. Development of ORMA

The development of ORMA starts with the identification of the industrial requirements the ontology must satisfy. A major need identified in the scientific literature and confirmed by authors’ experience in industrial projects, is the integration of data and information to guarantee coordinated and joint decision-making between organisational functions. Particularly, attention is given to maintenance and production. In the details, more effort should be put in correctly exploiting PHM potentialities in identifying asset health states to support reactive actions on the production scheduling and control, if required. Thus, ORMA aims at targeting this goal and is developed in the following according to the methodology presented in Figure 3.

4.1 Specification

The domain in which ORMA moves is the one of industrial or production engineering. Particularly, the interest is mainly towards companies in which production management is dictated by high flexibility/reconfigurability; in particular, it is interesting to apply ORMA in case of automated production systems featuring flexible routings (as it is the case of flexible manufacturing systems). In general, ORMA is coherent also with other configurations for discrete part production, and with flexible routings (job shops and manufacturing cells). The purpose is to support these companies in integrating and exploiting maintenance- and production-related data to promote joint decisions in case of assets experiencing faults or abnormal states, impacting on product quality. As such, in relation to the level of formality, the developed ontology could be classified as a *subdomain ontology* (according to classification by IOF [89]), that is an ontology enough specific for a specific industry, but with enough generality to be applicable to multiple contexts. Therefore, the scope of the ontology includes terms related mainly to the maintenance field, like *asset* and *component*, as well as terms related to the production field, like *product* and *process*. The selected foundational ontology is BFO [90], whose relevance in the development of ontologies for industries is underlined by the ongoing publication of the ISO 21838 [79]. Also, BFO provides a concise high-level conceptualisation with respect to other foundational ontologies [91].

The competency questions that ORMA must answer are the following:

CQ1 Which assets compose the system at hand?

CQ2 Which products does the system realise?

CQ3 Which are the processes required to realise product *x*?

CQ4 Which product/s is/are not feasible considering the current system/asset state?

Answering to these CQs will verify the ontology, that is, will certify that the ontology is able to represent the current knowledge about the system.

4.2 Knowledge acquisition

As relevant modelling choice, the development of ORMA relies on knowledge reuse, which enhances the ontology building, guaranteeing reduced workload in formalising new concepts and improved quality [92]. Contributions from the maintenance domain are retrieved, as well as those describing production systems, including product and process, through a selective literature review:

- On the side of knowledge for maintenance:
  - PHM knowledge: two works by Nuñez and Borsato [32,57] and the ISO 13374 [93].
  - Physical decomposition: the work by Zhou et al. [94], the ISO 14224 [95] and the FMECA-related IEC 60812 [96].
  - General knowledge: the work by Karray et al. [97], and the ontology developed by the IOF (Industrial Ontologies Foundry, link).
- On the side of knowledge for product and process:
  - Ontological modular structure and main concepts: the work by Colledani et al. [30].
  - Manufacturing process formalisation: the ontologies MSDL [98] and MRO [99].
- Scientific knowledge of the research group is also elicited.

Being in the scope of work also the understanding of algorithms useful for state/novelty detection and prognosis, the works by Pimentel et al. [100] and Lei et al. [101] are considered, respectively. The retrieval of all these knowledge resources allows balancing the several terminologies adopted and selecting the most appropriate, together with insights of already established relationships.

Finally, as relevant ontological sources to be reused, CCO (Common Core Ontologies) [102] and IAO (Information Artifact Ontology) [103] are introduced, which are domain independent ontologies. The identification of ontological and non-ontological resources coherent with the goal of ORMA paves the way for the conceptualisation phase.

4.3 Conceptualisation and Integration

Once the ontological and non-ontological resources are gathered, the definitions of the concepts should be defined, as well as the relationships that hold between them. Moreover, a relevant step in this phase is the one of integration that, according to METHONTOLOGY, is a way to speed up and ease the construction of the ontology [34]. Additionally, reusing extant resources guarantees advances in the ontological knowledge since already tested concepts do not need to be re-tested.

Following this practice and grounded on BFO as reference foundational ontology, ORMA extends from and reuses CCO and IAO ontologies. Three are the main concepts' modules that could be recognised as relevant to describe a production system [22,30]: asset, product, and process.

- The asset includes the description of the physical asset, considering its decomposition and the related functions as the basis to develop an asset-centric ontology for maintenance purposes [104].
- The product includes all the information related to the production cycle and the needed working steps to be performed to obtain the necessary features of the product.
- The process bounds the asset and the product by relating the functions provided by the asset with the needed process to be performed on the product.

Figure 4 depicts the ontology adopting an eagle's eye view. It is worth underlining that the link between the asset and the product module is not direct but happens through SWRL-based rules.

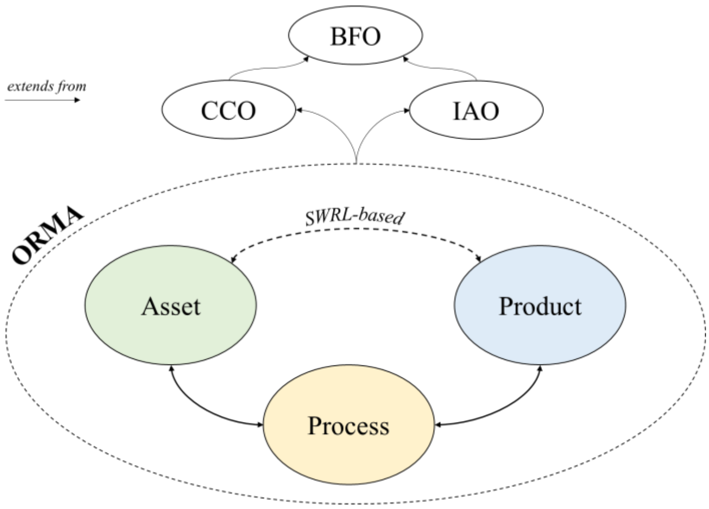

Figure 4 – Modular structure of ORMA.

The main and central module is the one of asset. This concepts' module describes the physical decomposition of the physical asset upward and downward in terms of granularity. At higher granularity, the *asset_plant* and *asset_system* are extended from *BFO:object_aggregate*. The relationship that holds between the two is *has_part* (or *part_of* as the inverse), and so the *asset_plant has_part* some *asset_system* (or, equivalently, some *asset_system* are *part_of asset_plant*). The definitions are hereinafter reported, integrated from extant related scientific and normative knowledge.

