Robotics and Computer-Integrated Manufacturing

Intelligent predictive maintenance of hydraulic systems based on virtual knowledge graph

--Manuscript Draft--

Manuscript Number:	
Article Type:	Research Paper
Keywords:	Industry 4.0; Predictive maintenance; Virtual knowledge graph; Ontology; Ontology-based data access; Hydraulic systems
Corresponding Author:	Qiushi Cao, Ph.D. Swansea University UNITED KINGDOM
First Author:	Wei Yan, Ph.D.
Order of Authors:	Wei Yan, Ph.D.
	Yu Shi
	Yuan Sui
	Zhenzhen Tian
	Wanjing Wang
	Zengyan Ji
	Qiushi Cao, Ph.D.
Manuscript Region of Origin:	Asia Pacific
Abstract:	In the manufacturing industry, a hydraulic system harnesses liquid fluid power to create powerful machines. Under the trend of Industry 4.0, the predictive maintenance of hydraulic systems is transforming to more intelligent and automated approaches that leverage the strong power of artificial intelligence and data science technologies. However, due to the knowledge-intensive and heterogeneous nature of the manufacturing domain, the data and information required for predictive maintenance are normally collected from ubiquitous sensing networks. This leads to the gap between massive heterogeneous data/information resources in hydraulic system components and the limited cognitive ability of system users. Moreover, how to capture and structure useful domain knowledge (in a machine-readable way) for solving domain-specific tasks remains an open challenge for the predictive maintenance of hydraulic systems. To address these challenges, in this paper we propose a virtual knowledge graph-based approach for the digital modelling and intelligent predictive analytics of hydraulic systems. We evaluate the functionalities and effectiveness of the proposed approach on a predictive maintenance task under real-world industrial contexts. Results show that our proposed approach is capable and feasible to be implemented for digital modelling, data access, data integration, and predictive analytics.
Suggested Reviewers:	Farhad Ameri fa11@txstate.edu
Opposed Reviewers:	

Paper Submitted to the Robotics and Computer-Integrated Manufacturing Journal

Title: Intelligent predictive maintenance of hydraulic systems based on virtual knowledge graph

Dear editors and reviewers,

We attach this letter to our submission of the paper "Intelligent predictive maintenance of hydraulic systems based on virtual knowledge graph". The paper is submitted to the journal *Robotics and Computer-Integrated Manufacturing.*

In this paper, we propose a virtual knowledge graph-based approach for the digital modelling and intelligent predictive analytics of hydraulic systems. We evaluate the functionalities and effectiveness of the proposed approach on a predictive maintenance task under real-world industrial contexts. Results show that our proposed approach is capable and feasible to be implemented for digital modelling, data access, data integration, and predictive analytics.

We would like to thank you in advance for your efforts and time devoted to examining and reviewing the submitted paper.

Best regards,

The authors

Title: Intelligent predictive maintenance of hydraulic systems based on virtual knowledge graph

Authors: Wei Yan, Yu Shi, Yuan Sui, Zhenzhen Tian, Wanjing Wang, Zengyan Ji, Qiushi Cao*

*Corresponding author. Email: qiushi.cao@cn.bosch.com

Highlights:

- A virtual knowledge graph-based predictive maintenance approach is proposed for hydraulic systems.
- A novel domain Ontology for Hydraulic Systems (HSO) has been introduced.
- The functionalities and effectiveness of the proposed approach is evaluated on a real-world case study.
- Results show that our proposed approach is capable and feasible to be implemented for digital modelling, data access, data integration, and predictive analytics of hydraulic systems.

Highlights

Intelligent predictive maintenance of hydraulic systems based on virtual knowledge graph

Wei Yan, Yu Shi, Yuan Sui, Zhenzhen Tian, Wanjing Wang, Zengyan Ji, Qiushi Cao

- A virtual knowledge graph-based predictive maintenance approach is proposed for hydraulic systems.
- A novel domain Ontology for Hydraulic Systems (HSO) has been introduced.
- The functionalities and effectiveness of the proposed approach is evaluated on a real-world case study.
- Results show that our proposed approach is capable and feasible to be implemented for digital modelling, data access, data integration, and predictive analytics of hydraulic systems.

