



# ENERGY-AWARE FACTORY ANALYTICS FOR PROCESS INDUSTRIES

Deliverable D3.3

## Factory Knowledge for Cognition

**Version**  
1.2

**Lead Partner**  
EPFL

**Date**  
25/10/2023

**Project Name**  
FACTLOG – Energy-aware Factory Analytics for Process Industries

<b>Call Identifier</b> H2020-NMBP-SPIRE-2019	<b>Topic</b> DT-SPIRE-06-2019 - Digital technologies for improved performance in cognitive production plants
<b>Project Reference</b> 869951	<b>Start date</b> November 1 <sup>st</sup> , 2019
<b>Type of Action</b> IA – Innovation Action	<b>Duration</b> 42 Months

## Dissemination Level

X	<b>PU</b>	Public
	<b>CO</b>	Confidential, restricted under conditions set out in the Grant Agreement
	<b>CI</b>	Classified, information as referred in the Commission Decision 2001/844/EC

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## Executive Summary

The main goal of this deliverable is to boost the cognition process (i.e., the management of enhanced cognitive digital twins) with the factory knowledge, derived mainly in WP4, required for the internal reasoning processes. One of the main challenges will be to understand the role of process and domain knowledge in the cognition process formalized in T3.1, leading to a completely new view on the factory knowledge and consequently on the methods for processing and validating it. The main outcome is a set of interfaces for accessing that knowledge. In addition, feedback about the validity of knowledge will be sent as feedback to support the FACTLOG platform development.

In this deliverable, ontology and knowledge graph models are first investigated. Then cognitive factory services and knowledge graph modelling are identified to provide all the functionalities of knowledge graph models. Then ontology based on the BFO is introduced. Based on the ontology, knowledge graph models are developed. Finally, the integration of knowledge graph models and FACTLOG platform is demonstrated including three approaches: 1) integration based on OWL models; 2) integration based on Neo4j; 3) integration based on HTTP.

## Revision History

Revision	Date	Description	Organisation
0.1	18/06/2022	First draft of the deliverable	EPFL
0.3	22/06/2022	Second draft of the deliverable	EPFL
0.3	28/06/2022	Third draft of the deliverable	JSI
0.4	29/06/2022	Final draft ready for internal review	EPFL
0.5	01/07/2022	Peer review	AUEB, TAGES
0.6	05/07/2022	Update based on the reviewers' comments	EPFL
1.0	05/07/2022	Final version ready for submission	EPFL
1.2	25/10/2023	Addressing the comments from EC	EPFL

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# Table of Contents

- Executive Summary .....3**
- Revision History .....4**
- 1 Introduction.....9**
  - 1.1 Purpose and Scope .....9
  - 1.2 Relation with other Deliverables .....9
  - 1.3 Structure of the Document.....9
- 2 Ontology for knowledge definition about factory .....11**
  - 2.1 Ontology Engineering and Semantic Modelling .....11
    - 2.1.1 Ontology Engineering.....11
    - 2.1.2 Semantic Modelling .....11
    - 2.1.3 Basic Ontology Concepts .....12
  - 2.2 Semantic Modelling Languages.....13
  - 2.3 Knowledge Graph Modelling .....15
  - 2.4 Semantic Reasoning based on Knowledge Graph Models.....16
  - 2.5 Summary and Motivation .....16
- 3 Cognitive Factory Services and KGM .....18**
  - 3.1 Cognitive Factory Twins based on Knowledge Graph Models .....18
  - 3.2 The functions of Knowledge Graph Models in FACTLOG Factory scenario .....18
- 4 Ontology definition for KGM.....19**
  - 4.1 Guidance to KGM for cognition services of factory .....19
    - 4.1.1 Knowledge Graph Modelling .....20
    - 4.1.2 Reasoning for the scenario.....21
  - 4.2 FACTLOG Ontology developed for KGM in FACTLOG.....23
    - 4.2.1 Principles.....23
    - 4.2.2 Methodology.....23
    - 4.2.3 Ontology Framework.....24

- 4.3 Ontology for each Pilot and Technical Partner .....27
- 4.4 Ontology for Anomaly Detection .....28
- 5 Knowledge Graph Modelling based on FACTLOG Ontology.....29**
  - 5.1 Knowledge Graph Modelling for BRC .....29
    - 5.1.1 Pilot description .....29
    - 5.1.2 PN model formalism .....30
    - 5.1.3 Optimization formalism .....30
  - 5.2 Knowledge Graph Modelling for PIA.....31
    - 5.2.1 Pilot description .....31
    - 5.2.2 Optimization formalism .....32
  - 5.3 Knowledge Graph Modelling for JEMS.....33
    - 5.3.1 Pilot description .....33
  - 5.4 Knowledge Graph Modelling for TUPRAS .....33
    - 5.4.1 Pilot description .....34
    - 5.4.2 PM model formalism.....34
    - 5.4.3 Optimization formalism .....35
    - 5.4.4 Data analysis formalism .....36
  - 5.5 Knowledge Graph Modelling for CONT .....36
    - 5.5.1 Pilot description .....37
    - 5.5.2 Optimization formalism .....37
- 6 Integration of KGM and Cognition Services in the FACTLOG platform.....39**
  - 6.1 Integration based on OWL models .....39
  - 6.2 Integration based on Neo4j .....39
  - 6.3 Integration based on HTTP API.....40
  - 6.4 Cognition services for FACTLOG Factories.....41
    - 6.4.1 Cognition services based on OWL .....41



6.4.2 Cognition services based on Knowledge Graph Models in Graphical Database  
48

**7 Conclusion .....52**

**References .....53**

**Appendix I – Integrating KGM based on OWL.....55**

**Appendix II – Knowledge Graph Modeling tools.....57**

## List of Figures

Figure 1: Knowledge graph models and cognition services to FACTLOG factory [15] .....18

Figure 2: Scenario Overview -A: System of systems perspective; -B: Operational view....19

Figure 3: Knowledge graph models -A: Class; -B: Object property; -C: Data property; -  
Individuals.....20

Figure 4 Define relationship rules between classes .....21

Figure 5: Reasoning results .....21

Figure 6: Reasoning results .....22

Figure 7: Ontology development workflow .....23

Figure 8: Ontology framework based on BFO.....24

Figure 9: Ontology for describing anomaly detection processes.....28

Figure 10: Ontology classes for describing anomaly detection processes.....28

Figure 11: Knowledge graph models based on developed ontology .....29

Figure 12: Ontology class, object property and individuals for BRC pilot description .....29

Figure 13: Ontology class, object property and individuals for simulation in BRC pilot  
description .....30

Figure 14: Ontology class, object property, data property and individuals for optimization for  
BRC pilot.....30

Figure 15: Individuals for describing the optimization scenario for BRC pilot.....31

Figure 16: Ontology class, object property and individuals for PIA pilot description .....31

Figure 17: Ontology class, object property, data property and individuals for optimization  
for PIA pilot .....32

Figure 18: Individuals for describing the optimization scenario for PIA pilot .....32

Figure 19: Ontology class, object property, data property and individuals for optimization  
for JEMS pilot .....33

Figure 20: Ontology class, object property, data property and individuals for pilot description  
in TUPRAS pilot.....34

Figure 21: Individuals for process model description for TUPRAS pilot.....34

Figure 22: Ontology class, object property, and data property for optimization for TUPRAS  
pilot .....35

Figure 23: Individuals for optimization in TUPRAS pilot.....35

Figure 24: Ontology class, object property, and data property for data analysis in TUPRAS  
pilot .....36

Figure 25: Individuals for data analysis in TUPRAS pilot.....36

Figure 26: Ontology class, object property, data property and individuals for CONT pilot .37

Figure 27: Ontology class, object property, data property and individuals for optimization for CONT pilot .....37

Figure 28: Individuals for describing the optimization scenario for CONT pilot .....38

Figure 29: Workflow for visualizing knowledge graph model .....39

Figure 30: OWL model transformed into Neo4j.....39

Figure 31. Diagram displaying the components' interaction at the KG-based analytics for process optimization architecture. ....40

Figure 32: Anomaly scenario for CONT pilot .....41

Figure 33: Knowledge graph models for CONT pilot .....41

Figure 34: Reasoning result for CONT pilot.....42

Figure 35: Anomaly scenario for BRC pilot.....43

Figure 36: Knowledge graph models for BRC pilot.....43

Figure 37: Reasoning result for BRC pilot.....44

Figure 38: Anomaly scenario for JEMS pilot .....45

Figure 39: Knowledge graph models for JEMS pilot .....45

Figure 40: Reasoning result for JEMS pilot.....46

Figure 41: Anomaly scenario for PIA pilot.....46

Figure 42: Knowledge graph models for PIA pilot.....47

Figure 43: Reasoning result for PIA pilot .....47

Figure 44: Reasoning result for CONT pilot.....48

Figure 45. Diagram displaying how the KG-based analytics for process optimization service is used by the use cases we worked for. ....49

Figure 46. Graph visualization of the ontology we created. ....49

Figure 47. Individuals created in the ontology-based knowledge base based on data on multiple calls to the HTTP API. ....50

Figure 48. Motor power sensor .....50

Figure 49. Pressure sensor .....51

Figure 50. Temperature sensor.....51

Figure 51: Eclipse project .....55

Figure 52: Change the path for loading OWL files. ....55

Figure 53: Compile the whole project .....56

Figure 54: Visualize the OWL information.....56

## List of Tables

Table 1 – Mapping between ontology concepts and other deliverables.....27

Table 2 – Anomaly detection scenario for CONT pilot .....41

Table 3 – Anomaly detection scenario for BRC pilot.....42

Table 4 – Anomaly detection scenario for JEMS PILOT .....44

Table 5 – Anomaly detection scenario for PIA pilot .....46



# 1 Introduction

## 1.1 Purpose and Scope

This document refers to a technical report about ontology and knowledge definition in Task 3.3 and providing a guidance for defining all the entities and relations in the context of five FACTLOG Pilots and technical partners about enhanced cognitive digital for factory. Knowledge Graph Model (KGM) denotes a generic ontology representation and description with all related product and equipment elements which is considered as a domain knowledge defined in this report. The enhanced cognitive twins are developed based on AI methods, algorithms, mechanisms, services and tools with knowledge graph models integrated into an overall modelling application.

In each specialized FACTLOG use case, the enhanced cognitive digital twins are developed based on related products, methods, algorithms and mechanisms with the knowledge graph models which require a unified and high-level abstract ontology definition because of the domain specific knowledge across different pilots. In the whole FACTLOG platform, the knowledge graph models are used to describe the factory knowledge, the platform services and their interrelationships. KGM is used to interconnect and interoperate with external AI tools, Optimization tools, Analytics tools, data visualization tools, etc. These tools require to develop the data interfaces based on the developed ontology for importing and exporting knowledge graph models. According to specific cognition needs, the knowledge graph models can be developed to implement reasoning to support anomaly detection.

The main content deals with the design and implementation of knowledge and development of knowledge graph models for reasoning. To summarize, main objectives of this report are:

- Develop knowledge graph models based on a top-level ontology for cognition services for analytic and dynamic models in the factory scenarios across FACTLOG pilot;
- Provide a reasoning approach for anomaly detection and data analysis for factory scenarios of FACTLOG.
- An integration approach based on Neo4j is introduced to demonstrate how FACTLOG platform is integrated with knowledge graph models to support decision-making.

## 1.2 Relation with other Deliverables

D2.1 is the input of this deliverable for pilot information.

D3.1 is the input of this deliverable for Enhanced Cognitive Twin definition.

D4.2 is an important reference of this deliverable for ontology definition.

D8.3 is the input of this deliverable for knowledge graph modelling specification.

## 1.3 Structure of the Document

Section 2 introduces the background of ontology, semantic modelling and knowledge graph modelling. Section 3 introduces the cognitive factory services and knowledge graph models. Section 4 introduces FACTLOG ontology based on BFO for knowledge graph modelling.

Section 5 introduces the knowledge graph models which are developed based on FACTLOG ontology. Section 6 introduces integration of knowledge graph models and cognition services in FACTLOG platform. Section 7 offers conclusions.

## 2 Ontology for knowledge definition about factory

### 2.1 Ontology Engineering and Semantic Modelling

#### 2.1.1 Ontology Engineering

Ontology engineering is the general term of methodologies and methods for building ontologies. Ontology engineering refers to “The set of activities that concern the ontology development and the ontology lifecycle, the methods and methodologies for building ontologies and the tool suites and languages that support them”. The results of ontology engineering provide domain knowledge representation to be reused efficiently and prevent waste of time and money which are usually caused by non-shared knowledge. It helps Information Technology (IT) to operate with interoperability and standardization.

Ontology represents the nature of being, becoming, existence, and so on in the way of philosophy. One of the most well-known is: “ontology is an explicit, formal specification of a shared conceptualization of a domain of interest” [12].

Ontology represents the following ideas together [17]:

- Semantic modelling can help defining the data and the relationships between entities.
- An information model provides the ability to abstract different kind of data and provides an understanding of how the data elements are related.
- A semantic model is a type of information model that supports the modelling of entities and their relationships.
- The total set of entities in our semantic model comprises the taxonomy of classes we use in our model to represent the real world.

#### 2.1.2 Semantic Modelling

The main objective of semantic modelling techniques is to define the meaning of data within the context of its correlation, and to model the domain world in the abstract level. The benefits of exploiting semantic data models for business applications are mainly as follows:

- **Avoiding misunderstanding:** by providing a clear, accessible, agreed set of terms, relations as a trusted source and discussions, misunderstandings can easily be resolved.
- **Conduct reasoning:** by being machine-understandable and through the usage of logic statements (rules), ontologies enable automatic reasoning and inference which leads to the automatic generation of new and implicit knowledge.
- **Leverage resources:** by extending and relating an application ontology to external ontological resources, via manual or automatic mapping and merging processes, the need for repetition of entire design process for every application domain is eliminated.
- **Improve interoperability:** semantic models can serve as a basis for schema matching to support systems’ interoperability in close environments where systems,

tools and data sources have no common recognition of data type and relationships.

### 2.1.3 Basic Ontology Concepts

Ontologies provide formal models of domain knowledge exploited in different ways. Therefore, ontology plays a significant role in many knowledge-intensive applications. Depending on corresponding languages, a number of different knowledge representation formalisms exist.

Ontologies provide formal models of domain knowledge exploited in different ways. Therefore, ontology plays a significant role for many knowledge-intensive applications. Depending on corresponding languages, a number of different knowledge representation formalisms exist. However, they share a minimal set of components as follows:

- Classes represent concepts, which are taken in a broad sense. For instance, in the Product Lifecycle domain, concepts are: Life Cycle phase, Product, Activity, Resources, Even, and so on. Classes in ontology are usually organized in taxonomies through which inheritance mechanisms can be applied.
- Relations represent a type of association between concepts of the domain. They are formally defined as any subset of a product of  $n$  sets, that is:  $R \subset C_1 \times C_2 \times \dots \times C_n$ . Ontologies usually contain binary relations. The first argument is known as the domain of the relation, and the second argument is the range.
- Formal axioms serve to model sentences that are always true. They are normally used to represent knowledge that cannot be formally defined by the other components. In addition, formal axioms are used to verify the consistency of the ontology itself or the consistency of the knowledge stored in a knowledge base. Formal axioms are very useful to infer new knowledge.

For instance, Energy Efficiency at Buildings domain could be that it is not possible to build a public building without a fire door (based on legal issues).

- Instances are used to represent elements or individuals in an ontology.

As a Design Rationale (DR), ontology can be used as follows [6]:

- Level 1: Used as a common vocabulary for communication among distributed agents.
- Level 2: Used as a conceptual schema of a relational database. Structural information of concepts and relations among them is used. Conceptualization in a database is nothing other than conceptual schema. Data retrieval from a database is easily done when there is an agreement on its conceptual schema.
- Level 3: Used as the backbone information for a user of a certain knowledge base. Levels higher than this plays role of the ontology, which has something to do with "content".
- Level 4: Used for answering competence questions.
- Level 5: Standardization
  - Standardization of terminology (at the same level of Level 1)
  - Standardization of meaning of concepts
  - Standardization of components of target objects (domain ontology).
  - Standardization of components of tasks (task ontology)

- Level 6: Used for transformation of databases considering the differences of the meaning of conceptual schema. This requires not only the structural transformation but also semantic transformation.
- Level 7: Used for reusing knowledge of a knowledge base using DR information.
- Level 8: Used for reorganizing a knowledge base based on DR information.

## 2.2 Semantic Modelling Languages

Several semantic modelling languages are developed to support ontology definition and semantic modelling.

- **XML-based Ontology Exchange Language:** The US bioinformatics community designed XOL for the exchange of ontology definitions among a heterogeneous set of software systems in their domain. Researchers developed it after studying the representational needs of experts in bioinformatics. They selected Ontolingua (a Tool for Collaborative Ontology Construction) and OML as the basis for creating XOL, merging the high expressiveness of OKBC-Lite, a subset of the Open Knowledge Based Connectivity protocol, and the syntax of OML, based on XML. There are no tools that allow the development of ontologies using XOL. However, since XOL files use XML syntax, we can use an XML editor to author XOL files.
- **Simple HTML Ontology Extension:** SHOE is a small extension to HTML which allows web page authors to annotate their web documents with machine-readable knowledge. SHOE makes real intelligent agent software on the web possible. HTML was never meant for computer consumption; its function is for displaying data for humans to read. The "knowledge" on a web page is in a human-readable language (usually English), laid out with tables and graphics and frames in ways that we as humans comprehend visually. Unfortunately, intelligent agents aren't human. Even with state-of-the-art natural language technology, getting a computer to read and understand web documents is very difficult. This makes it very difficult to create an intelligent agent that can wander the web on its own, reading and comprehending web pages as it goes. SHOE eliminates this problem by making it possible for web pages to include knowledge that intelligent agents can actually read.
- **Ontology Markup Language:** OML, developed at the University of Washington, is partially based on SHOE. In fact, it was first considered an XML serialization of SHOE. Hence, OML and SHOE share many features. Four different levels of OML exist: OML Core is related to logical aspects of the language and is included by the rest of the layers; Simple OML maps directly to RDF(S); Abbreviated OML includes conceptual graphs features; and Standard OML is the most expressive version of OML. We selected Simple OML, because the higher layers don't provide more components than the ones identified in our framework. These higher layers are tightly related to the representation of conceptual graphs. There are no other tools for authoring OML ontologies other than existing general-purpose XML edition tools.
- **Ontology Interchange Language:** OIL, developed in the OntoKnowledge project ([www.ontoknowledge.org/OIL](http://www.ontoknowledge.org/OIL)), permits semantic interoperability between Web resources. Its syntax and semantics are based on existing proposals (OKBC, XOL, and RDF(S)), providing modelling primitives commonly used in frame-based approaches to ontological engineering (concepts, taxonomies of concepts, relations, and so on), and formal semantics and reasoning support found in description logic approaches (a subset of first order logic that maintains a high expressive power,

together with decidability and an efficient inference mechanism). OIL, built on top of RDF(S), has the following layers: Core OIL groups the OIL primitives that have a direct mapping to RDF(S) primitives; Standard OIL is the complete OIL model, using more primitives than the ones defined in RDF(S); Instance OIL adds instances of concepts and roles to the previous model; and Heavy OIL is the layer for future extensions of OIL. OILed, Protégé2000, and WebODE can be used to author OIL ontologies. OIL's syntax is not only expressed in XML but can also be presented in ASCII. We use ASCII for our examples.