- The *asset_plant* is defined as a *"group of asset systems that exchange material and energy without any significant logistic interruption"*. A similar concept in MRO and in the work by [105] is the one of "facility". However, the definition of a facility, and especially a manufacturing facility, is broad since it consists of areas and places where manufacturing processes are realised. Also, the ISO 14224 [95] does not provide a unique definition for plant. As defined in this work, the interpretation of "*without any significant logistic interruption*" could be generically used for different configurations of *asset_system* (i.e. different configurations of production systems) part of the *asset_plant.*

- The *asset_system* is defined as a *"group of assets that are similar in characteristics, being them technological or process-related"*. The main reference to define the asset system is the ISO 14224 [95] (also defined as "section" in this standard): *"[an asset system is the] main section/system of the plant"*. Therefore, it means the asset system is a group of assets that are similar according to some characteristics, both from a technological point of view (e.g., milling department in a job shop, which collects all the milling machines), or a process point of view (e.g., cleaning department in the food industry, which includes metal detector and agitator among others).

At lower granularity level, the concepts of *asset*, *functional_unit*, *component,* and *maintainable_item* are considered. They are *CCO:artifact* that is a *BFO:object*. The first three concepts are connected via a *has_part* relationship, in a descending granularity. The choice is to adopt a three-layered physical decomposition of the asset and the reason why will be explained later. The definitions are hereafter reported.

- The *asset* is defined as *"the artifact performing space and species processes on products, tools and pallets, i.e., their movements as well as the changing of their shape and dimension, respectively"* (adapted from [30]). It is worth noting that the definition of *asset* is consistent with the definition of *asset_system* and *asset_plant*. Besides production operations (i.e. to change shape and dimension), the *asset* could perform some logistic operations (as for internal logistic needs) without involving a change of plant.
- The *functional_unit* is defined as an *"artifact that is part of the asset and is charge of performing a simplest function concurring to the overall function of the asset"*. The definition is focused on the different complexity of the function that the *functional_unit* performs. Functional units perform a specific and well identifiable function that concur to a more complex function of the asset, which is the combination of simplest ones. Examples of *functional_unit* are refrigerating unit, machining unit, power supply unit.
- The *component* is defined as an *"artifact that is part of the functional unit and does not perform specific function per se, but concur, with other components to the realisation of a simple function"*. The assumption here is that a *component* does not have sufficient complexity to guarantee a function to be realised. Examples are bearings, belts, or gears. Some of them could be decomposed in further parts, e.g. the bearings, but their function could be not exploited if they are not interconnected with other components.

The decision to adopt a three-layer physical decomposition is based on the analysis of the functions, which are the discriminant between artifacts [106]. Even though the asset could realise a function, it is as such because of the realisation of simplest functions performed by its functional units. On the other side, a further decomposition is required since each functional unit has specific components that are not enough complex to perform a "simple" or "non-trivial" function per se, but they need to be interconnected. The definition of *asset*, *functional_unit*, and *component* leverages also upon an axiomatization for the asset (analogously for the other two) as follows [97]: the *asset* is a *CCO:artifact* and *bears* a *asset_role*. Finally, the *maintainable_item* is defined so to discern between the physical decomposition and the target of specific maintenance strategies, which could be applied at asset, functional unit, or component level. Indeed, a *maintainable_item* is a *CCO:artifact* that bears a *maintainable_item_role* in the context of maintenance strategy [97]. Figure 5 and Figure 6 report some extract of ORMA.

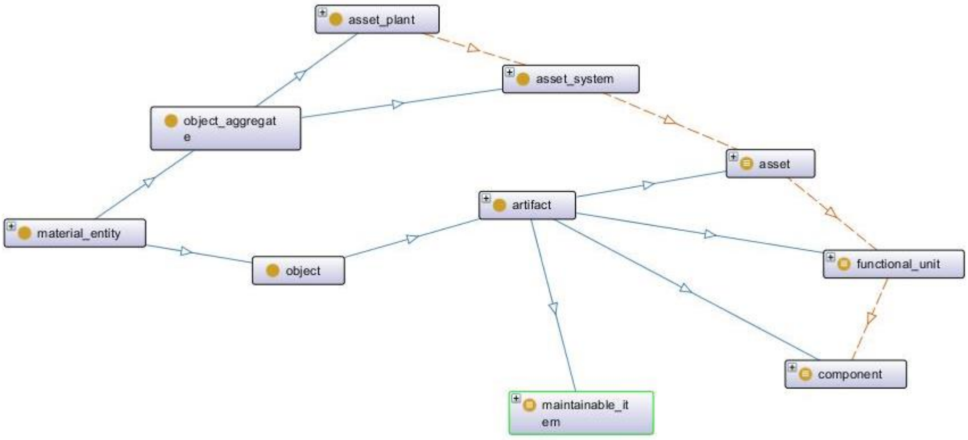

Figure 5 – ORMA: physical decomposition.

The *asset_function* and the *functional_unit_function* are realised in (*is_realized_in*) a *process* which aims at transforming the *product* in species or space, that is, modifying its shape (by realising holes, turning, chamfering, etc.), or moving it to another place. Indeed, the literature shows that these are the two basic processes that are needed to be realised, at least in the context of production systems [105]. Therefore, subclasses of the *process* are introduced, that are *transportation_process* and *manufacturing_process*. The definitions are the following:

- *process* is already defined by the BFO ontology as an *occurrent* since it has a start and an end in time, and depends on an *BFO:material_entity* to be realised (in ORMA, a *process* depends on the *asset* or *functional_unit* via their relative functions to be realised);
- *transportation_process* is a *BFO:process* where a material entity is modified in space by another material entity, which could be identified in ORMA as one of the *CCO:artifact*;
- *manufacturing_process* is a *BFO:process* where a material entity is modified in shape or composition by another material entity, a *CCO:artifact* artifact in ORMA.