Intelligent predictive maintenance of hydraulic systems based on virtual knowledge graph

Wei Yan[a], Yu Shi[a], Yuan Sui[a], Zhenzhen Tian[a], Wanjing Wang[a], Zengyan Ji[a], Qiushi Cao[b,*]

[a] *School of Information Science and Engineering, Shandong Normal University, Jinan, 250014, China*
[b] *Corporate Research, Bosch China*

Abstract

In the manufacturing industry, a hydraulic system harnesses liquid fluid power to create powerful machines. Under the trend of Industry 4.0, the predictive maintenance of hydraulic systems is transforming to more intelligent and automated approaches that leverage the strong power of artificial intelligence and data science technologies. However, due to the knowledge-intensive and heterogeneous nature of the manufacturing domain, the data and information required for predictive maintenance are normally collected from ubiquitous sensing networks. This leads to the gap between massive heterogeneous data/information resources in hydraulic system components and the limited cognitive ability of system users. Moreover, how to capture and structure useful domain knowledge (in a machine-readable way) for solving domain-specific tasks remains an open challenge for the predictive maintenance of hydraulic systems. To address these challenges, in this paper we propose a virtual knowledge graph-based approach for the digital modelling and intelligent predictive analytics of hydraulic systems. We evaluate the functionalities and effectiveness of the proposed approach on a predictive maintenance task under real-world industrial contexts. Results show that our proposed approach is capable and feasible to be implemented for digital modelling, data access, data integration, and predictive analytics.

Keywords:
Industry 4.0, Predictive maintenance, Virtual knowledge graph, Ontology, Ontology-based data access, Hydraulic systems

*Corresponding author. Email: qiushi.cao@cn.bosch.com

1. Introduction

In recent years, the digital transformation of the manufacturing industry is progressing rapidly. Embracing advanced technologies such as Artificial Intelligence (AI), Cyber-Physical Systems (CPS), and data science, this digital transformation is reshaping the individual lives of both customers and manufacturers. To meet the higher demand regarding global competition, manufacturers and suppliers are working hard to look for solutions to improve manufacturing effectiveness and efficiency. With the trend of Industry 4.0, the traditional manufacturing factories are transforming to "smart factories", where highly digitalised work stations continuously collect, share, and analyse data through a connected network of machines. Smart factories are also integrated with product life cycle management and supply chain activities, which significantly changes the way people work and live [1].

In the manufacturing industry, a hydraulic system harnesses liquid fluid power to create powerful machines. Within such a system, hydraulic fluid is pumped to various hydraulic motors and hydraulic cylinders throughout the machine. Then the hydraulic fluid is pressurised according to the current resistance. Within this process, the fluid is controlled directly or automatically by control valves and distributed through tubes or pipes. Because of these characteristics, this type of system is pervasively used in devices such as brakes, lifts, and compactors. Due to continuous usage, hydraulic systems may suffer from system deterioration problems such as exhaustion of the actuators or ageing of pipes [2]. This may lead to severe issues that can affect system efficiency and safety. Thus, condition-based monitoring and predictive analytics of this type of mechanical system during the system life cycle is key to their successful implementation in industry [3].

Following the current trend of Industry 4.0, the predictive maintenance of hydraulic systems is transforming to more intelligent and automated approaches that leverage the strong power of artificial intelligence and data science technologies. However, due to the knowledge-intensive and heterogeneous nature of the manufacturing domain, the data and information required for predictive maintenance are normally collected from ubiquitous sensing networks [4]. This leads to the gap between massive heterogeneous data/information resources in hydraulic system components and the limited cognitive ability of system users. Moreover, how to capture and structure useful domain knowledge (in a machine-readable way) for solving domain-specific tasks remains an open challenge for the predictive maintenance of hydraulic systems [5]. To solve these open challenges, the deduction and inference of new knowledge for system operation and maintenance management are crucial to support the predictive analytics for system operation. These described issues are considered important to enable *semantic interoperability.*