- **DARPA Agent Markup Language+OIL:** DAML+OIL has been developed by a joint committee from the US and the European Union (IST) in the context of DAML, a DARPA project for allowing semantic interoperability in XML. Hence, DAML+OIL shares the same objective as OIL. DAML+OIL is built on RDF(S). Its name implicitly suggests that there is a tight relationship with OIL. It replaces the initial specification, which was called DAML-ONT, and was also based on the OIL language. OILed, OntoEdit, Protégé2000, and WebODE are tools that can author DAML+OIL ontologies.
- **OWL:** OWL is the result of the work of the W3C Web Ontology Working Group. This language derived from DAML+OIL and, as the previous languages, is intended for publishing and sharing ontologies in the Web. OWL is built upon RDF(S), has a layered structure and is divided into three sublanguages: OWL Lite, OWL DL and OWL Full. OWL is grounded on Description Logics and its semantics are described in two different ways: as an extension of the RDF(S) model theory and as a direct model-theoretic semantics of OWL. Both of them have the same semantic consequences on OWL ontologies.
- **OWL 2:** OWL 2 is an extension and revision of OWL that adds new functionality with respect to OWL; some of the new features are syntactic sugar (e.g., disjoint union of classes) while others offer new expressivity. OWL 2 includes three different profiles (i.e., sublanguages) that offer important advantages in particular application scenarios, each trading off different aspects of OWL's expressive power in return for different computational and/or implementation benefits. These profiles are:
  - **OWL 2 EL:** It is particularly suitable for applications where very large ontologies are needed, and where expressive power can be traded for performance guarantees.
  - **OWL 2 QL:** It is particularly suitable for applications where relatively lightweight ontologies are used to organize large numbers of individuals and where it is useful or necessary to access the data directly via relational queries (e.g., SQL).
  - **OWL 2 RL:** It is particularly suitable for applications where relatively lightweight ontologies are used to organize large numbers of individuals and where it is useful or necessary to operate directly on data in the form of RDF triples. OWL 2 ontologies: The Direct Semantics that assigns meaning directly to ontology structures and the RDF- Based Semantics that assigns meaning directly to RDF graphs.
- **Resource Description Framework and RDF Schema:** RDF, developed by the W3C for describing Web resources, allows the specification of the semantics of data based on XML in a standardized, interoperable manner. It also provides mechanisms to explicitly represent services, processes, and business models, while allowing recognition of nonexplicit information. The RDF data model is equivalent to the semantic networks formalism. It consists of three object types:
  - ✓ Resources are described by RDF expressions and are always named by URIs plus optional anchor IDs
  - ✓ Properties define specific aspects, characteristics, attributes, or relations used



to describe a resource

- ✓ Statements assign a value for a property in a specific resource (this value might be another RDF statement)

The RDF data model does not provide mechanisms for defining the relationships between properties (attributes) and resources—this is the role of RDFS. RDFS offers primitives for defining knowledge models that are closer to frame-based approaches. RDF(S) is widely used as a representation format in many tools and projects, such as Amaya, Protégé, Mozilla, SilRI, and so on.

According to W3C, RDF model has advantages as follows:

- The RDF model is made up of triples: as such, it can be efficiently implemented and stored; other models requiring variable-length fields would require a more cumbersome implementation
- The RDF model is essentially the canonicalization of a (directed) graph and has all the advantages (and generality) of structuring information using graphs
- The basic RDF model can be processed even in absence of detailed information (an "RDF schema") on the semantics: it already allows basic inferences to take place, since it can be logically seen as a fact basis
- The RDF model has the important property of being modular

The union of knowledge (directed graphs) is mapped into the union of the corresponding RDF structures. Since RDF is a standard model for data interchange and is a W3C recommendation designed to standardize the definition and use of metadata-descriptions of Web-based resources, it is well suited to representing data. As knowledge representation, when it comes to semantic interoperability, RDF has significant advantages: The object-attribute structure provides natural semantic units because all objects are independent entities. A domain model—defining objects and relationships—can be represented naturally in RDF. To find mappings between two RDF descriptions, techniques from research in knowledge representation are directly applicable. Therefore, the Z-BRE4K ontology has been implemented in the RDF format.

## 2.3 Knowledge Graph Modelling

From several academic papers, we found different researchers and companies have proposed many different definitions. To synthesize a coherent definition that helps frame the discussion about KGs, the definitions in references ([8], [13], [5], [7], [14], [18], [2], [10], [4]) were reviewed. They had the following common features:

1. A KG represents interrelationships. All of the definitions specify this feature but do so in different ways.
2. A KG uses techniques to extract knowledge from one or more sources. The kinds of sources differ from one definition to another.
3. The organization is a graph, although the precise meaning of "graph" varies from one definition to another.
4. While a KG must have a schema, not all KG definitions mention it. Those that do mention it specify that the schema defines classes and relations.
5. The KG supports various graph-computing, search, and query interfaces. The supported operations and performance will vary, and the performance will depend on

how trade-offs among scalability, performance, and maintainability are handled as well as on other technical issues.

From these features it is apparent that a KG is not simply another way to represent facts. It involves a software architecture that includes active capabilities for extracting and processing the facts. Jans Aasman [1] characterized the operations of a KG as follows:

- Generation:
  - Collection: Ingestion, web extraction, catalogue extraction, ontology, ...
  - Processing: Schema mapping, entity resolution, cleaning, ...
- Storage
- Applications: Querying, graph mining, recommendation, search, question answering, ...
- Statistical and machine learning techniques are used for all of the above

Accordingly, these lead to the following proposal for a definition of a KG:

*A KG is a representation of a set of statements in the form of a node- and edge-labelled directed multigraph allowing multiple, heterogeneous edges for the same nodes. A collection of definitional statements specifying the meaning of the knowledge graph's labels is called its schema.*

In common, different graph database can support knowledge graph modelling which enables to integrate with IoT platform, such as Neo4j [9].

## 2.4 Semantic Reasoning based on Knowledge Graph Models

Based on knowledge graph models, semantic reasoning is the ability to infer new facts from existing knowledge graph data based on inference rules or ontologies. In simple terms, rules add new information to the existing knowledge graph models, adding context, knowledge, and valuable insights. The rules are declarative in nature that declare the desired logic of connections in the knowledge graph models and the process of inferring new facts happens either through pre-materialization, query rewriting or a combination of both.

Reasoning enables to manage consistent among knowledge graph models and speed up the intelligent services by minimizing the amount of information processing that needs to happen outside your database's reasoning engine, as well as the number of required operations. It also brings analysis closer to the knowledge graph models, meaning deeper insights can be gathered from a given knowledge graph model with far less computational effort.

A semantic reasoning engine (otherwise known as a semantic reasoner, inference engine, or rules engine) is a piece of software designed to perform reasoning—to apply rules to a knowledge graph model and conduct semantic inference as we've described. The semantic reasoning tools includes, SQWRL engine [11], SWRL engineer [16], etc.

## 2.5 Summary and Motivation

In summary, knowledge graph models are always developed based on semantic modelling languages. When developing knowledge graph models, ontology is used to support

specification definition of different knowledge graph model elements. Through the ontology, different domain specific knowledge can be integrated into a unified framework.

### 3 Cognitive Factory Services and KGM

In this section, cognitive factory twins based on knowledge graph models are introduced. Then the function of knowledge graph models in FACTLOG factory scenarios are demonstrated in Section 3.2.

#### 3.1 Cognitive Factory Twins based on Knowledge Graph Models

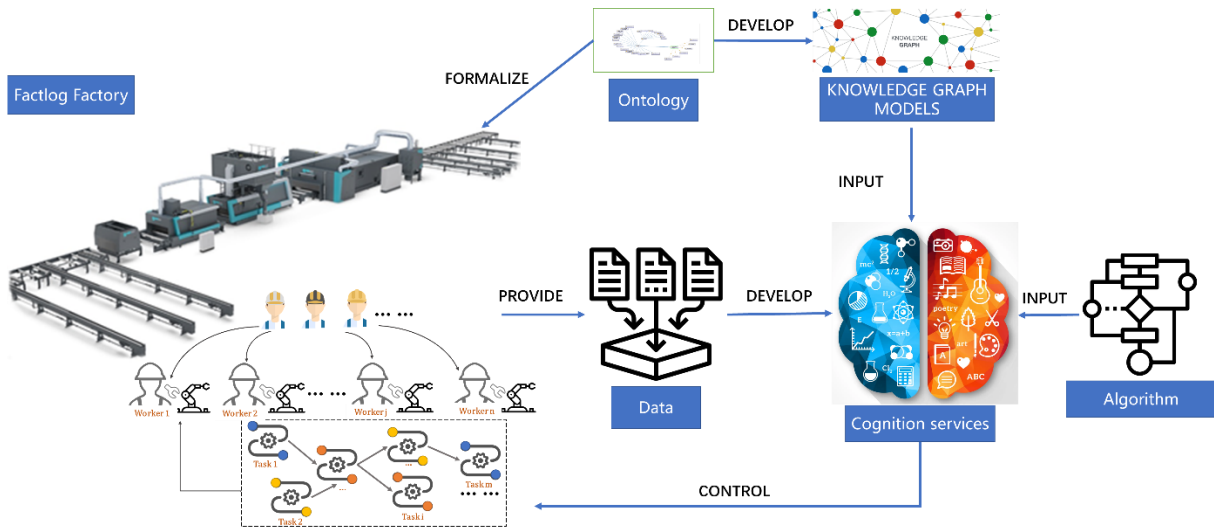


Figure 1: Knowledge graph models and cognition services to FACTLOG factory [15]

As shown in Figure 1, the interrelationships among FACTLOG factories and knowledge graph models are shown:

1. FACTLOG factory provides data to cognition services.
2. Ontology formalizes FACTLOG factory.
3. Ontology is used to develop knowledge graph models.
4. Knowledge graph models, algorithm and data are used to develop cognition services.
5. The cognition services control FACTLOG factory.

#### 3.2 The functions of Knowledge Graph Models in FACTLOG Factory scenario

The functions of knowledge graph models in the FACTLOG factory scenarios are listed:

- Unified description of digital twins and information across FACTLOG platform
- Anomaly detection for cognition
- Visualization of the interrelationships of all the ontology entities and individuals

## 4 Ontology definition for KGM

### 4.1 Guidance to KGM for cognition services of factory

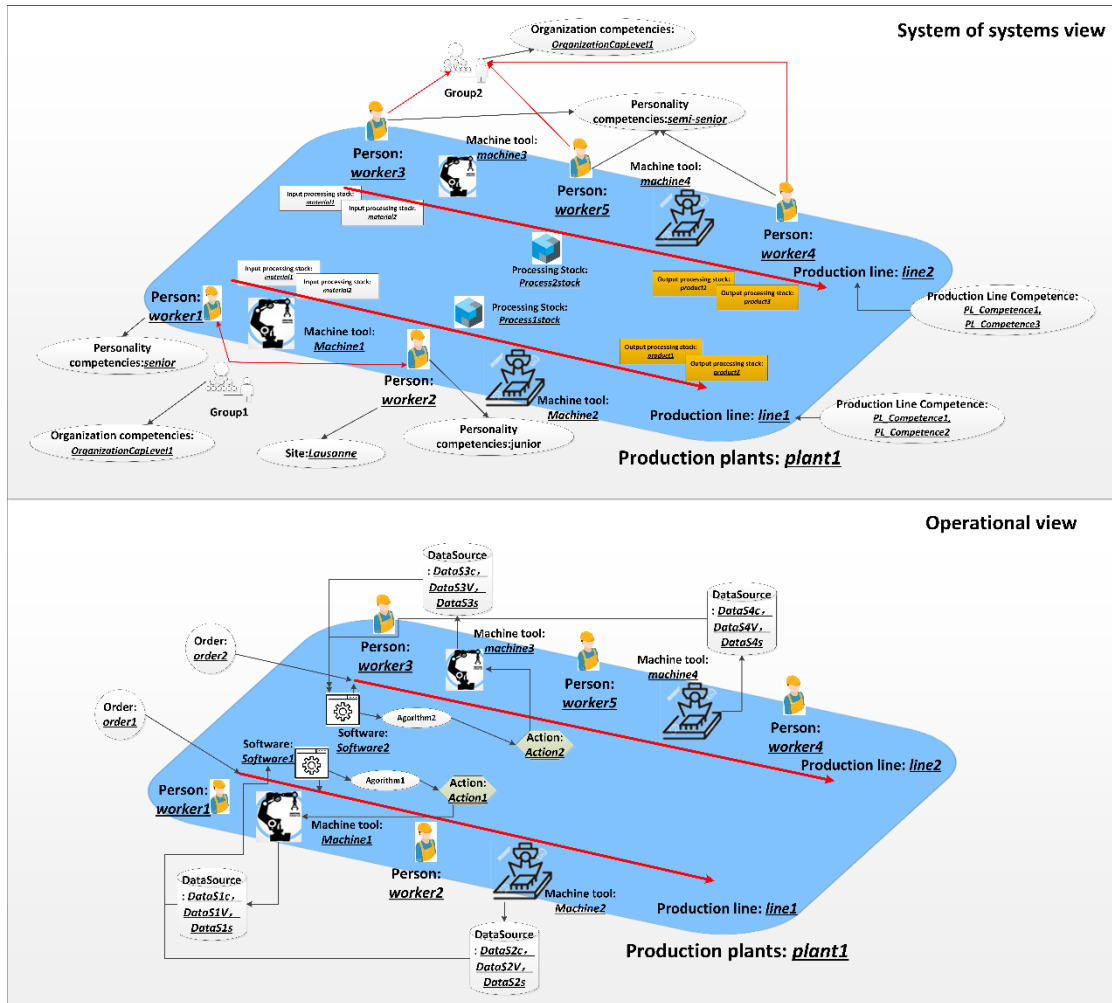


Figure 2: Scenario Overview -A: System of systems perspective; -B: Operational view.

In order to understand how the knowledge graph models, support the formalism of FACTLOG factory, an example is demonstrated as follow:

One scenario is proposed to develop a tutorial of knowledge graph modelling. The scenario is about a shop-plant. In Figure 2-A, the system of systems view is introduced. A production plants (plant1) is located in site (Lausanne). The plant1 includes two production lines (line1 and line2). Two workers (worker1 and worker2) work in line1. They are in Group1 which competence is OrganizationCompLevel1. The worker1 has senior competence and worker2 has junior competence. Three workers (worker3, worker4 and worker5) work in line2. They are in Group2 which competence is OrganizationCompLevel2. They have the same person competence: semi-senior. Machine1 and Machine2 are implemented in line1. Machine3 and Machine4 are implemented in line2. In line1, process stock(process1stock) is implemented. The process1stock has two input process stocks (material1 and material2) and two output process stocks (product1 and product2). The line1 has competences: PLCompetent1 and PLCompetent2 which produce product1 and product2. In line2, process stock(process2stock) is implemented. The process2stock has two input process stocks







**A: Class**

**B: Individuals**

Figure 4 Define relationship rules between classes

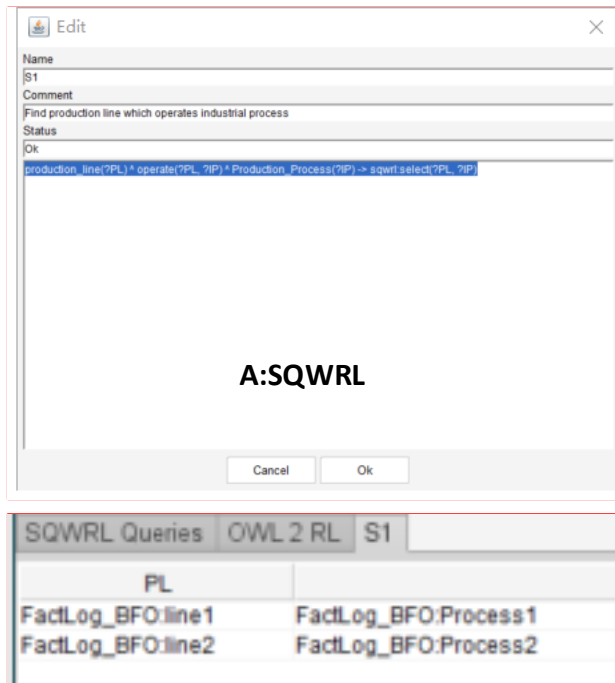
**4.1.2 Reasoning for the scenario**

**4.1.2.1 Reasoning using SQWRL**

SQWRL (Semantic Query-Enhanced Web Rule Language; pronounced squirrel) is a SWRL-based query language that provides SQL-like operators for extracting information from OWL ontologies, <https://github.com/protegeproject/swrlapi/wiki/SQWRL>. The SQWRL is used to reasoning the knowledge graph model in order to get the answer you want. In the scenario, when we finish the knowledge graph models, we want to know how many product lines operate production process. The SQWRL is defined as follow:

```
production_line(?PL) ^ operate(?PL, ?IP) ^ Production_Process(?IP) ->
sqwrl:select(?PL, ?IP)
```

Then the reasoning is implemented as Figure 5. The results are obtained in protégé.