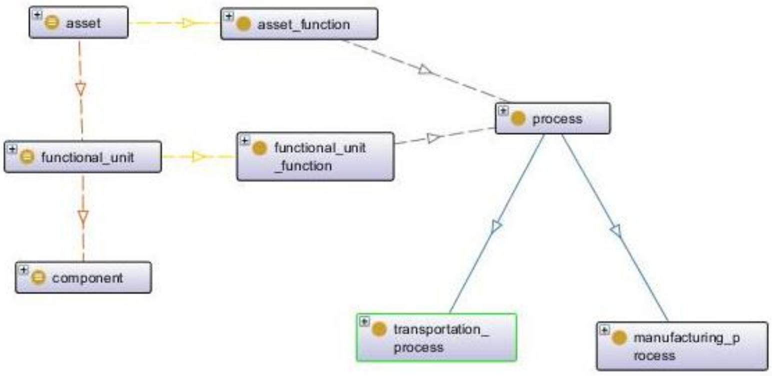

Figure 6 – ORMA: functions and processes.

The asset's and process's modules are completely defined in scope of ORMA. The *process* will be the "disjoint point" used to connect the asset and the product modules (see Figure 8) as suggested by Colledani et al. [30].

Consequently, the product and its related concepts must be properly formalised to infer product feasibility. The definitions of "product" are varied [107]. In the scope of this work, a *product* is a *BFO:artifact*, and so a *BFO:material_entity*, that absolves to some desired needs/uses. The following is the considered definition for product:

- *product* is defined as an *"artifact that is realised by one or more assets through the completion of a specific process, that is completed according to customer's requirements and delivered to a third party* *upon agreement"*. In addition to recognising a *product* as an artifact realised by one or more asset/s via a process, it is added also some key characteristics that allow to better define the product:

1. it is completed according to customer's requirements since it may be ready-to-use or semi-finished [108];
2. it is sold to a third party upon agreement of different types [109], as selling, rental or use.

To be properly processed, the product must have some accompanying information. Particularly, it is relevant to identify the cycle the product should follow, and the specific working step/s the product should undergo. For this reason, IAO is considered as a reference from which extending product information and, namely, *IAO:information_content_entity* and *CCO:directive_information_content_entity* are introduced in ORMA. The concepts related to product information are defined as follows.

- The *product_information* is defined as *"any type of directive information related to a product that could support its realisation by the assets of the system"*. It is a *CCO:directive_information_content_entity*. As such, it could include diversified information [110] related to its shape, to the material, or design-driven parameters as well as information for the machining operations or transportation modes. In the scope of this work, the *product_cycle* and the *product_working_step* are sub-concepts of *product_information*.
- The *product_cycle* is defined as a *"product information comprising more product working steps that all together allows a product to complete its processes"*. Indeed, the *product_cycle has_part* some *product_working_step* that details specific steps that the product should undergo.
- The *product_working_step* is defined as a *"product information that is the elementary working step the product should undergo to complete a part of its product_cycle"*.

The *product* is related to *product_cycle* via the *has_product_cycle* relationship and the *product_working_step* includes (*include*) a certain *process*. Figure 7 reports the view of this module of ORMA.

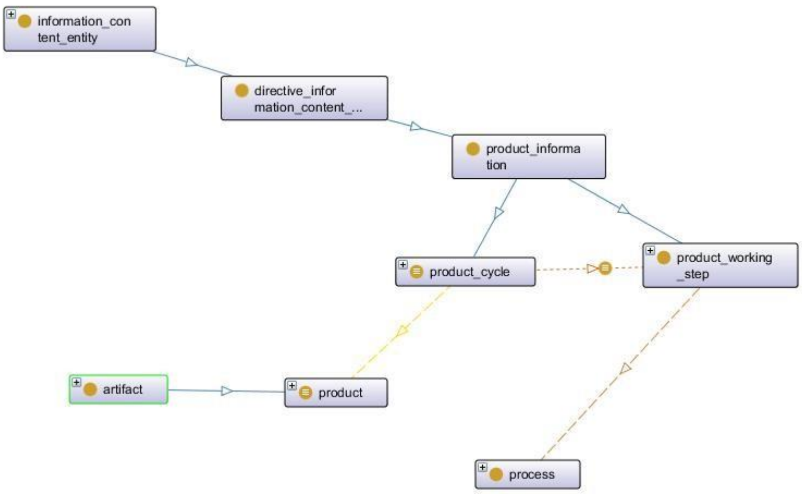

Figure 7 – ORMA: product and its related information.

Once the domain of interest is modelled, SWRL rules could be used to empower reasoning capabilities since they are able to create a "chain of relationships" effect and to modify data properties if needed [111]. They are used in the context of ORMA to modify the product and process feasibility according to the health state of the corresponding functional unit. Figure 8 sketches out the concepts of ORMA that are interested by the SWRL.

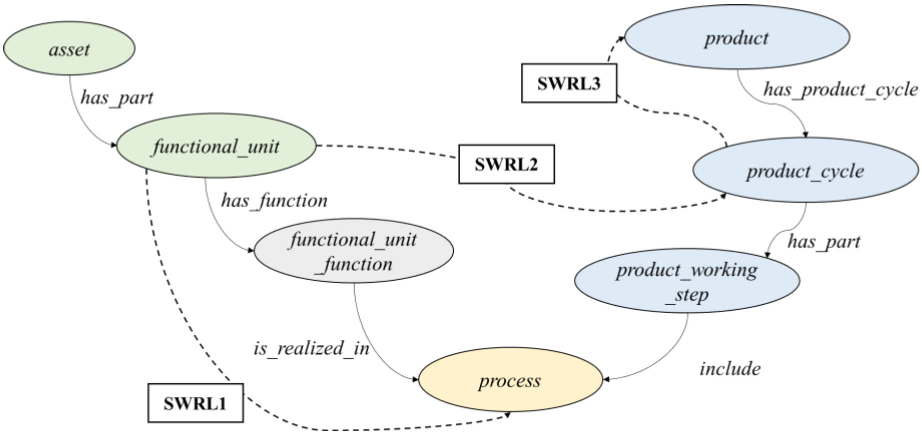

Figure 8 – Concepts interested by the SWRL rules.