To address the semantic interoperability issue, ontologies and knowledge graphs appear to be promising solutions [6, 7, 8, 9]. Among the commonly used AI technologies, knowledge graph is a prominent knowledge-driven technique that stores structured relational facts of concrete entities and abstract concepts in the real world [10]. The structured relational facts are obtained either automatically from plain text that is generated within manufacturing processes or manually from the cognitive knowledge from domain experts or machine operators. To manipulate the encoded knowledge, a knowledge graph uses *entities* to represent concepts within a domain from both abstract and concrete levels. On the other hand, *relations* indicate the relationships amongst different entities in a simple and generic data structure. Because of these characteristics, knowledge graphs are commonly used in knowledge-intensive smart manufacturing tasks. However, despite the recent proliferation of scientific contributions from data science community, when we refer to knowledge-driven predictive maintenance approaches, the contributions are far from sufficient. Knowledge-driven methods such as knowledge graph and ontologies provide unambiguous and machine-interpretable descriptions of industrial assets, processes, and services. In this context, knowledge graphs and ontologies are promising solutions for complex problems related to automated, flexible, and self-configurable systems like Industry 4.0 systems [11].

For the goal of digitalisation and automatic predictive maintenance of hydraulic systems, in this paper, we propose a knowledge graph-based approach for the digital modelling and intelligent predictive analytics of hydraulic systems. We first develop a domain ontology for describing the structure, behavior, and functions of hydraulic systems. During the ontology construction phase, we use a systematic ontology development approach and refer to a set of important international standards. Then we map the ontology to real-world data sets using Ontology-based Data Access (OBDA) technologies. This allows the construction of a Virtual Knowledge Graph (VKG) system, where the semantic access and integration of data sources are enabled by R2RML mappings from domain ontology to heterogeneous data sets. At last, we perform the condition-based and predictive maintenance task of a hydraulic system by executing task-specific queries to reason on real-world data sets. The execution results of queries prove that our proposed approach is capable and feasible to be implemented for digital modelling, data access, data integration, and predictive analytics of hydraulic systems. Unlike most of the knowledge graph-based approaches introduced in the literature, which focused mainly on the conceptual modelling perspective, we pay special attention to the real-world industrial implementation aspects of VKG systems.

The remainder of the paper is organised as follows. Section 2 gives a comprehensive review of the existing ontologies and knowledge graphs for both Industry 4.0 and hydraulic systems. Section 3 introduces the proposed knowledge graph-based approach for predictive maintenance of hydraulic systems. We give a detailed description of the systematic ontology development methodology, which enables the construction of a VKG system. We evaluate the effectiveness and usability of the proposed approach in Section 4, where the developed VKG system is tested on a real-world predictive maintenance task. Section 5 concludes the paper and points out future research perspectives.

2. Related work

Over the last decades, a significant number of ontology and knowledge graph-based approaches have been proposed to facilitate predictive maintenance tasks in the context of Industry 4.0. In this section, we first review those ontology and knowledge graph-based approaches that have been implemented for the vision of Industry 4.0. We then narrow the scope to those systems and approaches designed for hydraulic systems.

2.1. Ontologies and knowledge graphs for Industry 4.0

With the advent of the fourth industrial intelligence dominated revolution (Industry 4.0), traditional industry boundaries were gradually disappearing, new forms of work and cooperation were emerging. Industry 4.0 mainly relies on a CPS [12], and the core is to use the Internet of Things and other technologies to establish information connections for all links in the production process. Ontologies and knowledge graphs have been widely involved in the application of Industry 4.0 due to its great advantage in knowledge representation, semantic expression [13], and various resolutions for knowledge management [14]. Reference Architecture Model Industrie 4.0 (RAMI 4.0) is a framework model that describes Industry 4.0 from three dimensions, and multiple angles [15]. In the context of industry 4.0, Beden et al. categorised Industry 4.0-related ontologies and knowledge graphs into three categories: product-related, process-related, and resource-related [16].

Industry 4.0 mainly focuses on machine intelligence in the manufacturing domain. Aiming at the realisation of intelligent manufacturing, a comprehensive ontology generation and evolution method is demonstrated according to four stages [17]. Jardim-Goncalves et al. proposed a knowledge framework that can address the interoperability of intelligent manufacturing systems [18]. To improve industrial manufacturing efficiency and realise industrial automation, an ontology-based industrial environment model with versatility and scalability is proposed in [19]. As another similar work, a general ontology in the manufacturing field based on the automobile production process achieves greater versatility in factory automation [20]. Panetto et al. introduced a method to promote system interoperability. Based on a set of reasonable assumptions, a high-level Product Ontology (ONTO-PDM) is introduced in [21]. The biggest feature of this ontology is the integration of existing standards, including the IEC 62264 standard and ISO 10303 standard. From the authors' perspective, applying the standard to a practical manufacturing environment is conducive to improving the accuracy and reliability of the ontology. Cao et al. developed a knowledge-based system for Industry 4.0 predictive maintenance [22]. The system is named as KSPMI and it leverages both statistical and symbolic AI methods to perform predictive analytics of machine failures. The system is tested on semi-conductor manufacturing processes where ontology reasoning is enabled to predict the occurrence and temporal information of machine failures.