**B:Reasoning result**

Figure 5: Reasoning results

**4.1.2.2 Query using SPARQL**

SPARQL contains capabilities for querying required and optional graph patterns along with their conjunctions and disjunctions. SPARQL also supports extensible value testing and constraining queries by source RDF graph. The results of SPARQL queries can be results sets or RDF graphs <https://www.w3.org/TR/rdf-sparql-query/>. The SPARQL is also used to

query the knowledge graph models built by protégé. The query is implemented in twinkle. If we want to know how many workers, we have in the knowledge graph models and what are their own capabilities, we make use of the SPARQL as follow:

```

PREFIX owl: <http://www.w3.org/2002/07/owl#>

PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>

PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

PREFIX sp: <http://purl.obolibrary.org/obo/FACTLOG.owl#>

SELECT ?worker ?competency

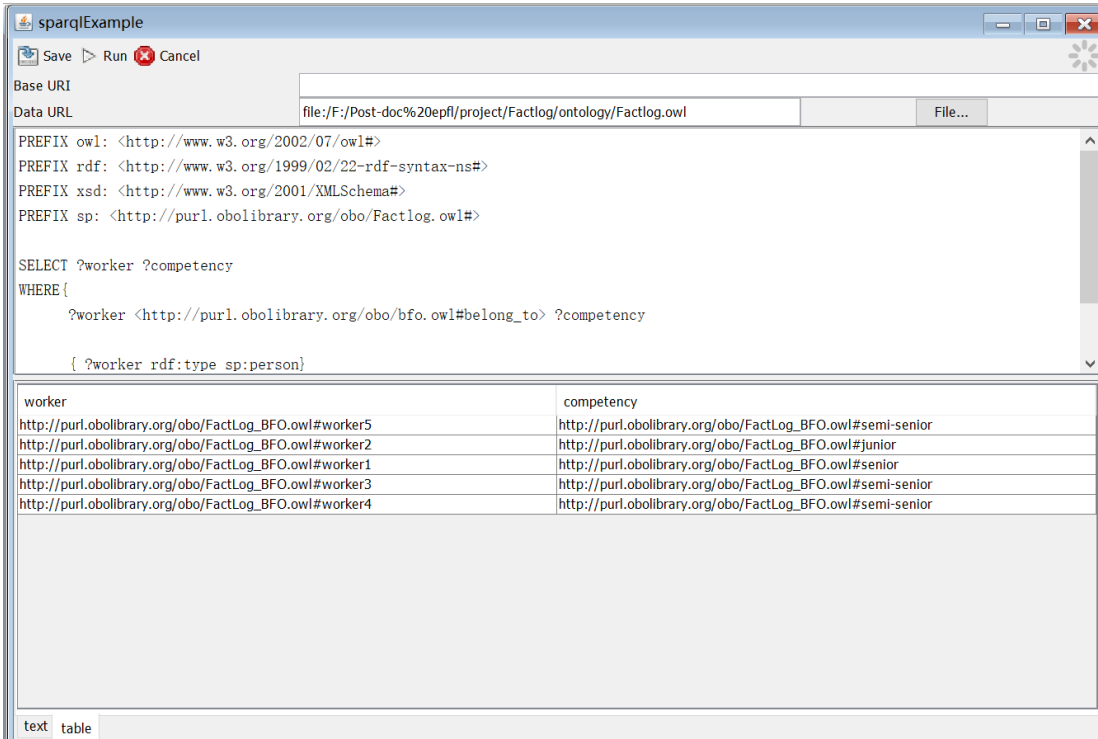
WHERE{

?worker <http://purl.obolibrary.org/obo/bfo.owl#belong_to> ?competency

{ ?worker rdf:type sp:person}

}

```



The screenshot shows a window titled 'sparqlExample' with a menu bar (Save, Run, Cancel) and a toolbar. The 'Data URL' field contains 'file:/F:/Post-doc%20epfl/project/Factlog/ontology/Factlog.owl'. The query text is displayed in a text area, and the results are shown in a table below.

worker	competency
http://purl.obolibrary.org/obo/FactLog_BFO.owl#worker5	http://purl.obolibrary.org/obo/FactLog_BFO.owl#semi-senior
http://purl.obolibrary.org/obo/FactLog_BFO.owl#worker2	http://purl.obolibrary.org/obo/FactLog_BFO.owl#junior
http://purl.obolibrary.org/obo/FactLog_BFO.owl#worker1	http://purl.obolibrary.org/obo/FactLog_BFO.owl#senior
http://purl.obolibrary.org/obo/FactLog_BFO.owl#worker3	http://purl.obolibrary.org/obo/FactLog_BFO.owl#semi-senior
http://purl.obolibrary.org/obo/FactLog_BFO.owl#worker4	http://purl.obolibrary.org/obo/FactLog_BFO.owl#semi-senior

Figure 6: Reasoning results

#### 4.1.2.3 Lessons learned from the Guidance

The ontology models enable to provide a unified description of the entire FACTLOG factory. Through some reasoning approaches, the knowledge graph model can support decision-makings for the FACTLOG services, such as identifying workers' skill through query.

## 4.2 FACTLOG Ontology developed for KGM in FACTLOG

### 4.2.1 Principles

Entities in the FACTLOG semantic framework have been arranged based on the Basic Formal Ontology (BFO) which is a formal ontology framework developed by Barry Smith and his associates [3]. In BFO, there are two varieties which are continuants comprehending continuant entities such as three-dimensional enduring objects and occurrent comprehending processes conceived as extended through (or as spanning) time. To adopt BFO framework will provide availability to merge the other CT domain ontology structured by BFO.

Originated from BFO, ontology design principles of FACTLOG are as follows:

- use single nouns (except data) and avoid acronyms
- ensure unicity of terms and relational expressions
- distinguish the general from particular
- provide all non-root terms with definitions
- use essential features in defining terms and avoid circularity
- start with the most general terms in the domain
- use simpler terms than the term you are defining (to ensure intelligibility)
- do not create terms for universals through logical combination
- structure ontology around is\_a hierarchy and ensure is\_a completeness
- single inheritance

### 4.2.2 Methodology

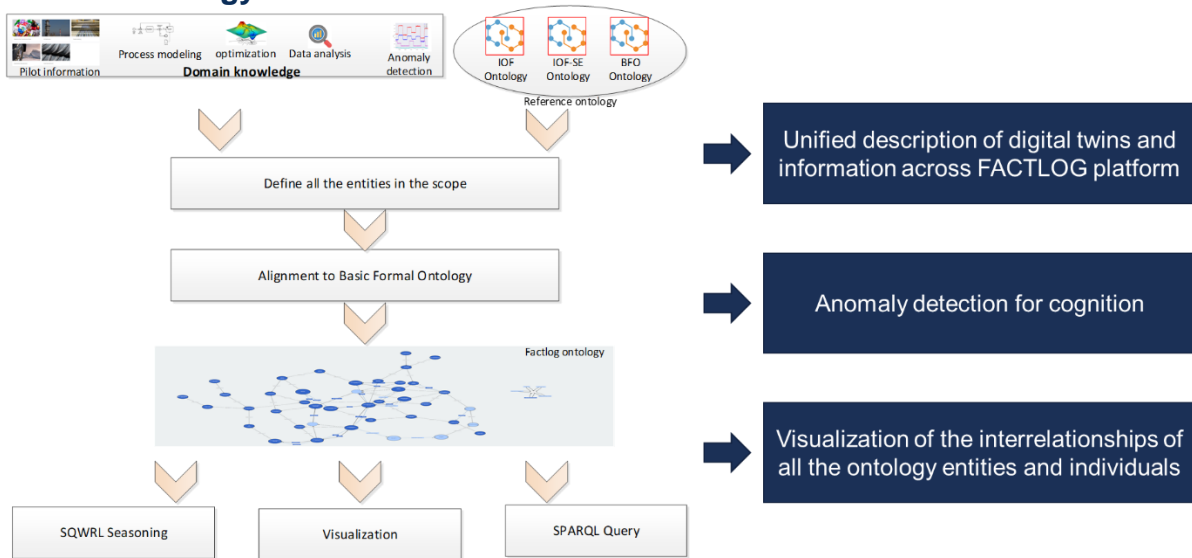


Figure 7: Ontology development workflow

In order to design the unified ontology for developing knowledge graph models supporting cognitive capabilities, the one of the well-known systems thinking development methodology (D 8.3) through domain knowledge has been applied to define the domain knowledge including: (i) pilot information; (ii) process modelling; (iii) optimization; (iv) data analysis; (v) anomaly detection. IoF ontology, BFO ontology and IoF SE ontology are three main

reference ontology. By composing a top-level overview, abstract concepts form domain specific knowledge from FACTLOG pilots and technical views. After the extraction of entities from FACTLOG pilots, the list of classes was updated in a comparison with existing ontology such as IOF-SE ontology, and IOF ontology. And then, all the entities were rearranged in the BFO structure. Finally, the SQWRL and SPARQL are used to support reasoning and query of the OWL models.

All the ontology concepts are mainly used for three aspects:

1. Unified description of digital twin and information across the FACTLOG platform.
2. Ontology reasoning for anomaly detection.
3. Visualization of the interrelationships of all the ontology entities and individuals.

### 4.2.3 Ontology Framework

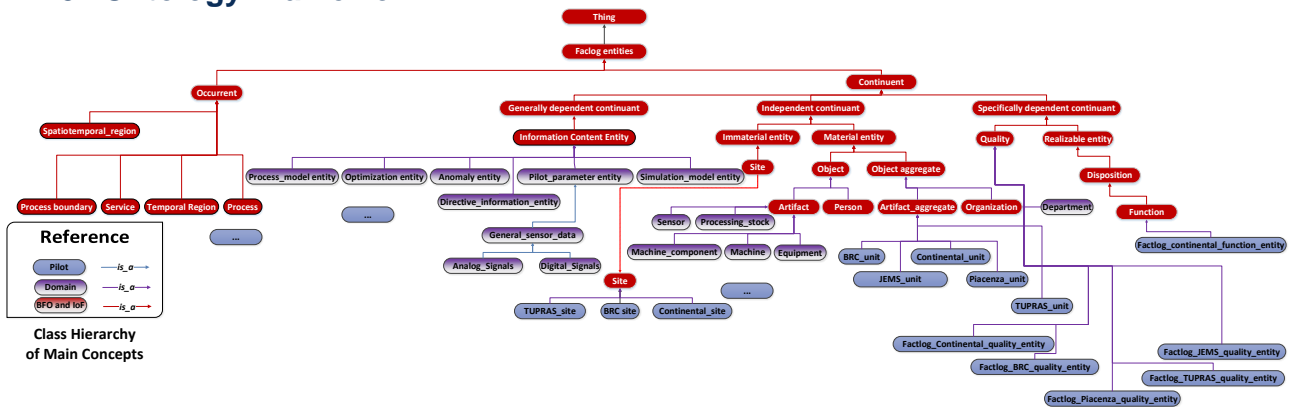


Figure 8: Ontology framework based on BFO

As shown in Figure 8, the FACTLOG ontology is developed based on basic formal ontology. The red blocks refer to BFO and IOF concepts. The purple blocks refer to domain concepts. The blue ones which are defined under BFO and domain concepts are used to define FACTLOG concepts. The whole entire FACTLOG entities include **occurrent** and **continuant** entity.

- A **continuant** is an entity that persists, endures, or continues to exist through time while maintaining its identity.
- An **occurent** is an entity that unfolds itself in time or it is the instantaneous boundary of such an entity (for example a beginning or an ending) or it is a temporal or spatiotemporal region which such an entity occupies\_temporal\_region or occupies\_spatiotemporal\_region.

Under the occurrent entity, several concepts are defined:

- **Process**: an **occurent** that has temporal proper parts and for some time t, p s depends\_on some material entity at t.
- **Process boundary**: a temporal part of a process & p has no proper temporal parts.
- **Service**: Service is delivered when the service implements the system function.
- **Spatiotemporal region**: an **occurent** entity that is part of spacetime.
- **Temporal region**: an **occurent** entity that is part of time as defined relative to some reference frame.

Under the **continuant** entity, several concepts are defined:

- **generically\_dependent\_continuant** is a continuant that generally depends on one or more other entities.
- **independent\_continuant**, a continuant which is such that there is no  $c$  and not such that  $b$  s-depends\_on  $c$  at  $t$ .
- **specifically\_dependent\_continuant**, a continuant & there is some independent continuant  $c$  which is not a spatial region and which is such that  $b$  s-depends\_on  $c$  at every time  $t$  during the course of  $b$ 's existence

Under **generically\_dependent\_continuant** entity, several concepts are defined:

- **Information\_content\_entity**, a generically dependent continuant that is about something.
  - **Process\_model\_entity**, a virtual concept used to define a process model.
  - **Optimization\_entity**, a virtual concept used to define an optimization concept.
  - **Simulation\_model\_entity**, a virtual concept used to define simulation model concepts.
  - **Pilot\_parameter\_concept**, a virtual entity to define FACTLOG pilot parameters.
    - **General sensor data**, sensor data used for all the FACTLOG pilots
  - **Directive\_information\_entity**, a plan specification that describes the inputs and output of mathematical functions as well as the workflow of execution for achieving a predefined objective. Algorithms are realized usually by means of implementation as computer programs for execution by automata.
  - **Anomaly\_entity**, a virtual entity to support anomaly detection.
  - **Data\_analysis\_entity**, a virtual entity used for data analysis.
- **Specifically\_dependent\_continuant**, is a continuant & there is some independent continuant  $c$  which is not a spatial region and which is such that  $b$  s-depends\_on  $c$  at every time  $t$  during the course of  $b$ 's existence
  - **Quality**, a specifically dependent continuant that, in contrast to roles and dispositions, does not require any further process in order to be realized.
    - **FACTLOG\_BRC\_quality\_entity**, quality used in the BRC pilot.
    - **FACTLOG\_Continental\_quality\_entity**, quality used in the CONT pilot.
    - **FACTLOG\_JEMS\_quality\_entity**, quality used in the JEMS pilot.
    - **FACTLOG\_Piacenza\_quality\_entity**, quality used in the PIA pilot.
    - **FACTLOG\_TUPRAS\_quality\_entity**, quality used in the TUPRAS pilot.
  - **realizable\_entity**, a specifically dependent continuant that exists essentially or permanently in some independent continuant which is not a spatial region and is of a type instance of which are realized in processes of a correlated type.
    - **Disposition**, a realizable entity &  $b$ 's bearer is some material entity &  $b$  is such that if it ceases to exist, then its bearer is physically changed, &  $b$ 's realization occurs when and because this bearer is in some special physical circumstances, & this realization occurs in virtue of the bearer's physical make-up.
      - **Function**, a disposition that exists in virtue of the bearer's physical make-up and this physical make-up is something the

- bearer possesses because it came into being, either through evolution (in the case of natural biological entities) or through intentional design (in the case of artifacts), in order to realize processes of a certain sort.
- **FACTLOG\_continental\_function\_entity**, functions used in CONT pilot.
  - **Role**, a realizable entity & b exists because there is some single bearer that is in some special physical, social, or institutional set of circumstances in which this bearer does not have to be & b is not such that, if it ceases to exist, then the physical make-up of the bearer is thereby changed.
  - **Independent\_continuant**, a continuant which is such that there is no c and no t such that b s-dependes\_on c at t.
    - **immaterial\_entity**, which are divided into two subgroups: boundaries and sites, which bound, or are demarcated in relation, to material entities, and which can thus change location, shape and size and as their material hosts move or change shape or size (for example: your nasal passage; the hold of a ship; the boundary of Wales).
      - **Site**, three-dimensional immaterial entity that is (partially or wholly) bounded by a material entity or it is a three-dimensional immaterial part thereof.
        - **BRC\_site**, site used in BRC.
        - **Continental\_site**, site used in CONT.
        - **TUPRAS\_site**, site used in TUPRAS.
    - **material\_entity**, which can preserve their identity even while gaining and losing material parts. Continuants are contrasted with occurrents, which unfold themselves in successive temporal parts or phases.
      - **Object**, a material entity which manifests causal unity of one or other of the types CUn listed above & is of a type (a material universal) instance of which are maximal relative to this criterion of causal unity.
        - **Artifact**, an Object that was designed by some Agent to realize a certain Function.
          - **Sensor**, a device that produces an output signal for the purpose of sensing of a physical phenomenon.
          - **Processing stock**, is an artifact in an industrial site corresponds to any material in the process of producing or manufacturing finished product.
          - **Machine component**, compositions for constructing machines.
          - **Machine**, a physical system using power to apply forces and control movement to perform an action.
          - **Equipment**, the set of physical resources serving to equip a person or thing implementing used in an operation or activity
        - **Person**, an object that is a human being.
      - **Object\_aggregate**, an object aggregates if and only if there is a mutually exhaustive and pairwise disjoint partition of a into objects.
        - **Artifact\_aggregate**, a collection of artifacts that designed or arranged by some Agent to realize a certain Function.



- **BRC\_unit**, a company group generally equivalent in size and character to implement BRC services.
- **Continental\_unit**, a company group generally equivalent in size and character to implement CONT services.
- **JEMS\_unit**, a company group generally equivalent in size and character to implement JEMS services.
- **Piacenza\_unit**, a company group generally equivalent in size and character to implement PIA services.
- **TUPRAS\_unit**, a company group generally equivalent in size and character to implement TUPRAS services.
- **Organization**, an object aggregate that corresponds to social institutions such as companies, societies etc. that does something.
  - **Department**, an organizational unit in FACTLOG.

### 4.3 Ontology for each Pilot and Technical Partner

Based on the ontology framework, ontology for each pilot and technical partners is designed in each deliverable as shown in Table 1.

*Table 1 – Mapping between ontology concepts and other deliverables*

Ontology concepts	Deliverable	Description
Ontology for Directive_information_entity	Deliverable 4.2	Ontology which describes the general information concepts in FACTLOG.
Ontology for Pilot Description	Deliverable 4.2	Ontology which describes the pilot concepts in FACTLOG.
Ontology for Optimization	Deliverable 4.2	Ontology which describes the optimization concepts in FACTLOG.
Ontology for Processing Modeling	Deliverable 4.2	Ontology which describes the process model concepts in FACTLOG.
Ontology for Data Analysis	Deliverable 4.4	Ontology which describes the concepts of data analysis in FACTLOG.
Ontology for Simulation Model	Deliverable 4.2	Ontology which describes the concepts of simulation models in FACTLOG.