The relationship *has_health_state* has *functional_unit* as domain and *xsd^^string* as range. It allows to be overwritten by an online PHM algorithm able to detect the current state of the functional unit. Once the range of these relationships is associated with a "faulty" or "healthy", then it triggers the SWRL that firstly make a specific process, either manufacturing or transportation, feasible or not (SWRL1) as well as the product cycle requiring that specific process (SWRL2). Finally, the SWRL3 makes the product unfeasible if the product cycle is not feasible. Table 2 summarises the atoms of the SWRL functions, which are defined as follows.

SWRL1: *functional_unit(?F) ^ has_health_state(?F, "faulty"^^rdf:PlainLiteral) ^ has_function(?F, ?FUN) ^ is_realized_in(?FUN, ?P) -> has_feasibility_state(?P, "not feasible"^^rdf:PlainLiteral)*

SWRL2: *has_function(?F, ?FUN) ^ process(?P) ^ is_about(?PC, ?PROD) ^ has_health_state(?F, "faulty"^^rdf:PlainLiteral) ^ include(?PWS, ?P) ^ is_realized_in(?FUN, ?P) ^ product_cycle(?PC) ^ has_part(?PC, ?PWS) -> has_feasibility_state(?PROD, "not feasible"^^rdf:PlainLiteral)*

SWRL3: *product_cycle(?PC) ^ product(?PROD) ^ has_product_cycle(?PROD, ?PC) ^ has_feasibility_state(?PC, "not feasible"^^rdf:PlainLiteral) -> has_feasibility_state(?PROD, "not feasible"^^rdf:PlainLiteral)*

Atom	Pointed concept	Explanation
?F	*functional_unit*	Retrieve all instances of *functional_unit*
?FUN	*functional_unit_function*	Retrieve all instances of *functional_unit_function*
?P	*Process*	Retrieve all instances of *process*
?PROD	*Product*	Retrieve all instances of *product*
?PWS	*product_working_step*	Retrieve all instances of *product_working_step*
?PS	*product_cycle*	Retrieve all instances of *product_cycle*

Table 2 – Atoms of the SWRL functions.

The SWRL rules point towards the *functional_unit_function* and not the *asset_function*. This happens because the *process* realises a specific *functional_unit_function* and, as such, it is the health state of the *functional_unit* to infer to understand if a specific product's process is not doable. Finally, ORMA has *faulty_functional_unit* and *not_feasible_product* concepts that are formalised via axiomatization:

faulty_functional_unit = functional_unit and (has_health_state value "faulty")

not_feasible_product = product and (has_feasibility_state value "not feasible")

This expedient allows to classify functional units and products as faulty or not feasible, respectively, based on contingent situation of the healthy state of the functional unit. Consequently, the reasoner could infer not feasible products. Figure 9 reports the entire ontology hierarchy.

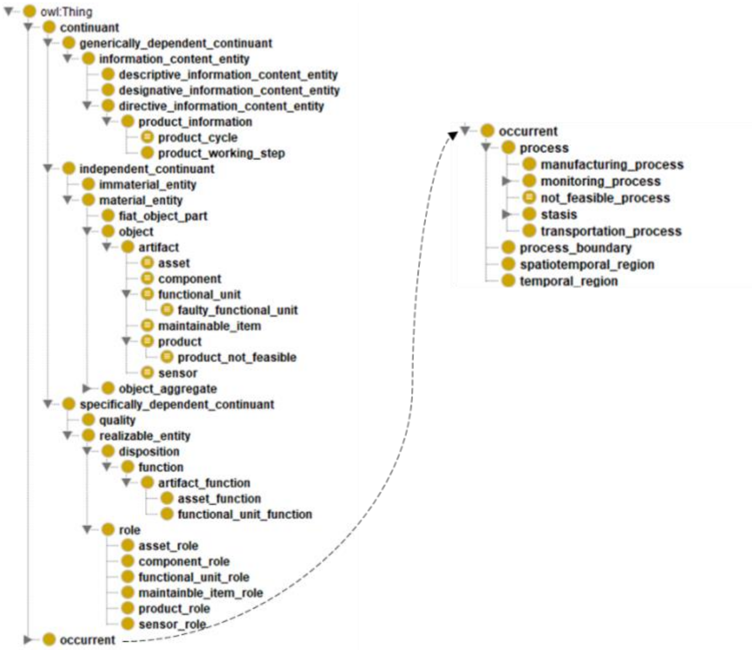

Figure 9 – ORMA ontology hierarchy.

In section 5, ORMA is applied in the context of a FML and, after having defined two products to test it, it is verified and an integrated solution, including a state detection algorithm, is deployed.

5. Application to a Flexible Manufacturing Line

In this section, the last phase of the research methodology is faced, that is the demonstration and evaluation. According to METHONTOLOGY, it includes the implementation of ORMA and its evaluation, based on the verification against CQs. Finally, the application in the FML at laboratory-scale allows to deploy an integrated solution in a controlled environment. Therefore, after providing insights on the FML in subsection 5.1, subsection 5.2 describes the implementation and verification phase where the CQs are answered; then, subsection 5.3 describes the integrated solution, where ORMA is put online to support the joint decision-making of the FML by leveraging upon shopfloor synchronised state identification and dashboarding; finally, subsection 5.4 sums up the results.

5.1 Case study details

The FML is composed by seven complex stations plus two branches for transportation only. The system aims at realising a fuzzy mobile phone with four main parts: one front cover, one PCB (Programmable Circuit Board), two fuses, one back cover. Each of the seven station accomplishes a specific operation on the semi-finished product. Figure 10 sketches out the product and the needed operations for a complete production cycle on the left-hand side, while the FML and the operations per station are reported on the right-hand side.