There are many other fields more closely related to intelligent manufacturing in Industry 4.0. In terms of condition monitoring, Cao et al. introduced an ontology for the development of an intelligent condition detection system, based on which the status monitoring tasks can be implemented through SWRL rule-based reasoning [9]. Grüninger et al. proposed PSL, which aims to improve information exchange between manufacturing systems [23]. To address the air pollution problem, an air pollution-related knowledge graph is introduced in [24], which can dynamically update the data in a map through an agent to monitor industrial air pollution.

Industry 4.0 is driving a global revolution and is committed to fundamentally changing the mode of production and value creation. It will not only promote corporate change but also affect employees. Based on the research on occupational health and safety (OHS), Badri et al. examined the impact of this change on typical manufacturing operations from four perspectives [25]. Industry 4.0 can also indirectly affect the domain of health and safety. For example, food safety has always been a hot issue in the agricultural industry, and Çelik et al. proposed a knowledge base called FoodWiki based on the health status of consumers and the degree of tolerance of the food, to achieve the function of food consumption advice to individuals [26]. Wan et al. proposed a reconfigurable pharmaceutical production model, in which the Manufacturing's Semantics Ontology (MASON) is built based on IEC 61499 standard [27]. Not only that, but ontology also has many other applications in the context of Industry 4.0. The powerful knowledge base and knowledge management ability of ontologies and knowledge graphs have great potential in data integration, knowledge sharing, knowledge acquisition and knowledge reasoning under different contexts.

RAMI4.0 is an important reference architecture in Industry 4.0 [28]. Porrmann et al. suggested using miHSOervice agents to implement rami4.0-related drive production systems [29]. Based on the three-dimensional RAMI 4.0 model, Reference Generalized Ontology Model (RGOM) is proposed. RGOM is a common framework composed of specific ontological concepts, and it is recommended for generating a knowledge graph that is able to respond to real-time questions, and answers [30]. Rather than a conceptual model, the application of knowledge graphs and ontologies also has a lot of potentials. Ontologies and knowledge graphs can express knowledge in intelligent manufacturing systems in order to enable seamless connectivity and interoperability between intelligent systems, including human, hardware, and software [14]. During the development phase of ontologies and knowledge graphs, the incorporation of standards is beneficial to improve the reliability and reusability of these knowledge models.

2.2. Ontologies and knowledge graphs for hydraulic systems

The structure of the hydraulic system is complex, and especially, its faults have the characteristics of contingency and concealment, which greatly increases the workload and cost of maintenance. With the continuous development of manufacturing technologies, intelligent diagnosis and maintenance of hydraulic systems have become an inevitable measure so as to improve maintenance efficiency and reduce maintenance costs. In view of the particularity of hydraulic systems, ontology and knowledge graph-based predictive fault diagnosis methods have attracted considerable interest since. These methods are able to establish a clear knowledge framework, improve the reusability of knowledge, and realise knowledge sharing among different systems.

Within the domain of hydraulics, Zhao et al. proposed a hierarchical diagnosis model based on ontology production rules, in which knowledge in fault diagnosis, including system composition and fault relationship, is stored in ontology, and then production rules link real-time data and faults, locating faults and implementing prediction [5]. Yang designed a fault diagnosis model of the excavator hydraulic system, which is based on a prediction model and expert system. The knowledge base of the hydraulic system fault diagnosis expert system is stored in the ontology, and the residual statistical information output by the prediction model is inferred by using SWRL language according to the fault characteristics so as to determine the fault location and put forward the maintenance method. Ren introduced the Ontology-based fault knowledge representation method of pump truck hydraulic system, realised global knowledge fusion through ontology mapping, and then applied the C-F model to fault knowledge reasoning to determine the matching degree of fault phenomenon and fault cause. Ren also designed a knowledge representation framework for fault diagnosis using a three-tier ontology structure model to further infer the ontology [31]. Klusch et al. introduced the intelligent condition monitoring hydraulic system for fault detection and diagnosis, and the developed ontology represents the knowledge in the field of condition monitoring. The concept of domain ontology defines component symptoms, faults and the relationship between fault factors and fault causes. Index the C-SPARQL query to realize online semantic symptom detection [32].