### 4.4 Ontology for Anomaly Detection

The ontology concepts are defined to support anomaly detection in FACTLOG pilot.

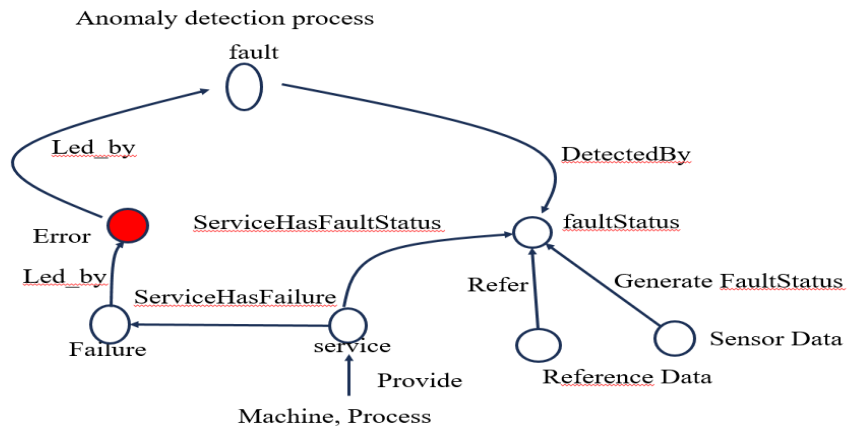


Figure 9: Ontology for describing anomaly detection processes

As shown in Figure 9, several concepts are defined to describe the anomaly detection process.

1. A **service** is defined as what is delivered when the service implements the system function.
2. A **service failure**, often abbreviated here as failure, is an event that occurs when the delivered service deviates from correct service.
3. An **error** is the deviation that at least one (or more) external state of the system deviates from the correct service state, since a service is a sequence of the system’s external states.
4. A **fault** is an adjudged or hypothesized cause of an error.
5. An **observation** of a fault is fault status.
6. **Sensor data** refers to the data directly generated from machine or sensor.
7. **Reference data** refers to the data from simulation models for decision-makings.

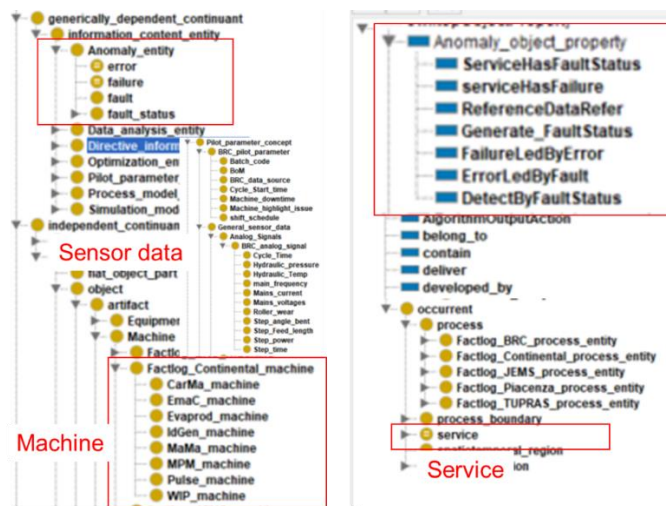


Figure 10: Ontology classes for describing anomaly detection processes

As shown in Figure 10, ontology classes are defined based on the Figure 9.

## 5 Knowledge Graph Modelling based on FACTLOG Ontology

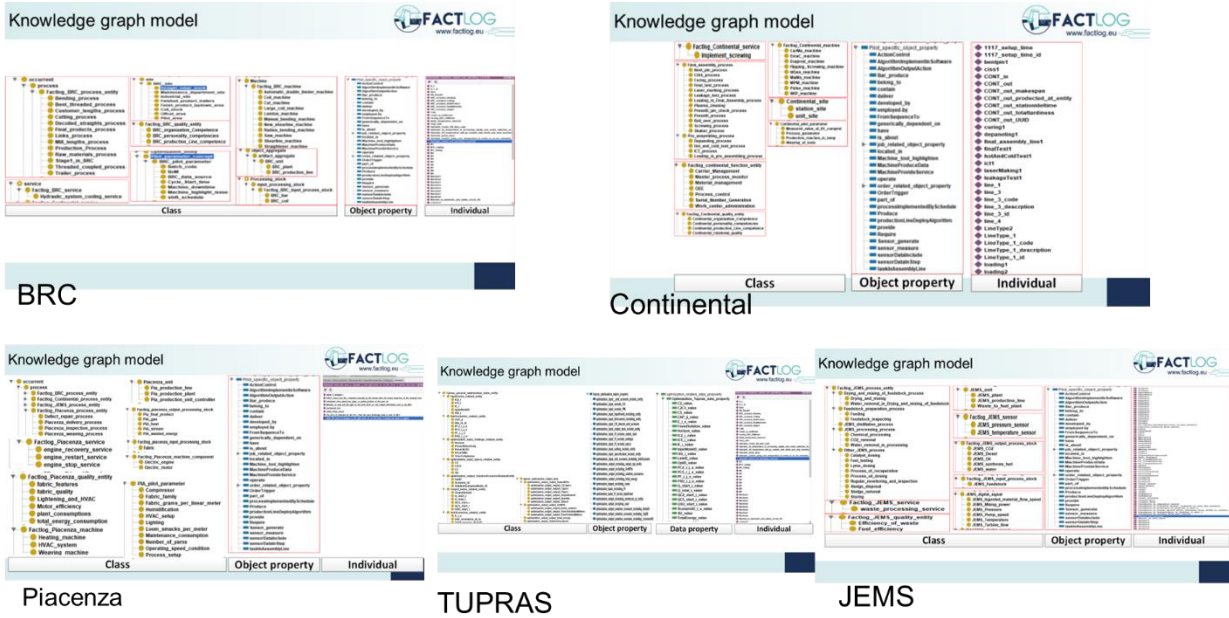


Figure 11: Knowledge graph models based on developed ontology

As shown in Figure 11, knowledge graph models are developed based on the ontology in Section 4. Details are shown in Deliverable 4.2.

### 5.1 Knowledge Graph Modelling for BRC

In the BRC pilot, four main concerns are first considered when knowledge graph models are developed to formalize the BRC pilot: 1) pilot description; 2) PN model formalism; 3) optimization formalism; 4) anomaly detection (introduced in Section 6.4.1.2).

#### 5.1.1 Pilot description

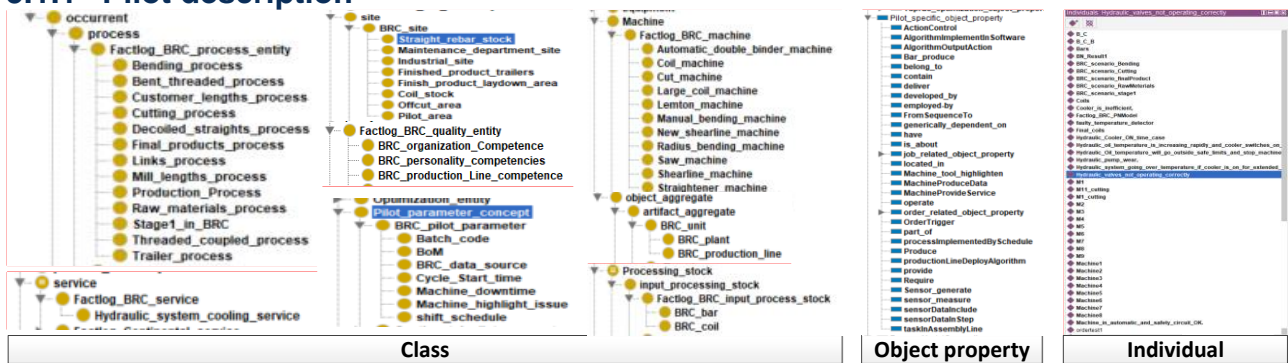


Figure 12: Ontology class, object property and individuals for BRC pilot description

As shown in Figure 12, BRC process entities, BRC services, BRC sites, BRC pilot parameter, BRC machine, BRC unit and BRC input process stock are the main ontology concepts defined in the knowledge graph models. General specific object properties are defined in order to support all the pilot description. Individuals are defined to describe an example of the BRC scenario.

### 5.1.2 PN model formalism

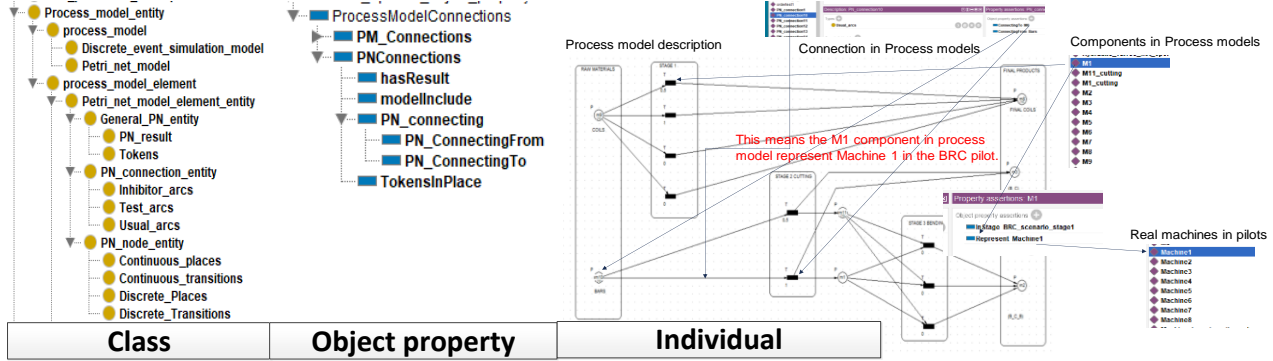


Figure 13: Ontology class, object property and individuals for simulation in BRC pilot description

As shown in Figure 14, classes of petri net model entities and object properties of petri net model connections are defined to describe the petri net model used in the BRC pilot. The PN node entities are used to represent the “model compositions” in the petri net model. The PN connection entities are used to represent the model connections in the petri net model. PN\_connectingFrom and PN\_connectingTo are used to connect the PN connections and PN nodes. Through this way, the entire PN model is described.

### 5.1.3 Optimization formalism

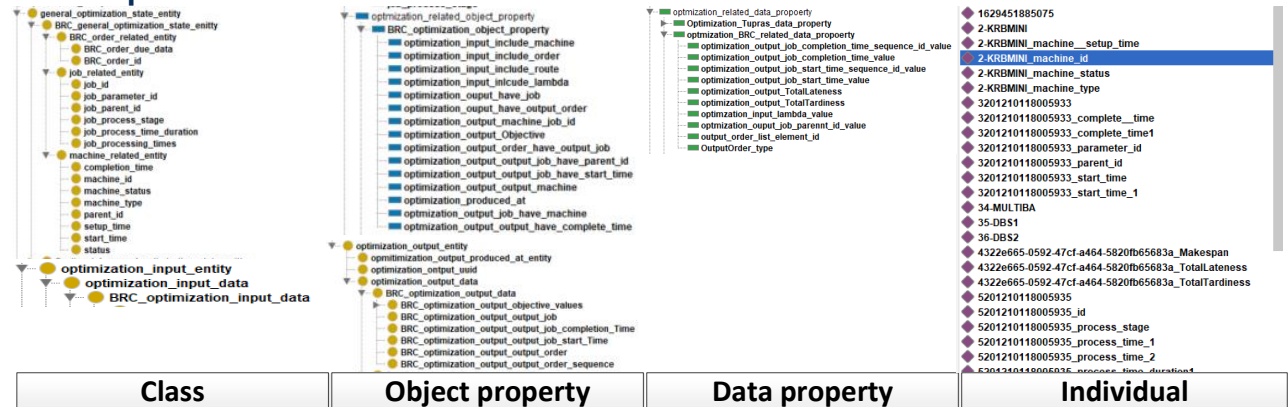


Figure 14: Ontology class, object property, data property and individuals for optimization for BRC pilot

As shown in Figure 14, optimization classes, object properties and data properties are defined to represent optimization scenario using individuals. In Figure 15, the individuals are used to represent the optimization input data structure. The BRC optimization input has a machine named “2KRBMINI” who has a machine id as 2-KRBMINI.



Optimization input

```
{
  "data": {
    "machines": [
      {
        "machineId": "2-KRBMINI",
        "machineType": "CUT",
        "setupTime": "00:00:57",
        "status": 1
      }
    ]
  }
}
```

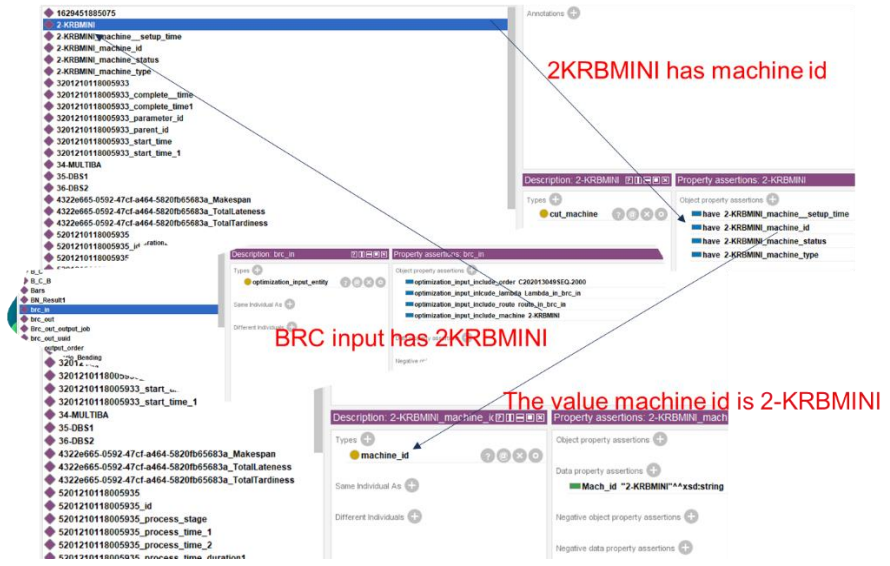


Figure 15: Individuals for describing the optimization scenario for BRC pilot

## 5.2 Knowledge Graph Modelling for PIA

In the PIA pilot, three concerns are first considered when knowledge graph models are developed to formalize the PIA pilot: 1) pilot description; 2) optimization formalism; 3) anomaly detection (introduced in Section 6.4.1.3).

### 5.2.1 Pilot description



Figure 16: Ontology class, object property and individuals for PIA pilot description

As shown in Figure 16, PIA process entities, PIA services, PIA pilot parameter, PIA machine, PIA unit, PIA input process stock and PIA output process stock are the main ontology concepts defined in the knowledge graph models. General specific object properties are defined in order to support all the pilot description. Individuals are defined to describe an example of the PIA scenario.

### 5.2.2 Optimization formalism



Figure 17: Ontology class, object property, data property and individuals for optimization for PIA pilot

As shown in Figure 17, optimization classes, object properties and data properties are defined to represent optimization scenario using individuals. In Figure 18, the individuals are used to represent the optimization input data structure. The PIA optimization output has an order1 named “order1” who has a processing time and its value is 1991.79.

#### Optimization output: Pia\_out

```

1 {
2   "uuid": "6dad1a7f-e3de-4aca-8651-0aa4971f9a8d",
3   "data": {
4     "orders": [
5       "objectiveValues": {
6         "makespan": 17985.88,
7         "totalTardiness": 1165.556666666673,
8         "totalEnergyCons": 33371.96624999999,
9         "totalCompletionTimes": 341741.81000000006
10      },
11      "loomsOrdersSequence": [
12      ],
13      "produced_at": 1632488761861
14    },
15  },
16  "orders": [
17    {
18      "type": "F",
19      "loomID": 49,
20      "partID": "ATEL-9101F",
21      "chainID": "ATEL-91",
22      "setupTime": 0,
23      "tardiness": 0,
24      "energyCons": 248.97375,
25      "deliveryDate": "06/14/2021",
26      "setupEndTime": "06/01/2021 06:00:00",
27      "targetMeters": 153.8112244897959,
28      "priorityWeight": 2,
29      "processEndTime": "06/02/2021 15:11:47",
30      "processingTime": 1991.79,
31      "setupStartTime": "06/01/2021 06:00:00",
32      "processStartTime": "06/01/2021 06:00:00"
33    },
34  ],
35  }

```

Property assertions: pia\_out

- optimization\_output\_include\_makespan pia\_out\_makespan
- optimization\_output\_include\_include\_total\_EnergyCons pia\_out\_total\_energy\_cons
- optimization\_output\_produce\_at\_entity\_produced\_at\_in\_pia\_out
- optimization\_output\_include\_order\_order1\_in\_pia\_out
- optimization\_output\_include\_totalTardiness pia\_out\_total\_tardiness
- optimization\_output\_include\_total\_completionTime pia\_out\_total\_completion\_times
- optimization\_output\_include\_looms\_order\_sequence 24\_pia\_out\_order\_sequence

Data property assertions

- order\_processing\_time\_value 1991.79

Property assertions: order1\_in\_pia\_out

- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_processing\_time
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_setup\_start\_time
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_process\_start\_time
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_deliverable\_data
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_energy\_com
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_order\_type
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_loom\_id
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_chain\_id
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_tardiness
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_partid
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_setup\_end\_time
- optimization\_output\_order\_include\_entity\_order1\_in\_pia\_output\_setup\_time

Figure 18: Individuals for describing the optimization scenario for PIA pilot



### 5.3 Knowledge Graph Modelling for JEMS

In the JEMS pilot<sup>1</sup>, two concerns are first considered when knowledge graph models are developed to formalize the pilot: 1) pilot description; 2) anomaly detection (introduced in Section **Errore. L'origine riferimento non è stata trovata.**).