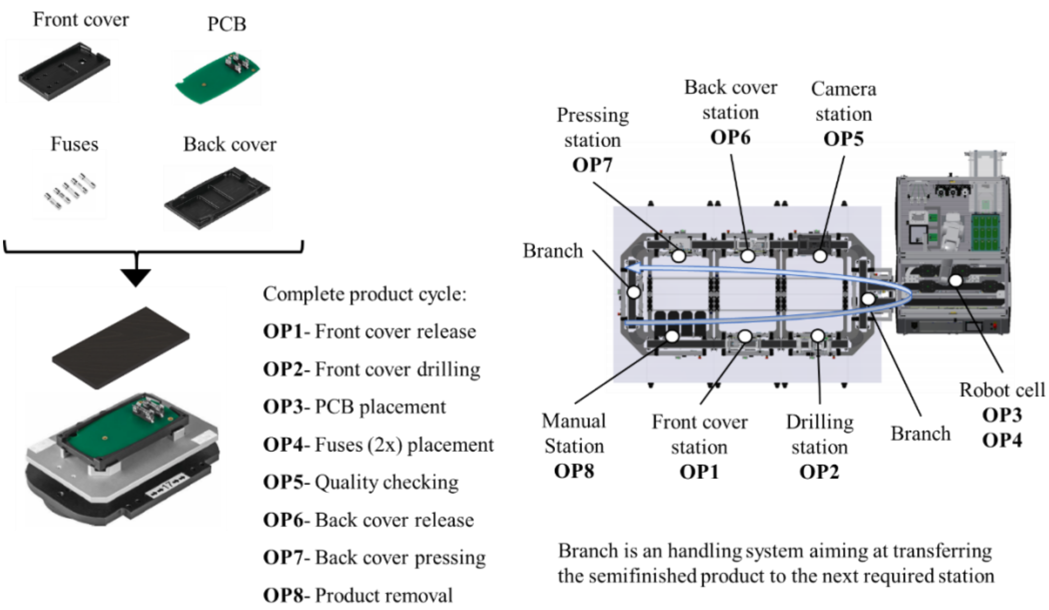

Figure 10 – Overview on the product, operations and FML.

The MES (Manufacturing Execution System) is used to select the product to be launched in production and to control the system during the operational phase with updates on product completion state.

The FML works as follows. When a certain product needs to be realised, an empty carrier starts upstream of the front cover station. When arrived in the front cover unit, the station verifies if some conditions are satisfied, like correct identification number of the carrier (through RFID, Radio Frequency IDentification) and if front cover release is needed for that product. After completing the operation, the carrier leaves the front cover station towards the drilling station. Here the process is similar to the front cover one, but the holes are realised. Also, for the other stations the overall process is the same, except for the specific manufacturing process. The branch between the drilling station and the camera station is in charge of deviating the carrier with the semifinished to the robot cell if the product requires the PCB and the fuses. Considering how the FML works, each station has, overall, two main functionalities to be performed: i) manufacture the product and ii) transport the product. Even though, the first one is optional and depends on the specific product cycle, the second one is mandatory for almost all station, except for the robot cell.

5.2 Implementation and verification of ORMA

The ontological model, namely ORMA, is implemented OWL (Web Ontology Language) since it supports reasoning [36] and it is a W3C (World Wide Web Consortium) recommendation. The used ontology editor is Protégé [112] as it is open-source and allows to install several plug-ins. For the implementation and verification of ORMA, two products are considered: *product_complete* represents the complete product that requires all the operations; *product_covers_only* represents a product that does not require the holes, nor the PCB, the fuses, the camera checking, and the pressing operation. Table 3 reports the two product cycles.

Product	Product cycle								
	Front cover station	Drilling station	Branch	Robot cell	Camera station	Back cover station	Pressing station	Branch	Manual station
product_complete	■ ●	■ ●	■ ●	■ ●	■ ●	■ ●	■ ●	■ ●	□ ●
product_covers_only	■ ●	□ ●	■ ●	□ ○	□ ●	■ ●	□ ●	■ ●	□ ●
Legend:	■ manufacturing process required					□ manufacturing process not required			
	● transportation process required					○ transportation process not required			

Table 3 – Products considered to test the ontology.

In Figure 11, an extract of the instantiated model of ORMA is presented.

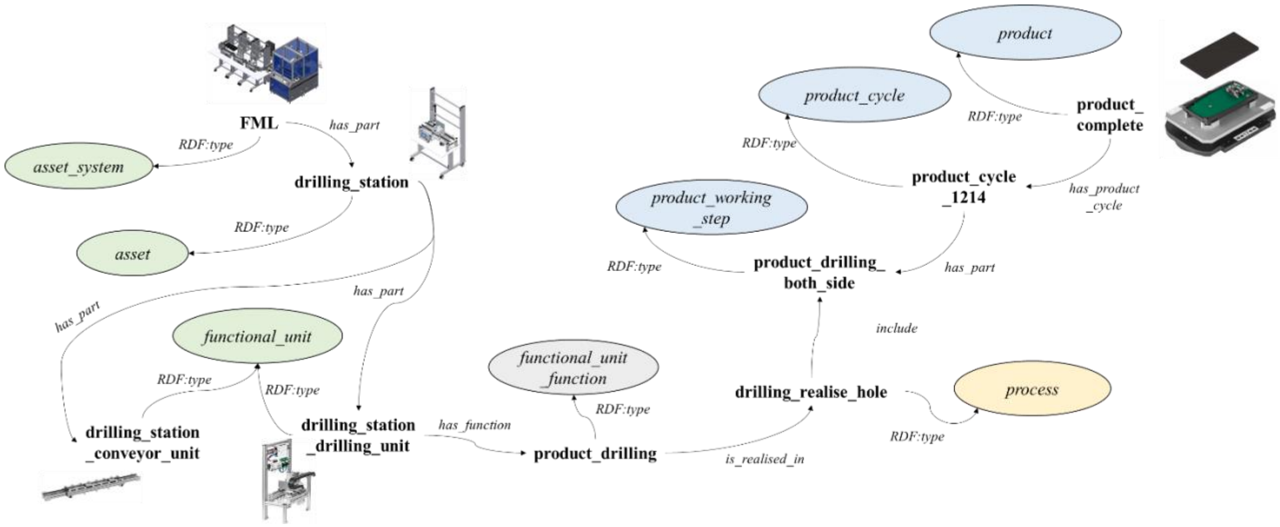

Figure 11 – Extract of the instantiation of ORMA.

To interrogate the ontology, SPARQL queries are used. The prefixes are the same for all the queries related to the asserted knowledge, whereas for the inferred knowledge (i.e., faulty functional unit/s and not feasible product/s) the Snap SPARQL query plugin is used. The CQs tested are the ones derived from the specification phase (see subsection 4.1) of the methodology, that are: the assets composing the system (CQ1), the products realised (CQ2), the processes for each product (CQ3) and the not feasible product given certain health state of the functional units (CQ4). As an extract, the screenshot of Protégé for CQ3 is reported in Figure 12. For CQ4, the *has_health_state* data values are changed from faulty to healthy and vice versa to test the answers in several combinations.