Aiming for sharing and integrating hydraulic system fault knowledge, Xing et al. proposed a method based on ontology knowledge modelling. Ontology is constructed with Protégé. On this basis, class and individual reasoning of ontology are realised by using reasoning tools such as Pellet and Hermit so as to realise fault location [33]. K.W. Chau developed an ontology-based knowledge management system (KMS) for modelling flow and water quality [34]. KMS simulates human expertise and couple various descriptive knowledge, procedural knowledge and reasoning knowledge for the problem solving during coastal hydraulic and transport processes.

3. The knowledge graph-based approach for predictive maintenance of hydraulic systems

In this section, we introduce the proposed knowledge graph-based approach for predictive maintenance of hydraulic systems. The whole approach starts with the development of a domain Ontology for Hydraulic System (HSO) predictive maintenance. During the ontology development phase, a list of existing internatinoal standards and ontologies were reused to ensure rigorous conceptualisation. We also introduce key classes and relationships within HSO.

3.1. The overall approach

The overall approach consists of three main steps:

1. The approach starts with the knowledge acquisition and extraction step aiming for the construction of a domain ontology. During this step, we acquire domain knowledge about industrial predictive maintenance from technical documents. These technical documents include research papers, machine specification documents, International Organization for Standardization (ISO) (e.g. ISO 17800, ISO 3450, ISO 10972, ISO 5598, ISO/TR 8059, ISO 15086, ISO 13533, ISO 5598) and International Electrotechnical Commission (IEC) standards (e.g. ISO/IEC 15286). This conceptual modelling process is referred to as the *top-down* strategy. On the other hand, real-world data sets are used as resources to learn relevant parameters/features regarding different types of

machinery anomalies such as machine errors, faults, and failures. This process is called the *bottom-up* strategy. As a result, a domain ontology called HSO is built using the *middle-out* approach introduced in [35]. This domain ontology will be instantiated with individuals representing status of the system. The instantiation process is enabled by OBDA technologies.

2. The second step is the mapping from HSO to industrial data sets. The goal of this step is to instantiate HSO with individuals that represent different system status. The mapping step starts with the generation of R2RML mappings and followed by the materialisation of triples using the generated triples. The triples are used within an instaintiation process which populates HSO using real-world data. The used data set is experimentally collected from a hydraulic test rig. This step constructs a VKG and enables the condition-based and predictive maintenance of the hydraulic system.
3. The third step is the condition-based and predictive maintenance of the hydraulic system. To do this, SPARQL queries are used to examine the status of system components. We pay special attention to four important system components: cooler, valve, internal pump, and hydraulic accumulator. We also aim to detect whether the system is under stable conditions by reasoning on the data about system stable flags. By this, we evaluate the usefulness and effectiveness of the constructed VKG under real-world industrial contexts.

3.2. Ontology development methodology

To develop HSO, we complement the middle-out approaching using the Ontology Description Capture Method called IDEF5. IDEF5 methodology covers a wide range of ontology engineering topics, such as creation, modification and maintenance [36]. The key distinguishing characteristic of IDEF5 is the gradual refinement process during ontology development. This advantage allows the developed ontology to acts as an evolving prototype model, which ensures the ontology is progressively enriched with real data while following its original structure. This methodology is a general procedure for developing ontologies, which includes five main steps:

1. *Organizing and scoping.* In this step, the purpose, viewpoint, and context for ontology development is clarified. *Purpose* includes objectives and requirements, and *scope* defines the boundaries of the ontology.
2. *Data collection.* Raw data is acquired for ontology development. Traditional knowledge acquisition techniques are used in this step, such as protocol analysis and expert interview.
3. *Data analysis.* The ontology is extracted from the data collection results. Objects are listed, followed by the identification of the boundaries of the ontology.