#### 5.3.1 Pilot description

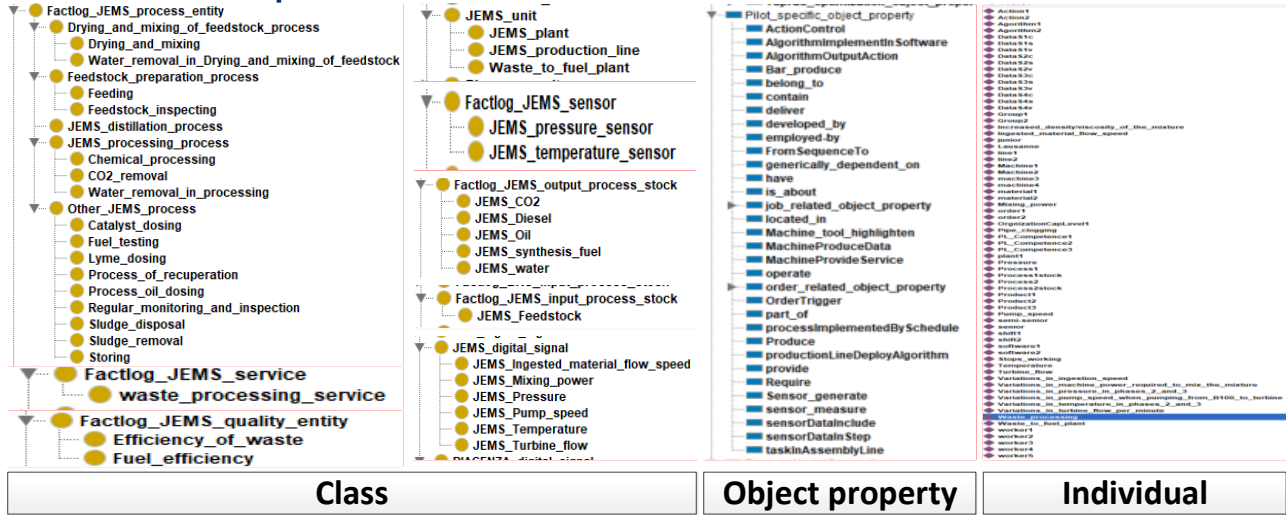


Figure 19: Ontology class, object property, data property and individuals for optimization for JEMS pilot

As shown in Figure 19, JEMS process entities, services, pilot parameter, sensor, JEMS unit, quality, digital signal, unit, input process stock and output process stock are the main ontology concepts defined in the knowledge graph models. General specific object properties are defined in order to support all the pilot description. Individuals are defined to describe an example of the JEMS scenario.

### 5.4 Knowledge Graph Modelling for TUPRAS

In the TUPRAS pilot, four main concerns are first considered when knowledge graph models are developed to formalize the TUPRAS pilot: 1) pilot description; 2) PM model formalism; 3) optimization formalism; 4) Data analysis formalism.

<sup>1</sup> JEMS pilot did not meet its objectives, especially with regards to the integration of the FACTLOG system to its plant since there is not yet an operative plant in Slovenia.

### 5.4.1 Pilot description

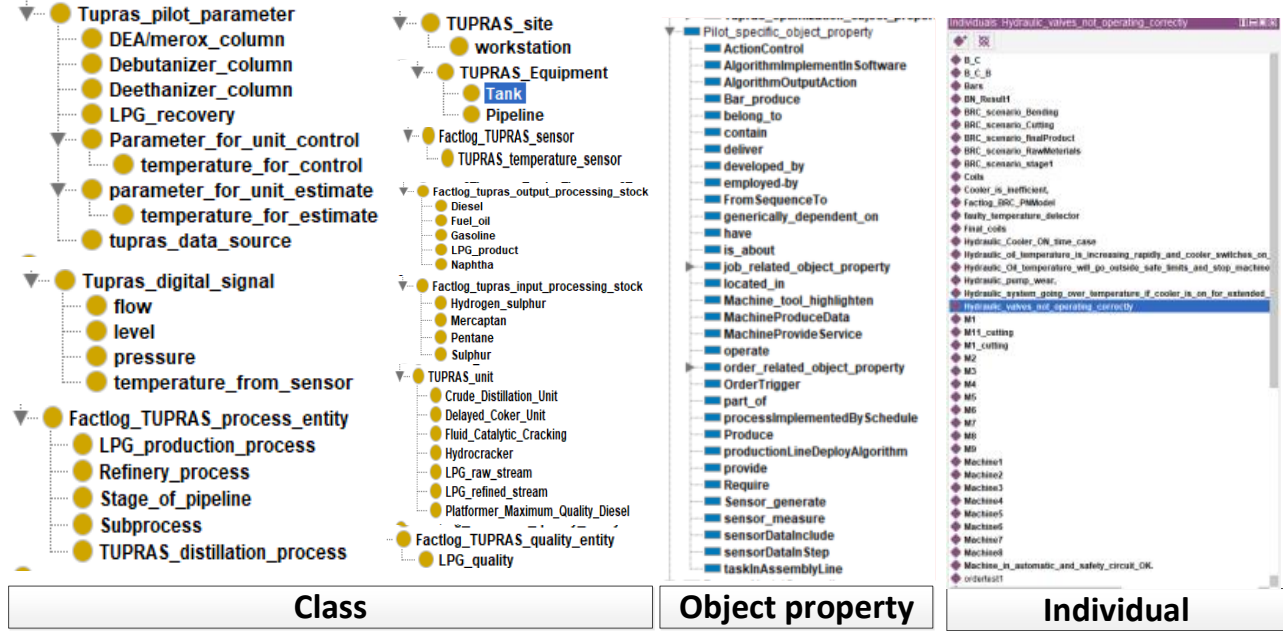


Figure 20: Ontology class, object property, data property and individuals for pilot description in TUPRAS pilot

As shown in Figure 20, TUPRAS process entities, TUPRAS services, TUPRAS pilot parameter, TUPRAS unit, TUPRAS quality, TUPRAS digital signal, TUPRAS site, TUPRAS input process stock and TUPRAS output process stock are the main ontology concepts defined in the knowledge graph models. General specific object properties are defined in order to support all the pilot description. Individuals are defined to describe an example of the TUPRAS scenario.

### 5.4.2 PM model formalism

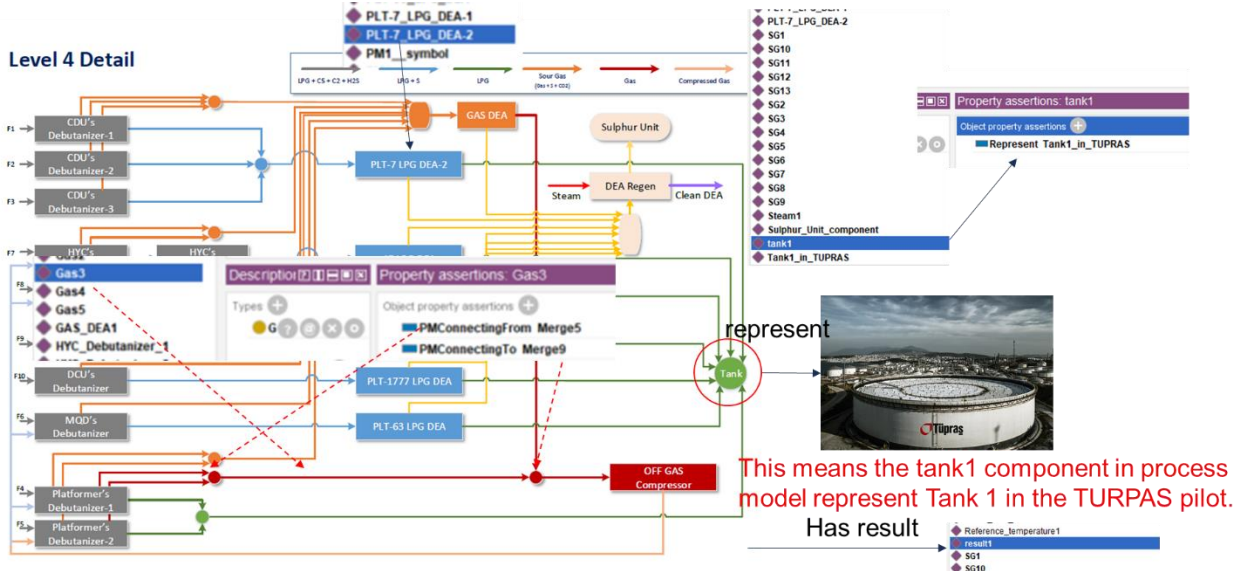


Figure 21: Individuals for process model description for TUPRAS pilot

Using the ontology in Section 5.4.2, the Figure 21 shows the individuals which are used to represent model structure for TUPRAS. For example, the individuals of PM\_links are used to represent the connections among PM\_nodes. The individuals of PM\_nodes are used to

represent each model composition in the model. The model composition is defined to represent the real equipment in the TUPRAS pilot.

### 5.4.3 Optimization formalism



Figure 22: Ontology class, object property, and data property for optimization for TUPRAS pilot

As shown in Figure 23, optimization classes, object properties and data properties are defined to represent optimization scenario using individuals. In Figure 28, the individuals are used to represent the optimization output data structure. The TUPRAS optimization output has a solKPIs, solution scenario, outputKPIs and etc.

Optimization output: Tupras\_out

```

1 }tupras_injson {}*tupras_outjson {}
2 {
3   "uid": "6044026-70fa-4363-bd98-ea031e032dd3",
4   "data": {
5     "TotalEnergy": 2378.64,
6     "SolKPIs": {
7       "FoundSolution": true,
8       "TimeToSolveMilliSec": 1123,
9       "TimeToInitializeMilliSec": 67
10    },
11    "SolutionScenarios": [
12      {
13        "OptID": "0",
14        "NodeID": "ace52190-7019-4fbf-8d80-cc977ed891bf",
15        "ScenarioID": "d966f9e7-cc85-4d1d-872c-3b18574e5f21"
16      }
17    ],
18    "OutputKPIs": [
19      {
20        "C2perc": 0.0094,
21        "C5perc": 0.02,
22        "SuperC": 0.0097,
23        "C2C5perc": 0.0294,
24        "Quantity": 966624.6814173539,
25        "OutputNodeID": "da3ec667-4a08-44b2-83ed-aaf22b5a03d3"
26      }
27    ],
28    "produced_at": 1625065678174
29  }
30 }
                
```

Figure 23: Individuals for optimization in TUPRAS pilot

### 5.4.4 Data analysis formalism

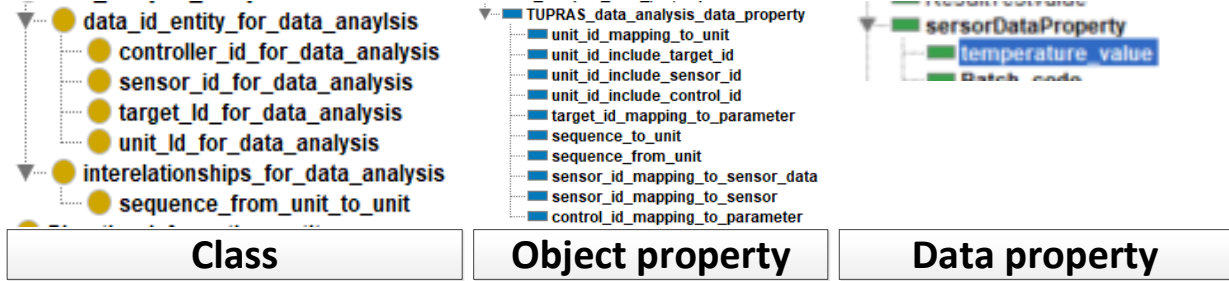


Figure 24: Ontology class, object property, and data property for data analysis in TUPRAS pilot

As shown in Figure 24, optimization classes, object properties and data properties are defined to represent data analysis scenario using individuals. In Figure 25, the individuals are used to represent the data analysis scenario. The TUPRAS data analysis scenario has a uuid which is mapping to the unit “crude distillation unit”.

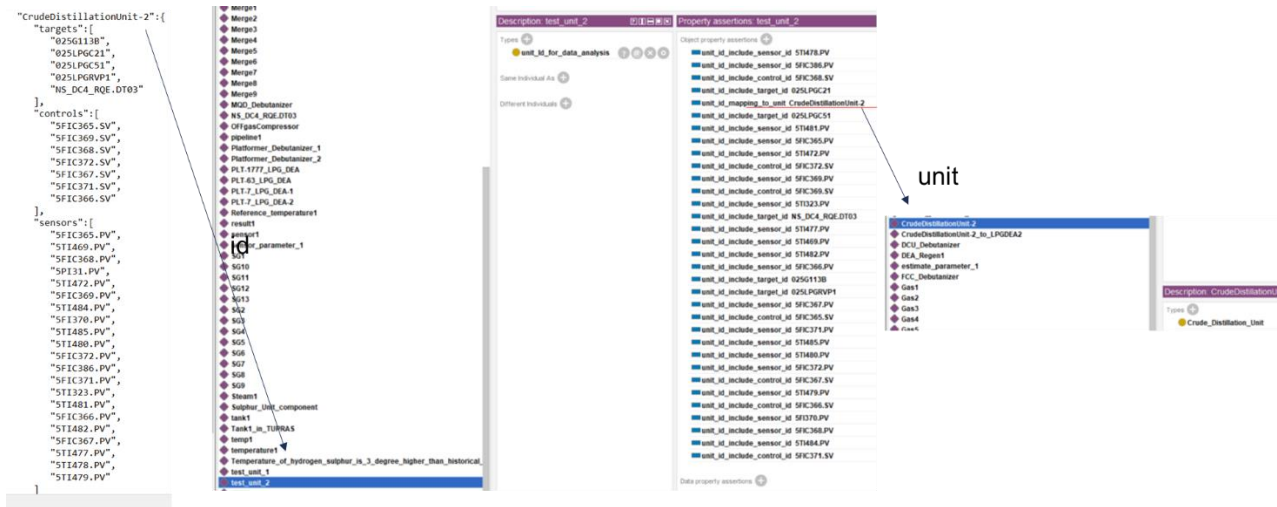


Figure 25: Individuals for data analysis in TUPRAS pilot

## 5.5 Knowledge Graph Modelling for CONT

In the CONT pilot, three main concerns are first considered when knowledge graph models are developed to formalize the CONT pilot: 1) pilot description; 2) optimization formalism; 3) anomaly detection (introduced in Section 6.4.1).



### 5.5.1 Pilot description

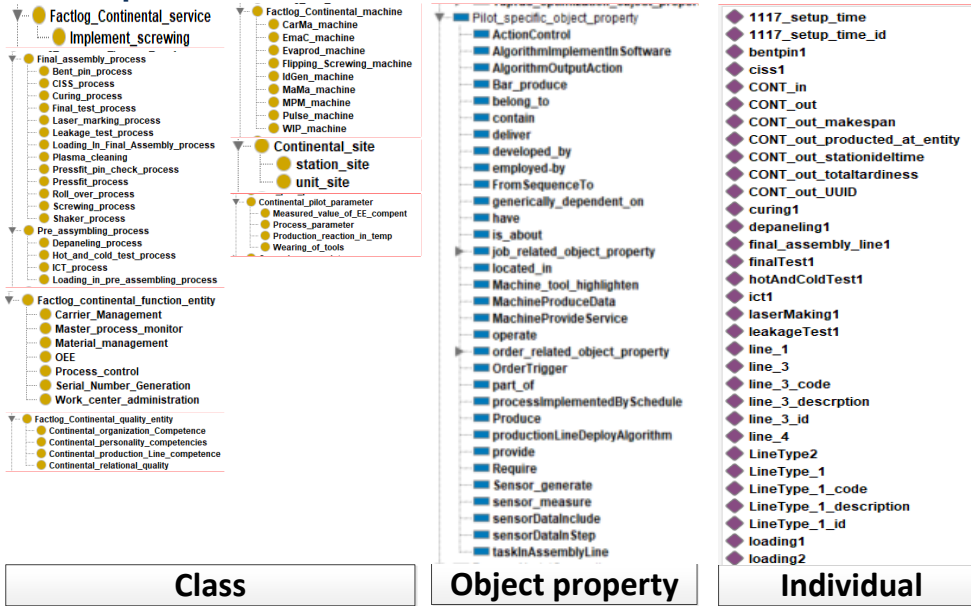


Figure 26: Ontology class, object property, data property and individuals for CONT pilot

As shown in Figure 26, CONT process entities, CONT services, CONT pilot parameter, CONT site, CONT machine, and CONT function are the main ontology concepts defined in the knowledge graph models. General specific object properties are defined in order to support all the pilot description. Individuals are defined to describe an example of the CONT scenario.

### 5.5.2 Optimization formalism



Figure 27: Ontology class, object property, data property and individuals for optimization for CONT pilot

As shown in Figure 27, optimization classes, object properties and data properties are defined to represent optimization scenario using individuals. In Figure 28, the individuals are used to represent the optimization input data structure. The CONT optimization input has a route named “prod-and-maint-sched” whose value is “prod-and-maint-sched”.

Optimization input: **CONT in**

```

{
  "route": "prod-and-maint-sched",
  "data": {
    "staticData": {
      "WorkplaceTypes": [{
        "Id": 38,
        "Code": "ICT test",
        "Description": "ICT test"
      }],
      "LineTypes": [{
        "Id": 1,
        "Code": "FA",
        "Description": "FA"
      }],
    },
  },
}
    
```

CONT-in has route "pro-and-maint-sched"

Route is valued as "pro-and-maint-sched"

Figure 28: Individuals for describing the optimization scenario for CONT pilot



## 6 Integration of KGM and Cognition Services in the FACTLOG platform

In this chapter, two approaches are used to integrate the designed knowledge graph models into cognition services in the FACTLOG platform.