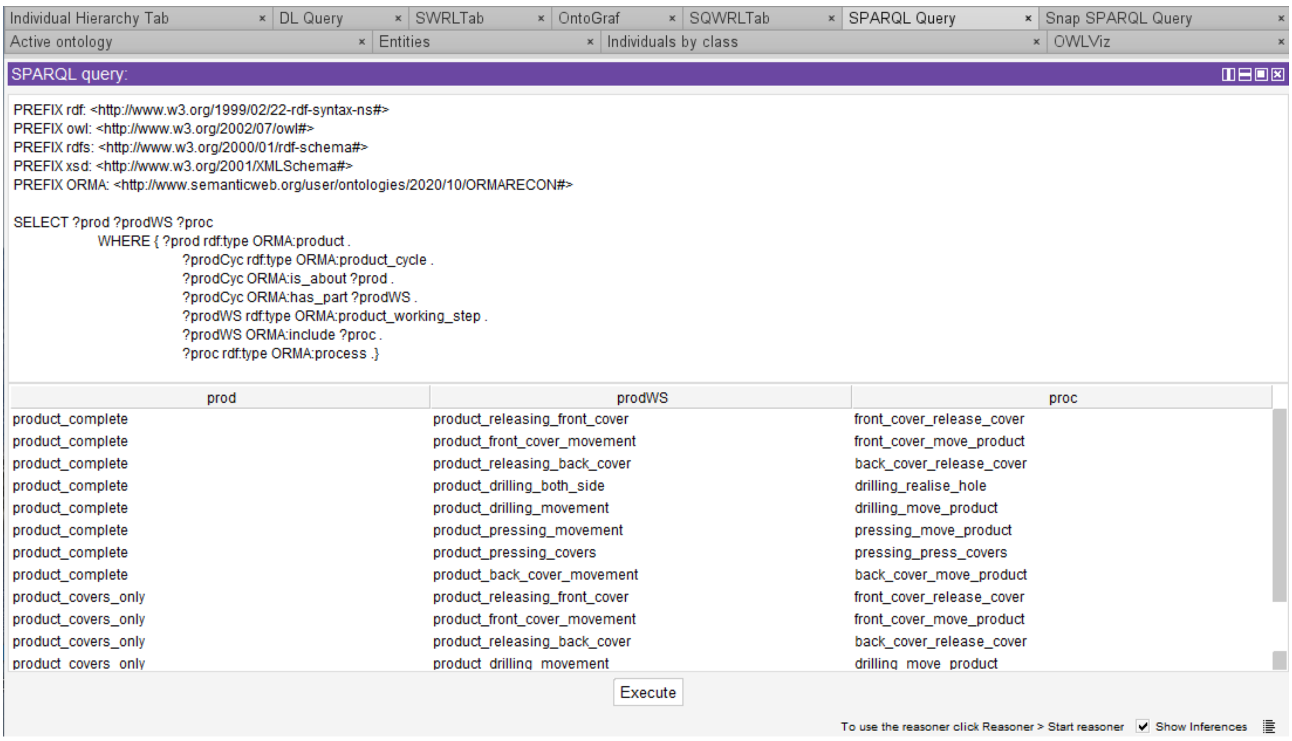

Figure 12 – SPARQL query outputs for CQ3.

5.3 Integrated solution deployment

The deployment of the integrated solution is pursued to support reconfigurability-related decisions. As such, the ontology is made operative by interacting with the assets and sensors installed in the FML to infer product feasibility. A set of requirements (Rx) is defined that the solution should accomplish to be effective:

R0 The data must be gathered from the assets via proper mean/s, collecting directly from onboard devices (like PLC, Programmable Logic Controller or Raspberry Pi) or from centralised storages (like relational or non-relational databases).

R1 The health state needs to be recognised through suitable state detection algorithm/s.

R2 The data values in the ontology have to be updated accordingly with the new information coming from the shopfloor, i.e., health states, if needed.

R3 The reasoner needs to be launched, inferring properly the feasibility or not of products.

R4 The results of the reasoner should be made available to a human decision-maker to promptly let her/him be aware of possible infeasibilities, activating a reconfigurability-related decision.

Figure 13 graphically summarises the structure of the solution, with evidence on the Rx. The solution realises on Protégé as ontology editor (see subsection 5.2), OWLAPI to synchronise the reasoner and Python to manage the algorithms and the knowledge base (ORMA) in a flexible way via ad-hoc functions and libraries, as RDFLIB (link) and OWLREADY2 (link). The web-based dashboard is developed in HTML (HyperText Markup Language). The technological choices behind the solution are aligned with the state-of-the-art [22].

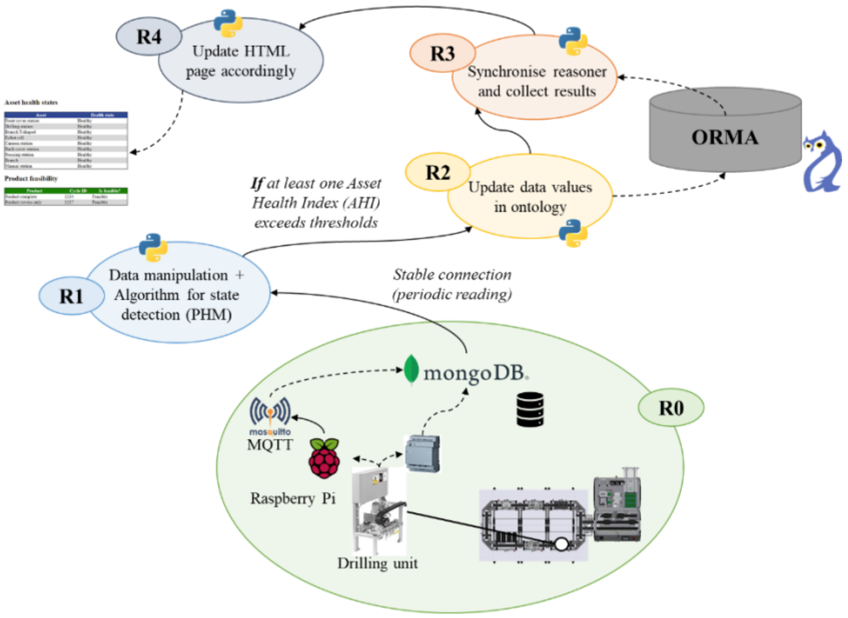

Figure 13 – Structure of the integrated solution.