4. *Initial ontology development.* A preliminary ontology is developed, including initial descriptions of concepts, relations and properties.
5. *Ontology refinement and validation.* The developed ontology is iteratively refined and tested. As the ontology is instantiated with real data, the results of instantiation are compared with the original ontology structure.

3.3. Ontology encoding and development environment

To develop HSO, we choose Web Ontology Language (OWL) [37] as the ontology encoding language. OWL is a standard semantic web language that designed to formally describe complex knowldge about things and their interrelationships. It is a logic-based language that is made computer-interpretable, which means computer programs can easily process the knowledge it encodes. We also use Protégé 5.5.0[1] as the ontology editor to create the main class hierarchy and relationships of HSO. Protégé provides powerful tools and plug-ins to modify and visialise ontology structure. It also supports OBDA modules that allows for querying relational data sources. This is a key functionality that enables the mapping between HSO to real-world data sets.

3.4. Ontology reuse

The goal of ontology reuse is to save the manual efforts for ontology development and to avoid developing ontologies from scratch. To ensure ontology reusability, it is a good practise to resort to available ontological frameworks and models that provide domain-relevant knowledge. During the development of HSO, the following ontologies are reused. We list these ontologies in Table 1.

Table 1: Reused ontologies during the development of HSO.

Reused Ontologies	**Ontology description**
UFO [38]	A top-level ontology of universals.
MSDL [39]	An upper-level ontology for describing manufacturing services.
MASON [40]	An OWL-based ontology to facilitate knowledge sharing in manufacturing.
OntoProg [41]	An ontology for the predictive maintenance aspect of manufacturing activities.
DOSCM [9]	A domain ontology for smart condition monitoring.
MPMO [42]	An ontology for failure prediction in Industry 4.0.
Time Ontology [43]	An ontology to formalise temporal properties of resources in the world.

[1]https://protege.stanford.edu/

3.5. Main classes

Within HSO, *System*, *Structure*, *Function*, *Behavior*, *Equipment_ component*, and *Issue* are the main classes. The *System* superclass describes a set of hydraulic systems that we aim to describe. The *Structure* superclass describes the components of the designed hydraulic system and their relationships. *Function* describes the purposes of each system component object. *Behavior* describes how a hydraulic system component reacts or responses to different events. *Equipment_ component* models an element of a tool or equipment assembled for a specific purpose. Fig. 1 shows the overall structure of HSO. Table 2 gives a detailed class description for HSO. Due to clarity reasons, here we only list important classes of HSO.