### 6.1 Integration based on OWL models

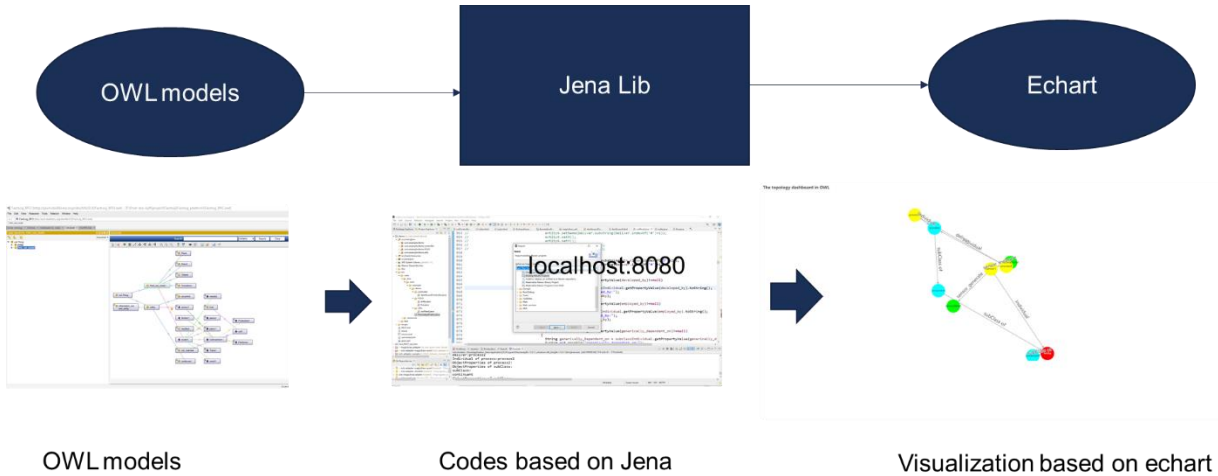


Figure 29: Workflow for visualizing knowledge graph model

As shown in Figure 29, a React and java project is developed based on Jena Lib in order to visualize a knowledge graph model which is built for the FACTLOG project. Totally, there are three steps to realize the visualization:

1. OWL models are developed in Protégé based on the developed ontology.
2. Through the java project we proposed, which details are shown in ANNEX III.
3. The OWL files are shown in the web.

### 6.2 Integration based on Neo4j

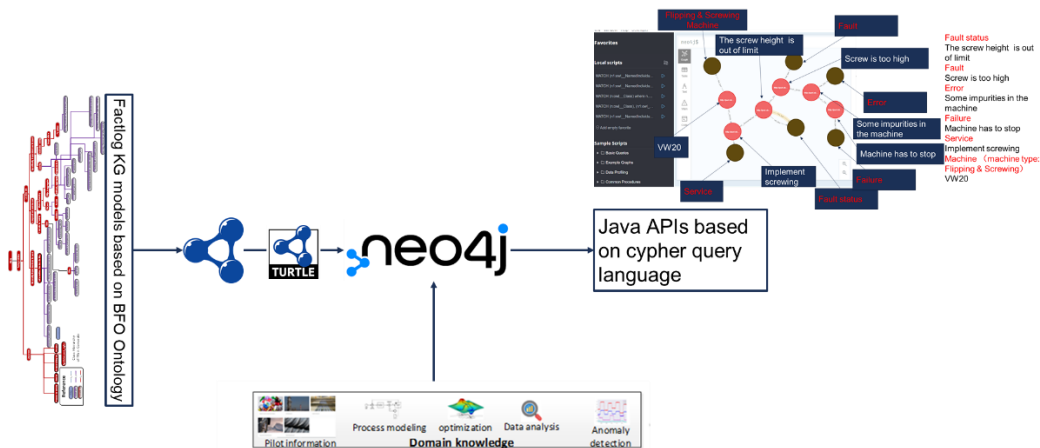


Figure 30: OWL model transformed into Neo4j

As shown in Figure 30, ontology models which are developed based on BFO framework is generated into Neo4j knowledge graph models through turtle. The cypher query language is used to support reasoning of knowledge graph models.

### 6.3 Integration based on HTTP API

As shown in Figure 14, we developed a Python application that leverages an OWL ontology developed based on the BFO framework to instantiate a knowledge graph. An HTTP API is offered to the external services to enable the training of machine learning models based either on domain knowledge regarding a specific use case, or regarding specifications for building such a model. When detailed specifications are provided to build a certain model, a parser is used to interpret how the features must be built and build them. In all cases, the machine learning model is trained and persisted into the filesystem, so that it can be later accessed along with metadata of interest. Model training is performed asynchronously. All information regarding the characteristics of the model, their instantiation and performance are recorded in the knowledge graph.

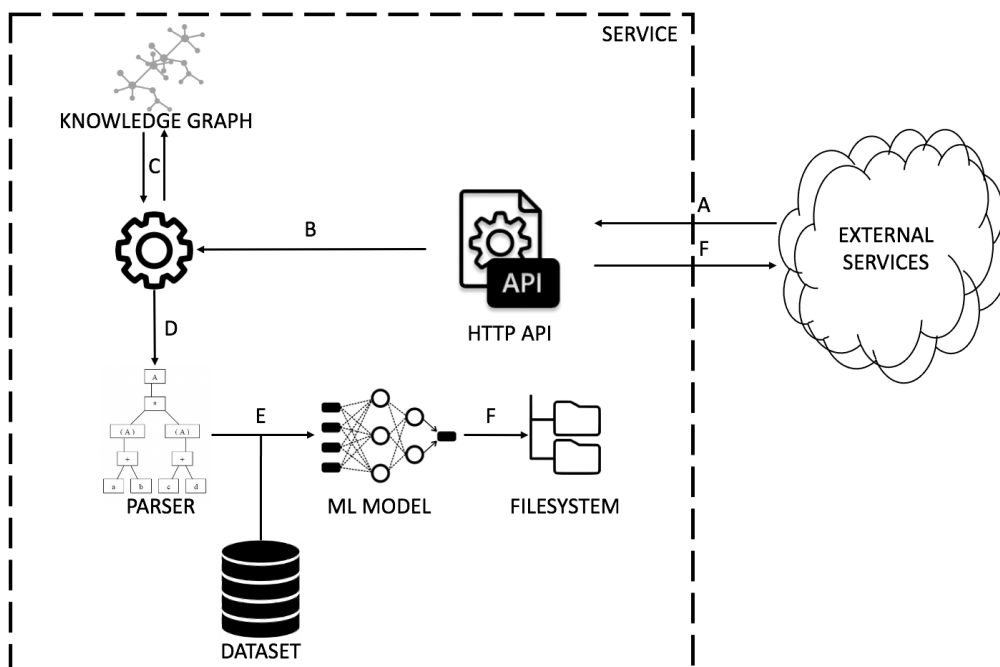


Figure 31. Diagram displaying the components' interaction at the KG-based analytics for process optimization architecture.

## 6.4 Cognition services for FACTLOG Factories

### 6.4.1 Cognition services based on OWL

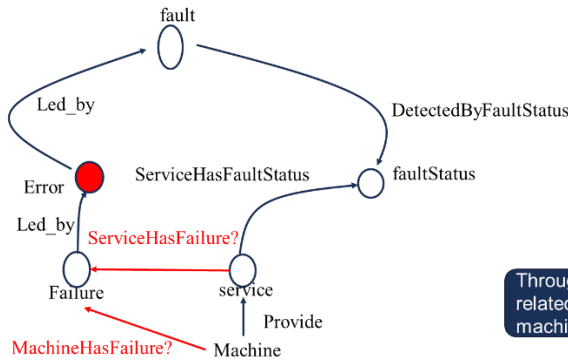
#### 6.4.1.1 Anomaly detection for CONT Pilot

Based on ontology for anomaly detection, a knowledge graph model is defined to represent the rational of anomaly detection for the CONT pilot.

Table 2 – Anomaly detection scenario for CONT pilot

Anomaly								
Sensor Data	Possible Error detection (Error)	Required additional data inputs (Reference data)	Drift Measure (Fault status) extral (ontology for natural data)	Possible Causes (Fault)	Possible outcomes (Failure)	Service	Machine	Machine type
-	Some impurities in the machine	-	The screw height is out of limit	Screw is too high	Machine has to stop	Implement screwing	VW20	Flipping & Screwing

Identify the anomaly scenarios for Continental



- Fault status**
- The screw height is out of limit
- Fault**
- Screw is too high
- Error**
- Some impurities in the machine
- Failure**
- Machine has to stop
- Service**
- Implement screwing
- Machine (machine type: Flipping & Screwing)**
- VW20

Through reasoning, failure can be captured which related to service. Failure can be captured for the machine.

Figure 32: Anomaly scenario for CONT pilot

As shown in Figure 32, based on Table 2, an anomaly scenario is defined. The knowledge graph model is built based on the given data and anomaly ontology. The relationships between failure and two other concepts including service and machine are not defined in the knowledge graph. Thus, a reasoning is executed based on the developed knowledge graph models in order to capture a machine or service has a failure.

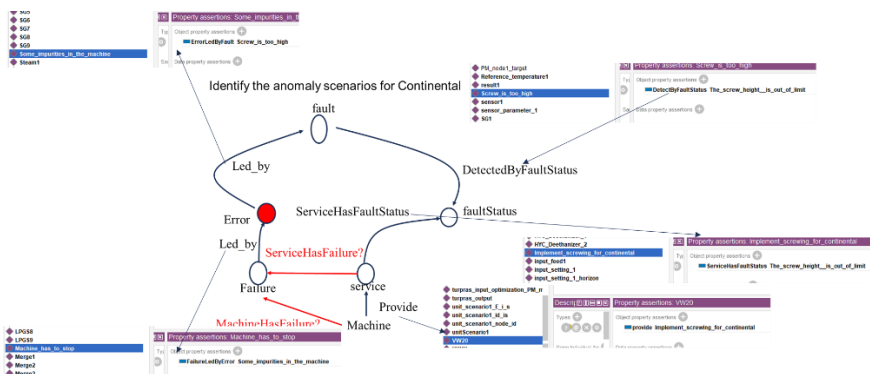


Figure 33: Knowledge graph models for CONT pilot

As shown in Figure 33, knowledge graph models are defined to define the anomaly scenario. Through SQWRL rule, a reasoning is implemented:

```

FACTLOG_BFO:Flipping_Screwing_machine(?mac) ^
FACTLOG_BFO:provide(?mac, ?servi) ^ FACTLOG_BFO:Implement_screwing(?servi) ^
FACTLOG_BFO:ServiceHasFaultStatus(?servi, ?fsta) ^ FACTLOG_BFO:fault_status(?fsta)
^ FACTLOG_BFO:DetectByFaultStatus(?fau, ?fsta) ^ FACTLOG_BFO:fault(?fau) ^
FACTLOG_BFO:ErrorLedByFault(?err, ?fau) ^ FACTLOG_BFO:error(?err) ^
FACTLOG_BFO:FailureLedByError(?imser, ?fal) ^ FACTLOG_BFO:failure(?fail) ->
sqwrl:select(?mac, ?servi, ?fail)
    
```

mac	servi	fail
FactLog_BFO:VW20	FactLog_BFO:Implement_screwing_for_continental	FactLog_BFO:Machine_has_to_stop
FactLog_BFO:VW20	FactLog_BFO:Implement_screwing_for_continental	FactLog_BFO:Machine_has_to_stop

machine
service
failure

**Figure 34: Reasoning result for CONT pilot**

Finally, a reasoning result is obtained. From the result, we can understand VW20 machine has a failure: Machine has to stop.

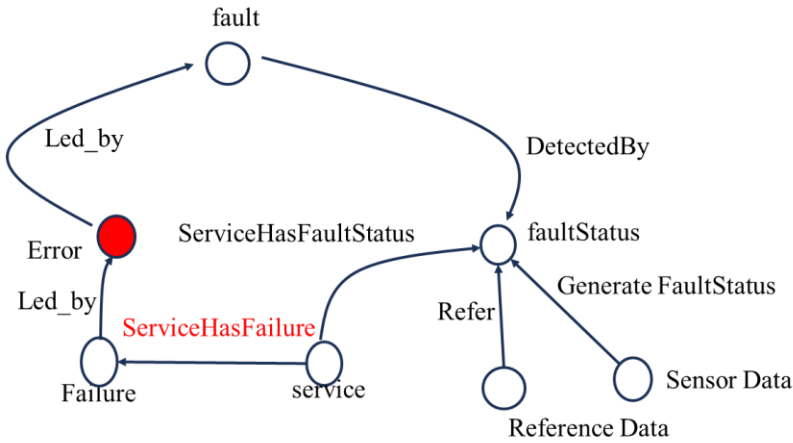
**6.4.1.2 Anomaly detection for BRC Pilot**

Based on the ontology for anomaly detection, a knowledge graph model is defined to represent the rational of anomaly detection for the BRC pilot.

**Table 3 – Anomaly detection scenario for BRC pilot**

Sensor Data	Possible Error detection ( <b>Error</b> )	Required additional data inputs ( <b>Reference data</b> )	Drift Measure ( <b>Fault status</b> ) extral (ontology for natural data)	Possible Causes ( <b>Fault</b> )	Possible outcomes ( <b>Failure</b> )	<b>Service</b>
Digital Signals						
Hydraulic Cooler ON time	Hydraulic system going over temperature if cooler is on for extended periods	Machine in automatic and safety circuit OK.	The time the cooler is on when the machine is running is varying outside normal operational parameters so system is less efficient	1) Hydraulic pump wear 2) Hydraulic valves not operating correctly. 3) Cooler is inefficient. 4) faulty temperature detector	Hydraulic Oil temperature will go outside safe limits and stop machine	Cooling for Hydraulic system is running

Identify the anomaly scenarios



Through reasoning, failure can be captured which related to service.

**Sensor data**  
Hydraulic Cooler ON time  
**Reference data**  
Machine in automatic and safety circuit OK.  
**Fault status**  
The time the cooler is on when the machine is running is varying outside normal operational parameters so **system is less efficient.**  
**Fault**  
1) Hydraulic pump wear  
2) Hydraulic valves not operating correctly  
3) Cooler is inefficient  
4) Faulty temperature detector  
**Error**  
Hydraulic system going over temperature if cooler is on for extended periods  
**Failure**  
Hydraulic Oil temperature will go outside safe limits and stop machine  
**Service**  
Cooling for Hydraulic system is running

Figure 35: Anomaly scenario for BRC pilot

As shown in Figure 35, based on Table 3, an anomaly scenario is defined. The knowledge graph model is built based on the given data and anomaly ontology. The relationships between failure and two other concepts including service are not defined in the knowledge graph. Thus, a reasoning is executed based on the developed knowledge graph models in order to capture a service has a failure.

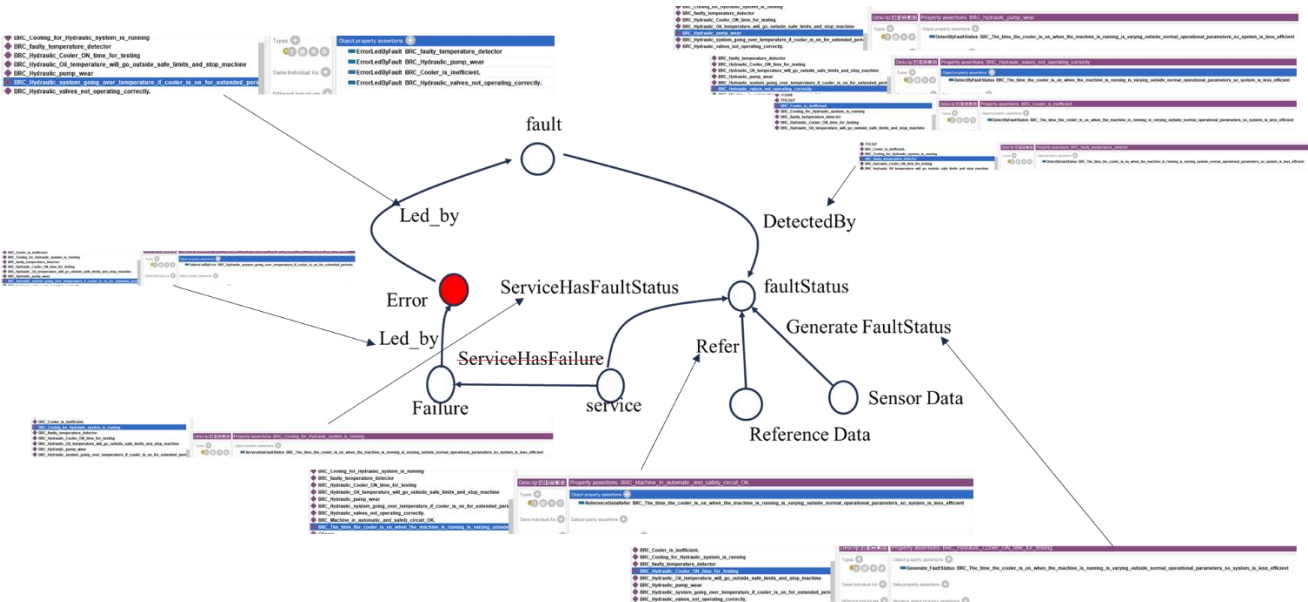


Figure 36: Knowledge graph models for BRC pilot

As shown in Figure 36, knowledge graph models are defined to define the anomaly scenario. Through SQWRL rule, a reasoning is implemented:

```

FACTLOG_BFO:Hydraulic_system_cooling_service(?servi) ^
FACTLOG_BFO:ServiceHasFaultStatus(?servi, ?fsta) ^
FACTLOG_BFO:Hydraulic_Cooler_ON_time(?senData) ^
FACTLOG_BFO:Generate_FaultStatus(?senData, ?fsta) ^
FACTLOG_BFO:fault_status(?fsta) ^ FACTLOG_BFO:DetectByFaultStatus(?fau, ?fsta) ^
FACTLOG_BFO:fault(?fau) ^ FACTLOG_BFO:ErrorLedByFault(?err, ?fau) ^
FACTLOG_BFO:error(?err) ^ FACTLOG_BFO:FailureLedByError(?imser, ?fal) ^
FACTLOG_BFO:failure(?fail) -> sqwrl:select(?servi, ?fail)
    
```

Finally, a reasoning result is obtained. From the result, we can understand BRC\_Cooling\_for\_Hydraulic\_system\_is\_running service has a failure: BRC\_Hydraulic\_Oil\_temperature\_will\_go\_outside\_safe\_limits\_and\_stop\_machine.



Figure 37: Reasoning result for BRC pilot

### 6.4.1.3 Anomaly detection for JEMS pilot

Based on the ontology for anomaly detection, a knowledge graph model is defined to represent the rationale of anomaly detection for the JEMS pilot<sup>2</sup>.