To absolve to R0, the traditional PHM-related steps inspired by the ISO 13374 [93] are followed. The data acquisition step is made easy by the already present architecture of the laboratory [113] (**R0)**. In the laboratory, the operational data are collected for the drilling unit only, i.e., the functional unit of the drilling station in charge of realising the holes on the product. For the conveyor as functional unit and all the other assets, only sensors for the automation of the FML are installed and are Boolean values with very few, even no, informative content in the scope of reconfigurability. The accelerations on the *x*, *y*, and *z* axes (measured in *g*, that is, 9.81 m/s^2) are the operational variables related to the drilling unit and sent to a non-relational document database, i.e., mongoDB after being collected through Raspberry Pi.

To satisfy R1, some intermediary steps are needed as schemed out in [114]. Firstly, the operational data of 100 products are collected, where the drilling unit was always in healthy state. After the pre-processing activities that include coping with outliers and missing data, relevant features are extracted and the ones better representing are selected. The Root Mean Square (RMS) has been identified as the relevant feature (three RMS, one for each axis). The RMS is selected due to its physical meaning, that is energy dissipated due to vibrations. The RMS on each axis is assumed to follow a normal distribution. The normality test demonstrates the goodness of the assumption and so each RMS could be described as follows:

$$RMS_X \sim N(\mu_X = 1.134\ , \sigma_X = 0.1004)\ [\mathrm{g}]$$

$$RMS_Y \sim N(\mu_Y = 1.090, \sigma_Y = 0.06446)\ [\mathrm{g}]$$

$$RMS_Z \sim N(\mu_Z = 1.101, \sigma_Z = 0.08749)\ [\mathrm{g}]$$

If at least one RMS values exceeds an upper threshold set to $\mathrm{RMS}_{\mathrm{fault}} = \mu + 3\sigma$ the drilling unit could be considered in a faulty state [115]. In so doing, the algorithm is able to recognise the state of the drilling unit, absolving to **R1**. As such, the RMS is also identified as a relevant AHI (Asset Health Index), thus being three AHIs, one per axis.

If the health state of the drilling unit changes from healthy to faulty or vice versa, the data values in the ontology should be changed accordingly. The data property *has_health_state^^xsd:string* is modified through the main Python script. This guarantees the informative content in the ontology is synchronized with the shopfloor (**R2**). HermiT reasoner is then launched to infer which set of products is not feasible (**R3**). In this task, a proper definition of the SWRL rules (Figure 8) is fundamental to guarantee suitable functioning of the reasoning.

Finally, the HTML is updated according to the new information retrieved by the ontology (**R4**), that involves:

- Change of the healthy/faulty label of the assets in the FML.
- Change of the feasibility/not feasibility label of the product.

As a proxy, an asset that has at least one functional unit in a faulty state is faulty itself. So, for instance, if the conveyor of the drilling is healthy and the drilling unit is faulty, the drilling station is shown as faulty. Nevertheless, products not requiring holes will be feasible since the only required function to the drilling station is transportation and the conveyor is healthy. Figure 14 and Figure 15 show the terminal’s displayed information used for debugging the solution.

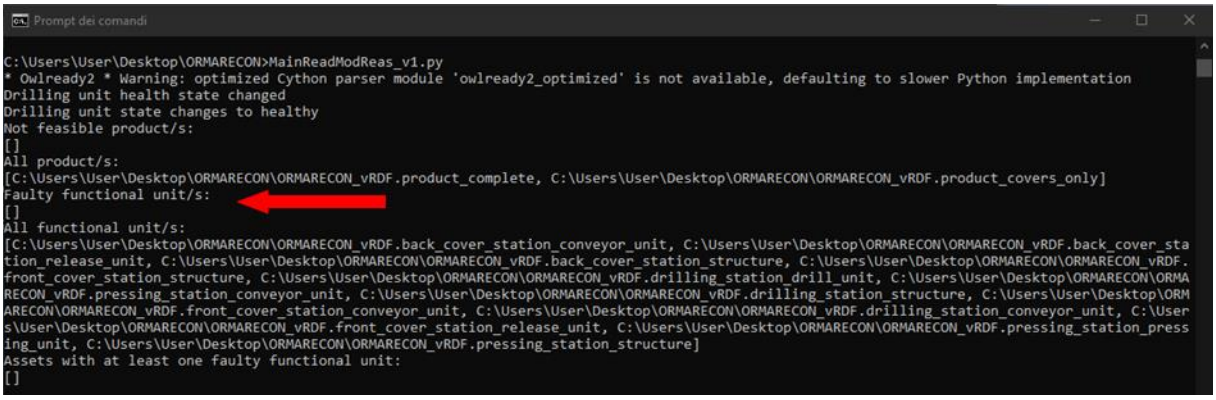

Figure 14 – Terminal’s displayed information for debugging: drilling unit is healthy, so there are no faulty functional units, and all products are feasible.