Table 4 – Anomaly detection scenario for JEMS pilot

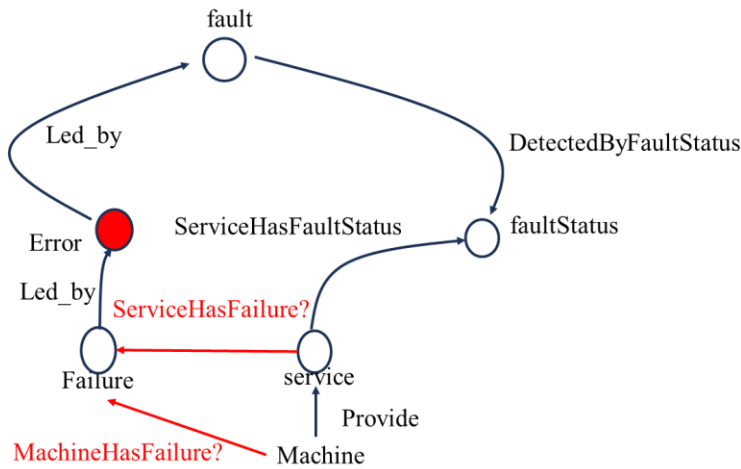
Sensor Data	Possible Error detection (Error)	Required additional data inputs (Reference data)	Drift Measure ( Fault status) extra (ontology for natural data)	Possible Causes (Fault)	Possible outcomes (Failure)	Service	Machine
<ul style="list-style-type: none"> <li>Ingested material flow speed</li> <li>Mixing power</li> <li>Temperature</li> <li>Pressure</li> <li>Turbine flow</li> <li>Pump speed</li> </ul>	<b>clogged pipe</b>	Machine in automatic and safety circuit OK.	<ul style="list-style-type: none"> <li>Ingested material flow speed: decreasing ingestion speed</li> <li>Mixing power: increasing machine power required to mix the mixture</li> <li>Temperature: temperature above 160C or 300C in phases 2 and 3</li> <li>Pressure: increased pressure in phases 2 and 3</li> <li>Turbine flow: decreased turbine flow per minute</li> <li>Pump speed: decreased pump speed when pumping from B100 to turbine</li> </ul>	The fault status signals highly increased density/viscosity of the mixture preventing normal operation	The machine stops working / must be stopped	The machine provides the waste processing.	Waste to fuel plant

As shown in Figure 38, based on Table 4, an anomaly scenario is defined. The knowledge graph model is built based on the given data and anomaly ontology. The relationships between failure and two other concepts including service are not defined in the knowledge graph. Thus, a reasoning is executed based on the developed knowledge graph models in order to capture a machine has a failure.

<sup>2</sup> JEMS pilot did not meet its objectives, especially with regards to the integration of the FACTLOG system to its plant since there is not yet an operative plant in Slovenia.



Identify the anomaly scenarios for JEMS



- **Sensor data (ID)**
  - Ingested material flow speed
  - Mixing power
  - Temperature
  - Pressure
  - Turbine flow
  - Pump speed
- **FaultStatus**
  - Ingested material flow speed: decreasing ingestion speed
  - Mixing power: increasing machine power required to mix the mixture
  - Temperature: temperature above 160C or 300C in phases 2 and 3
  - Pressure: increased pressure in phases 2 and 3
  - Turbine flow: decreased turbine flow per minute
  - Pump speed: decreased pump speed when pumping from B100 to turbine
- **Fault**
  - The fault status signals highly increased density/viscosity of the mixture preventing normal operation (fault).
- **Error**
  - The fault is led by Error (clogged pipe).
- **Failure**
  - The machine stops working / must be stopped.
- **Service**
  - The machine provides the waste processing.
- **Machine**
  - Waste to fuel plant

Through reasoning, failure can be captured which related to service. Failure can be captured for the machine.

Figure 38: Anomaly scenario for JEMS pilot

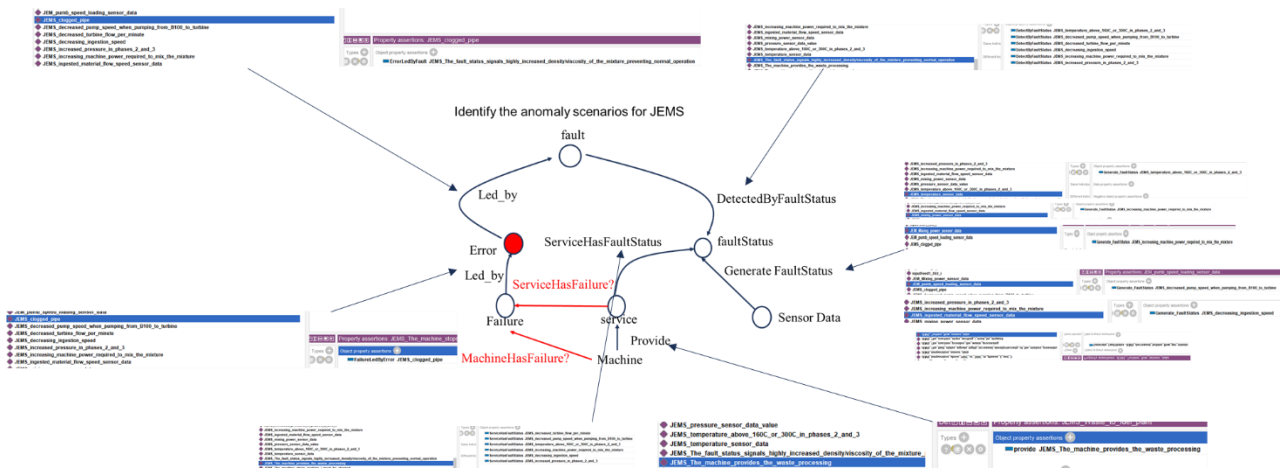


Figure 39: Knowledge graph models for JEMS pilot

As shown in Figure 39, knowledge graph models are defined to define the anomaly scenario. Through SQWRL rule, a reasoning is implemented:

```

FACTLOG_BFO:Waste_to_fuel_plant (?mac) ^ FACTLOG_BFO:provide(?mac, ?servi) ^
FACTLOG_BFO:waste_processing_service(?servi)
FACTLOG_BFO:ServiceHasFaultStatus(?servi, ?fsta) ^ FACTLOG_BFO:fault_status(?fsta)
^ FACTLOG_BFO:DetectByFaultStatus(?fau, ?fsta) ^ FACTLOG_BFO:failure(?fau) ^
FACTLOG_BFO:ErrorLedByFault(?err, ?fau) ^ FACTLOG_BFO:error(?err) ^
FACTLOG_BFO:FailureLedByError(?imser, ?fal) ^ FACTLOG_BFO:failure(?fail) ->
sqwrl:select(?mac, ?servi, ?fail)
    
```

Finally, a reasoning result is obtained. From the result, we can understand the machine JEMS\_Waste\_to\_fuel\_plant provides a service (JEMS\_The\_machine\_provides\_the\_waste\_processing) has a failure: JEMS\_The\_machine\_must\_be\_stopped.

FactLog_BFOJEMS_Waste_to_fuel_plant	FactLog_BFOJEMS_The_machine_provides_the_waste_processing	FactLog_BFOJEMS_The_machine_must_be_stopped
FactLog_BFOJEMS_Waste_to_fuel_plant	FactLog_BFOJEMS_The_machine_provides_the_waste_processing	FactLog_BFOJEMS_The_machine_must_be_stopped
FactLog_BFOJEMS_Waste_to_fuel_plant	FactLog_BFOJEMS_The_machine_provides_the_waste_processing	FactLog_BFOJEMS_The_machine_must_be_stopped
FactLog_BFOJEMS_Waste_to_fuel_plant	FactLog_BFOJEMS_The_machine_provides_the_waste_processing	FactLog_BFOJEMS_The_machine_must_be_stopped

machine

service

failure

Figure 40: Reasoning result for JEMS pilot

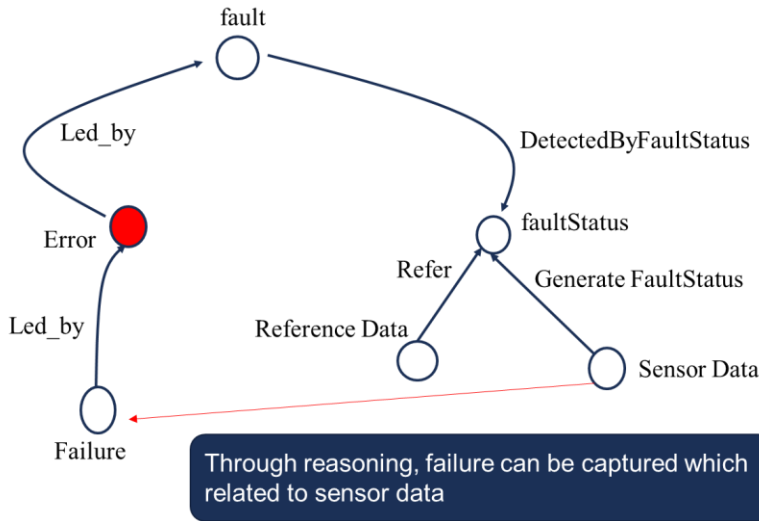
6.4.1.4 Anomaly detection for PIA pilot

Based on the ontology for anomaly detection, a knowledge graph model is defined to represent the rational of anomaly detection for the PIA pilot.

Table 5 – Anomaly detection scenario for PIA pilot

Sensor Data	Possible Error detection (Error)	Required additional data inputs (Reference data)	Drift Measure ( Fault status) extral (ontology for natural data)	Possible Causes (Fault)	Possible outcomes (Failure)
Mechanical lock	The error is detected by the PLC. Then the yarn brokerage data is sent to MES	Failure cause tyoe the i sinputed manually by the human after the visual inspection of the stopepd loom	The error is detected by the PLC. Then the yarn brokerage data is sent to MES	Digital 0 (stopped)	The error is detected by the PLC. Then the yarn brokerage data is sent to MES

Identify the anomaly scenarios for PIACENZA



Through reasoning, failure can be captured which related to sensor data

- **Sensor data**
  - Mechanical lock
- **Reference data**
  - Failure cause tyoe the i sinputed manually by the human after the visual inspection of the stopepd loom
- **FaultStatus**
  - Digital 0 (stopped)
- **Fault**
  - Inadequate loom speed (too high), or quality problem of the yarn lot
- **Error**
  - The error is detected by the PLC. Then the yarn brokerage data is sent to MES
- **Failure**
  - When the loom is stopped, a red light turns on the loom. It means the loom is topped.

Figure 41: Anomaly scenario for PIA pilot

As shown in Figure 41, based on Table 5, an anomaly scenario is defined. The knowledge graph model is built based on the given data and anomaly ontology. The relationships between failure and sensor data are not defined in the knowledge graph. Thus, a reasoning is executed based on the developed knowledge graph models in order to capture a sensor data has a failure.

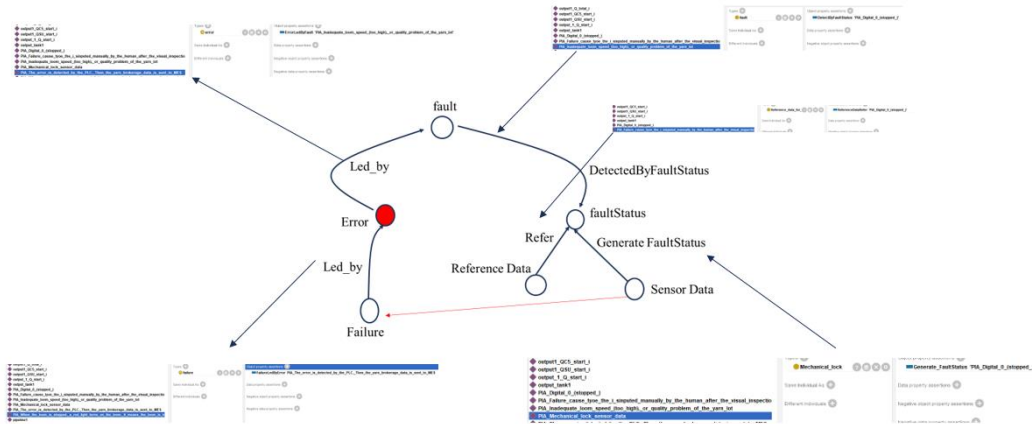


Figure 42: Knowledge graph models for PIA pilot

As shown in Figure 42, knowledge graph models are defined to define the anomaly scenario. Through SQWRL rule, a reasoning is implemented:

```
FACTLOG_BFO:Mechanical_lock (?sendata) ^ FACTLOG_BFO:Generate_FaultStatus
(?sendata, ?fsta) ^ Reference_data_for_anomaly_analysis (?refedata) ^
FACTLOG_BFO:ReferenceDataRefer (?refedata, ?fsta) ^
FACTLOG_BFO:fault_status(?fsta) ^ FACTLOG_BFO:DetectByFaultStatus(?fau, ?fsta) ^
FACTLOG_BFO:fault(?fau) ^ FACTLOG_BFO:ErrorLedByFault(?err, ?fau) ^
FACTLOG_BFO:error(?err) ^ FACTLOG_BFO:FailureLedByError(?imser, ?fal) ^
FACTLOG_BFO:failure(?fail) -> sqwrl:select(?sendata,?fail)
```

SOWRL Queries   OWL 2 RL   S7   S8   S9	
sendata	fail
FactLog_BFO:PIA_Mechanical_lock_sensor_data	autopen?_3_red_light_turns_on_the_loom_#_means_the_loom_is_topped
Sensor data	failure

Figure 43: Reasoning result for PIA pilot

Finally, a reasoning result is obtained. From the result, we can understand the sensor data (Mechanical\_lock) has a failure: “When the loom is stopped, a red light turns on the loom. It means the loom is topped.”.

## 6.4.2 Cognition services based on Knowledge Graph Models in Graphical Database

### 6.4.2.1 Anomaly detection for CONT Pilot

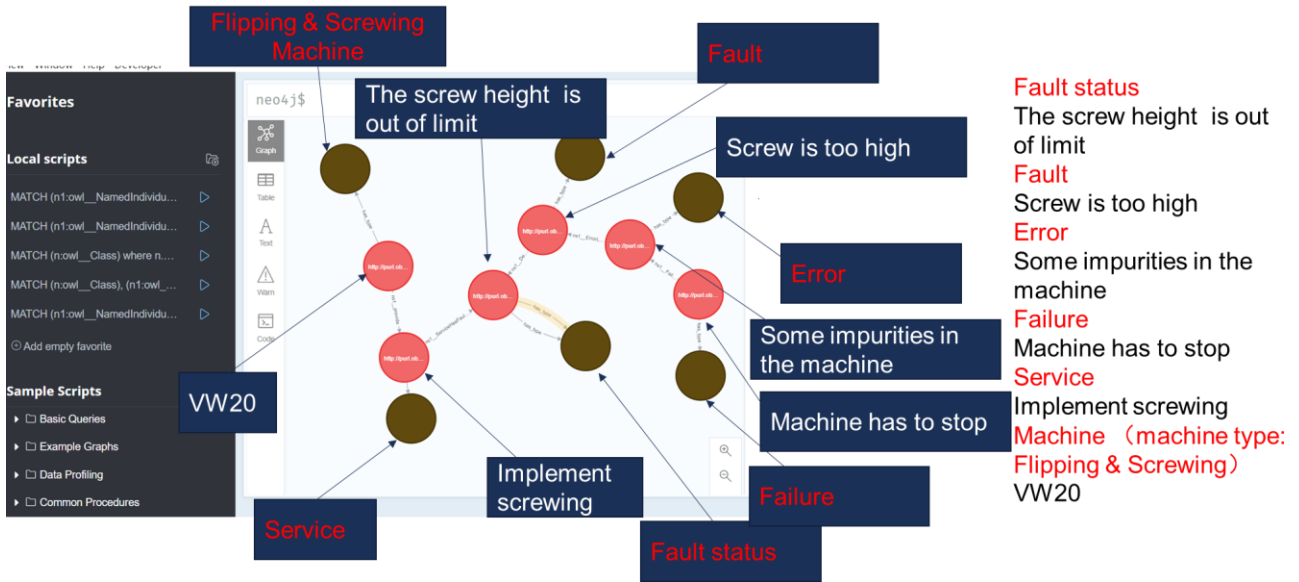


Figure 44: Reasoning result for CONT pilot

As shown in Figure 44, through the integration of KGM and cognition services, the OWL model (Section 6.4.1.1) for anomaly detection is used to generate Neo4j knowledge graph model. Through the reasoning in Neo4j by using cypher, the VW20 machine has fault status The screw height is out of limit.

### 6.4.2.2 Sensor values forecasting for JEMS pilot

While the cognitive services exposed for sensor values forecasting work based on induction, leveraging machine learning models to issue predictions based on patterns learned from past data, such models are created based on domain knowledge encoded in knowledge graphs and specific endpoints described and presented in D4.4. In Figure 45 we show a high-level architecture diagram based on the one introduced in Section 6.3, and relating it to our knowledge graph and external services consuming it.

We leveraged the owlready2 library to create an in-memory knowledge graph based on a custom ontology we developed that represents the relevant entities required to create the machine learning model (see Figure 46). The ontology had 31 classes, extended from the BFO upper ontology, and leveraged concepts from four related ontologies: OntoDM, IAO, DAMON, DMOP. Individuals created in the process were persisted, and could be later exported in the OWL format when required, and later imported and merged along with the ontology to the aforementioned Neo4j instance (see Figure 47).

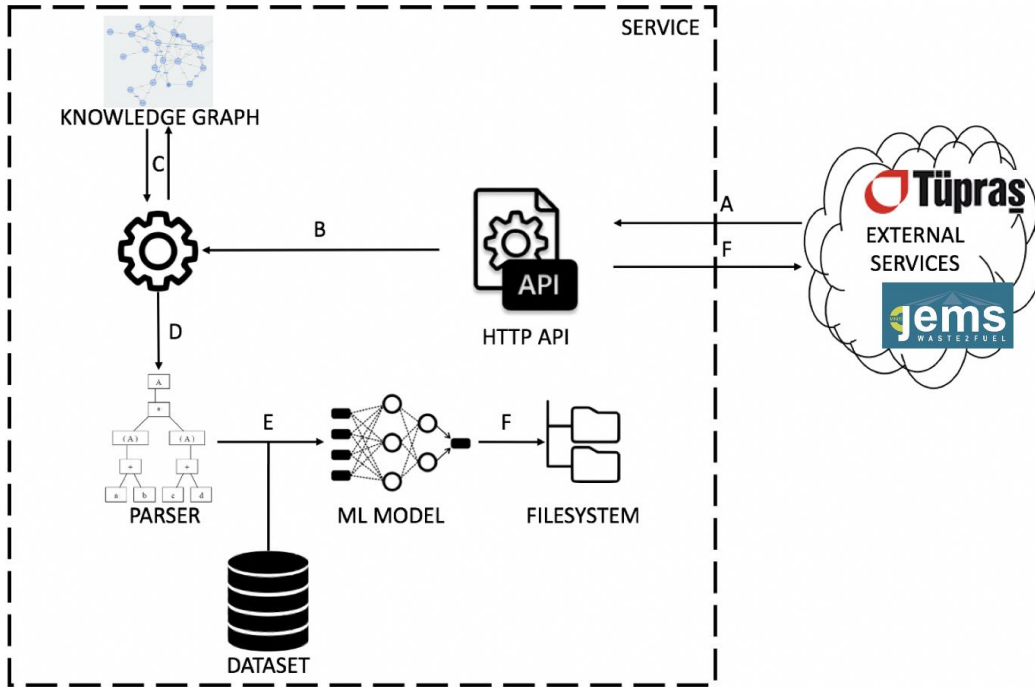


Figure 45. Diagram displaying how the KG-based analytics for process optimization service is used by the use cases we worked for.

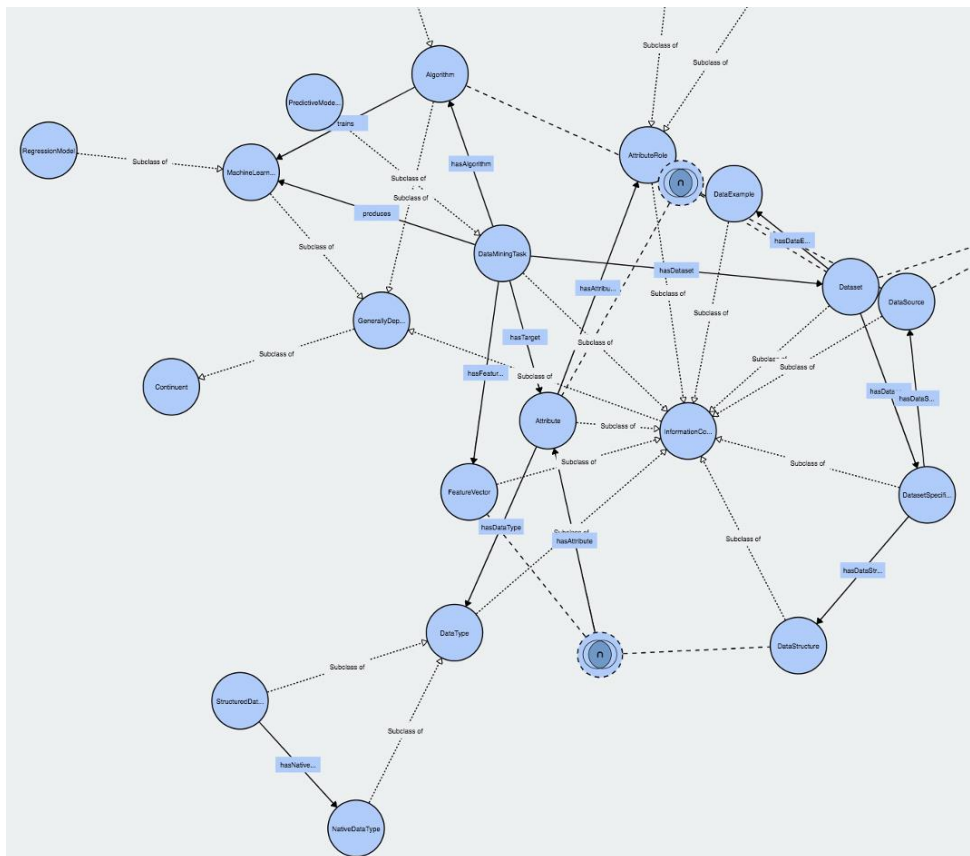


Figure 46. Graph visualization of the ontology we created.

The screenshot shows an ontology editor interface. On the left, a list of individuals is displayed, including various attributes and specific task instances like `dataminingtask_0c9a69be-3dc7-4a76-9306-d218d526b527`. The right pane shows the usage of a selected individual, listing 16 uses with property assertions such as `hasDataset CrudeDistillationUnit`, `hasAlgorithm CatBoostRegressor`, `hasFeatureVector featurevector_0c9a69be-3dc7-4a76-9306-d218d526b527`, `hasTarget attribute_0c9a69be-3dc7-4a76-9306-d218d526b527`, and `produces regressionmodel_0c9a69be-3dc7-4a76-9306-d218d526b527`. Below these are object and data property assertions, including a `uuid` assertion.

Figure 47. Individuals created in the ontology-based knowledge base based on data on multiple calls to the HTTP API.

The service described above enables to use API calls to retrain a model based on particular data (e.g., new data available) and later deployed to replace the stale ones. The architecture supporting the deployment of such machine learning models was described in detail in D3.2, along with the results obtained for the different use cases. Below we reproduce the results obtained for particular motor power, pressure, and temperature sensors (Figures 48-50).

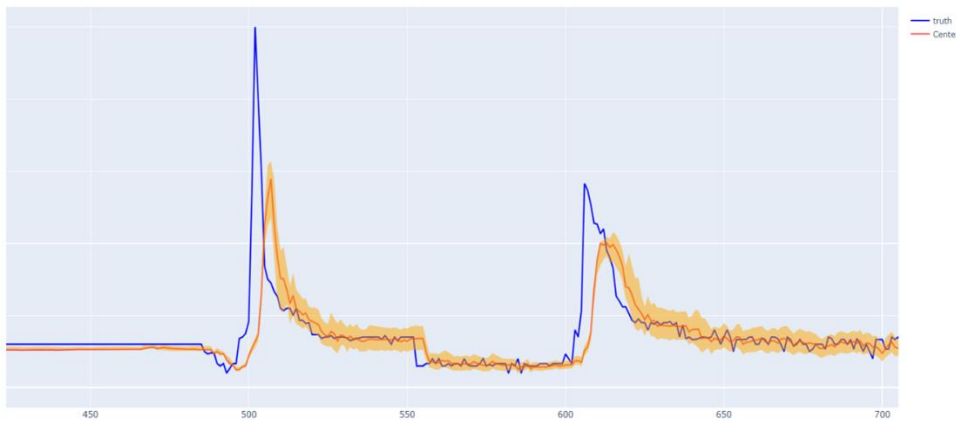
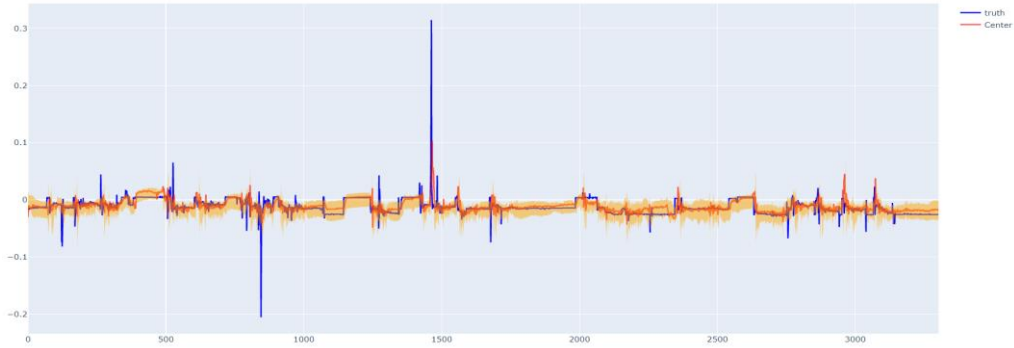
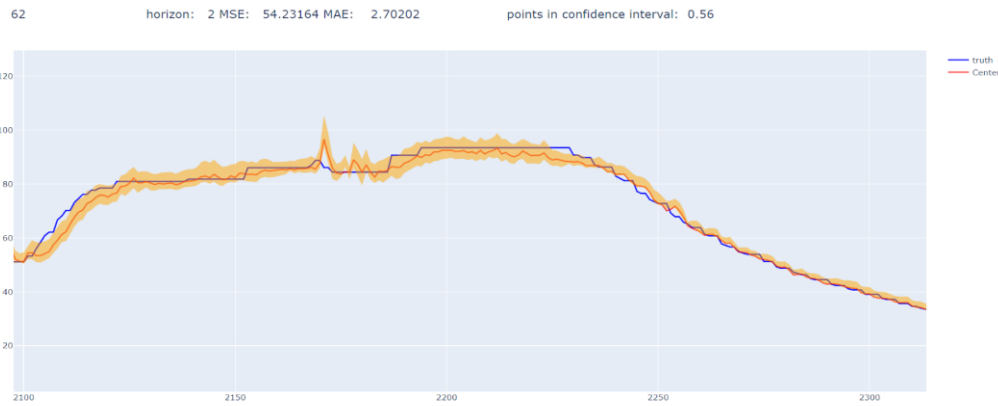


Figure 48. Motor power sensor





**Figure 49. Pressure sensor**



**Figure 50. Temperature sensor**

Ontology-defined ML model and analytical pipeline enables to apply the initial cognitive services designed in a more generalized approach. While the initial configuration demanded predefined models and feature vector configurations, the upgraded services with knowledge graph semantics enable configuration using API abstraction. This key difference enables the integrator to self-define (automatically configure) the internal analytical data structures, to match the use case requirements. A step towards generalizable services use.

## 7 Conclusion

This report demonstrates basic background of ontology, ontology engineering and knowledge graph modelling for factory cognition first. Then ontology for the entire FACTLOG project is introduced including pilot description, optimization, process modelling, etc. Moreover, knowledge graph models which are developed for each pilot are introduced. Finally, integration of knowledge graph models and FACTLOG platform is reported including cognition services based on OWL and Neo4j. In summary, we have three important outputs from this deliverable:

- Top level ontology, such as BFO and IOF ontology, is used to construct an ontology framework to support the standardization of our ontology development.
- Five pilots and four technical partners including data analysis, process models, optimization and anomaly detection are defined based on the developed ontology framework.
- The developed knowledge graph models are integrated with FACTLOG platform. Thus, all the FACTLOG components can access the knowledge graph models to capture related data.

Based on the lessons learned from the FACTLOG project, through the top-level ontology, the knowledge graph models have a good scalability. All the pilot concepts and domain concepts of technical partners can be integrated under a unified ontology framework.

## References

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## Appendix I – Integrating KGM based on OWL

We have made a project for the visualization for BFO. In this project, two resource classes (Entity and Line) were constructed for the parse of BFO model. The OWL file was read by the *Jena* ontology API. The objects of Entity Class and Line Class stored the topological relation of BFO model. The open source JavaScript visualization library ECHART was used for visualization in this project. Due to the large number of properties of BFO, we only show the properties needed in this particular OWL file in this demo. The details of the project are shown as follow.

### HOW TO RUN THE DEMO IN ECLIPSE

#### (1) Import project

In Eclipse, select the File -> Import. Then the dialog box is shown as Figure 51. Select the *Existing Maven Project* and choose the demo directory and the maven project is import in the Eclipse. It may take some time to load the libraries.

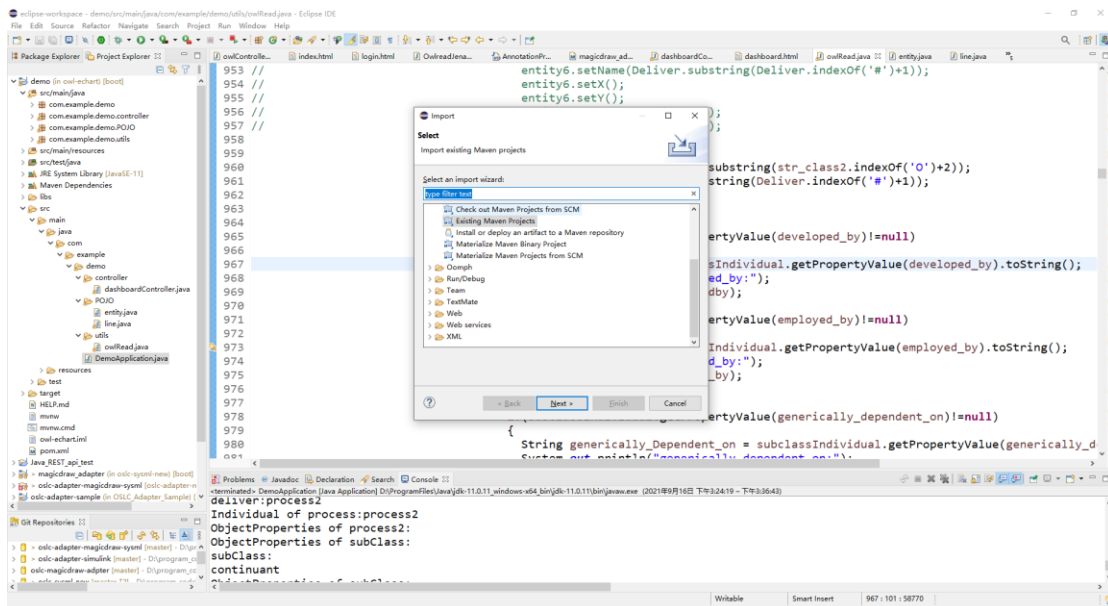


Figure 51: Eclipse project

#### (2) modify the file path

Modify the OWL file path in line 33 and line 1828 in owlRead.java. Change file path to your own file path of the OWL file.



Figure 52: Change the path for loading OWL files.

### (3) run the application

Run the springboot project as Java Application, shown as Figure 53.

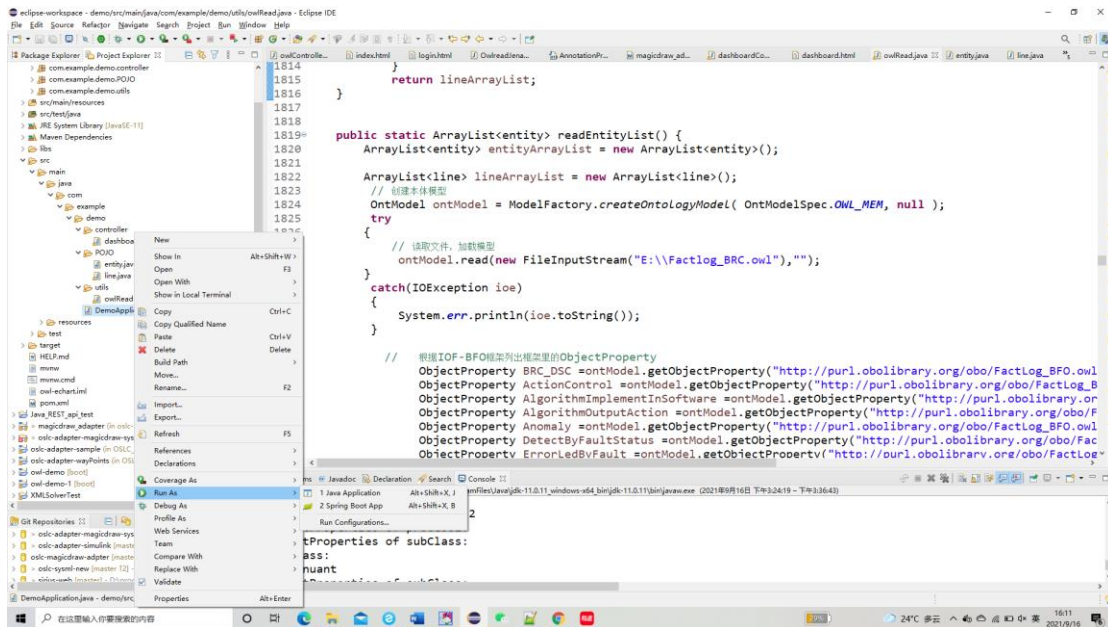


Figure 53: Compile the whole project

### (4) Result Browser

Open a browser and type in the url localhost:8080. Then the result is shown as follow which is localhost:8080.

The topology dashboard in OWL

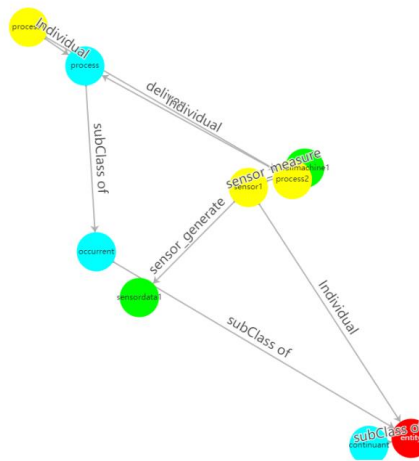


Figure 54: Visualize the OWL information



## Appendix II – Knowledge Graph Modeling tools

### 1. Protégé

Protégé is supported by a strong community of academic, government, and corporate users, who use Protégé to build knowledge-based solutions in areas as diverse as biomedicine, e-commerce, and organizational modeling <https://protege.stanford.edu/> In our project, we make use of it to model knowledge graph models using OWL.

*Unzip the Protege-5.5.0-win and open Protege.exe. Then start your knowledge graph modeling journey.*

### 2. Twinkle

Twinkle is a simple GUI interface that wraps the ARQ SPARQL query engine. The tool should be useful both for people wanting to learn the SPARQL query language, as well as those doing Semantic Web development <http://www.ldodds.com/projects/twinkle/>. In this project, we make use of it to implement SPARQL query.

*Unzip the twinkle-2.0-src and open twinkle.jar. Then start your query journey.*

### 3. Neo4j

Neo4j is the only enterprise-strength graph database that combines native graph storage, advanced security, scalable speed-optimized architecture, and ACID compliance to ensure predictability and integrity of relationship-based queries. In FACTLOG, it is used to integrate knowledge graph models with FACTLOG platform <https://neo4j.com/> .