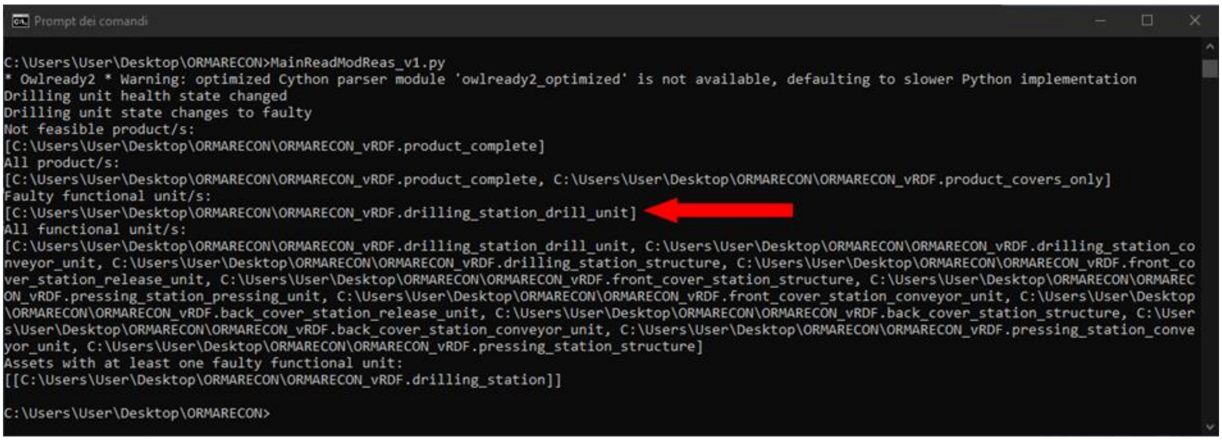

Figure 15 – Terminal's displayed information for debugging: drilling unit is faulty, so there is one faulty functional unit, and the drilling station results faulty; the *product_complete* is not feasible.

Figure 16 shows the dashboard with information on the health states of the assets installed in the FML and the feasibility of the product with evidence on the product cycle ID that each product is following, as retrieved a priori from the MES.

Asset health states

Asset	Health state
Front cover station	Healthy
Drilling station	Healthy
Branch T-shaped	Healthy
Robot cell	Healthy
Camera station	Healthy
Back cover station	Healthy
Pressing station	Healthy
Branch	Healthy
Manual station	Healthy

Product feasibility

Product	Cycle ID	Is feasible?
Product complete	1214	Feasible
Product covers-only	1217	Feasible

Figure 16 – Laboratory dashboard with information on assets' health states and product feasibility.

The entire architecture is running on a local computer with 12 GB of RAM and an Intel® Core™ i5-8250U CPU @1.80 GHz. Overall, the solution guarantees adequate computational performance, and the time scale of the evaluation is comparable with the time scale of the production process. The most cumbersome activity is the RMS evaluation and comparison with predefined health state population. Moreover, additional time is required to update the data values in OWL and synchronise the reasoner. The HTML page has a refresh rate of 10 seconds. In the worst case, the change in the health state of an asset and the unfeasibility of a product is shown 25 seconds after the product left the drilling station.

5.4 Results and discussion

The integrated solution shows some advantages, especially related to the possibility to merge and augment information from PHM-related algorithms and the asserted knowledge in ORMA. Indeed, the usage of this solution, even though in the controlled environment of the laboratory scaled FML, highlights the following points, worth to mention:

1. The three-module structure of ORMA, encompassing the main concepts related to asset, process, and product, allows to infer new information by augmenting the outputs of the state detection algorithms, in a synchronised manner with the shopfloor.

2. The visualisation of the results via a web-based dashboard supports human decision-making by showing in a synthetic way the current health states of the assets and the feasibility of the various products.
3. Through the MES, the products being realised and scheduled could be removed if needed. Indeed, the MES allows to modify the orders, eventually by annulling some products already in the system, so to dynamically adjust to the contingent state of the assets.

The developed solution demonstrates that ORMA, and ontologies in general, could be used in two ways in smart factories:

1. **To augment information**, by inferring the asserted knowledge through reasoning capabilities, in order to feedback augmented information that could be of interest to multiple stakeholders within and, even beyond, outside the factory.
2. **To dispatch information**, by routing the right information to the right person at the right time, thus improving the information management and integration strategy of the company and boosting multiple decision-making processes at the same time.

Therefore, ontologies could play a significant role in the future for smart factories, given that data, information, and knowledge will continuously rise up and their management and integration is more challenging than ever.

6. Conclusions

This research work aims at improving ontologies for PHM, so far limited in their scope to maintenance only. Therefore, reconfigurability at operational and shopfloor level is tackled, by inferencing product feasibility according to the current health state of the system/asset. As such, a shopfloor-synchronised and joint decision-making process for maintenance and production is established. This has been understood as a main gap from previous literature on ontologies for PHM, which generally lack integrating product- and process- related knowledge. Hence, ORMA ontology is proposed, which makes the three-module structure as one of its core characteristics. Despite being an asset-centric ontology, ORMA connects traditional PHM-related concepts with process and product ones. Then, through the establishment of proper axioms and SWRL rules, the inferencing capabilities are enhanced. Upon verification, ORMA is made operative in an integrated solution developed in a FML at laboratory scale. A health state detection algorithm checks the current state of the functional units; then, if the state has changed from the previous evaluation, the data values in ORMA are updated and the reasoner is synchronised. The inferred and augmented information about product feasibility is displayed via a web-based dashboard to support human-based decision-making. Different decisions could be taken, balancing maintenance and production requirements and objectives. When scaled up, the developed ontology and ontology-based solution could promote a joint maintenance and production planning and control, making conscious the company managers of the current state of their assets and the feasibility of their production schedule. Hence, multiple and separated decision-making processes are aligned and harmonised, overcoming the traditional silo approach and concurring to value creation for the company.

Limitations of this research are both on the ontological modelling side as well as the technological deployment. Firstly, ORMA could not manage multiple cycles a product may have. Therefore, ORMA is limited in managing the knowledge in situations where a product may be realised by different machines of the same type in the same working step. On the side of technological deployment, the FML has today few sensors able to gather operational variables. Therefore, the knowledge extractable from the system is limited by their availability. About ORMA, further research will involve these limitations to build a more extended solution, in terms of managed routings and operational variables.

More generally, future research regarding ontologies based on PHM-related approaches should: i) exploit more product-related knowledge, e.g., product cycles and routings, to promote cross-functional decisions that is fundamental in knowledge-intensive smart factories, ii) entail investigations on automated decision-making, i.e., autonomous selection of alternative routings and, in general, autonomous reorganisation of the production scheduling, iii) extension to other relevant dimensions, like product quality and energy management that are vital to guarantee sustainable performance of the operations.

The long-term vision is to realise an asset-centric and ontology-based solution for smart factories based on CPS. Once the semantic and technical interoperability is overcome, the solution will be able to properly balance automated and human decision-making, and to dispatch the right information in the right moment and to the right person in a reactive and proactive way towards operational excellence.

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