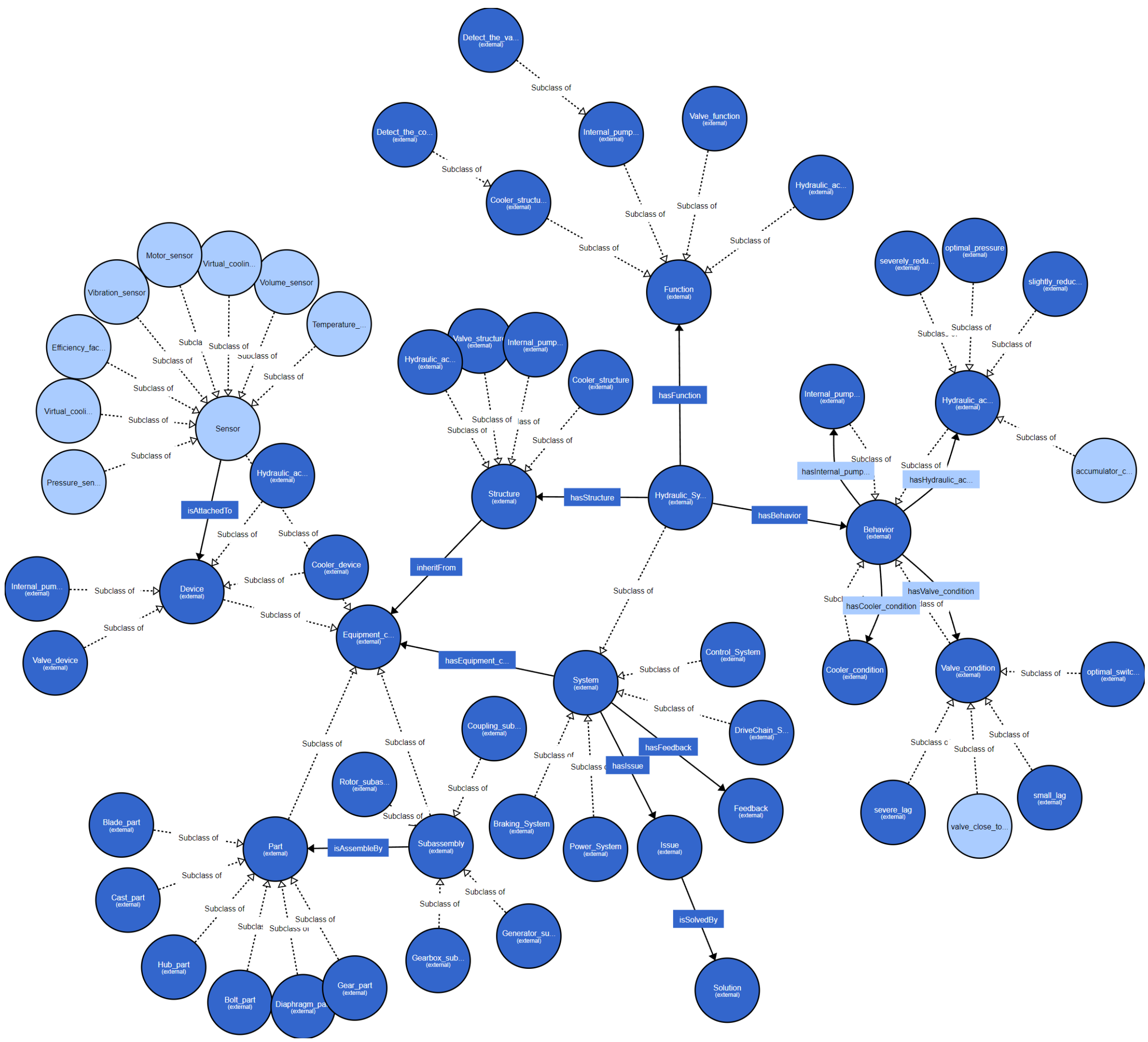

Figure 1: The global structure of HSO.

Table 2: Major classes and their sub-classes in the HSO

Ontology classes	Description
OntoHSO:Hydraulic System ontology	HS function and perform tasks through using a fluid that is pressurized.
OntoHSO:Behavior	How an element in HSO acts and reacts.
OntoHSO:Cooler condition	Condition(s) under the cooling of the workpiece takes place.
OntoHSO:Hydraulic accumulator condition	Pressure storage reservoir to cope with extremes of demand and to smooth out pulsations.
OntoHSO:Internal pump leakage condition	Material flex, internal leakage, wear, and other variables result in varying amounts of pressure dependence.
OntoHSO:Valve condition	A mode or state of valve.
OntoHSO:Function	Describe each component's function of HSO.
OntoHSO:Cooler structure function	Detect the conditions for workpiece cooling.
OntoHSO:Hydraulic accumulator function	Cope with extremes of demand and to smooth out pulsations.
OntoHSO:Internal pump leakage function	Detect the variables, i.e., internal leakage, material flex and wear degree.
OntoHSO:Valve function	Represent the mode or state of valve.
OntoHSO:Structure	Organization of relations among objects of a system describing constituency relations.
OntoHSO:Cooler structure	Component that lowers the temperature of the fluid.
OntoHSO:Hydraulic accumulator structure	Pressure storage reservoir that enables a hydraulic system to cope with extremes of demand.
OntoHSO:Internal pump leakage structure	An internal machine or device for lifting, compressing, or conveying liquids.
OntoHSO:Valve structure	Any of various devices that regulate the flow of gases, liquids, or loose materials.
OntoHSO:Issue	Matter in question or in dispute which is not settled
OntoHSO:Condition issue	Status of occupancy, operation of service systems, requirement for the functions of the technical building systems.
OntoHSO:Feature issue	Abstraction of real world phenomena.
OntoHSO:Phenomenon issue	An occurrence, circumstance, or fact that is perceptible by the senses.
OntoHSO:Problem cause issue	Circumstance, condition, event or action that in a hazardous situation contributes to the production of an effect.
OntoHSO:Solution	A method or process of dealing with a problem.
OntoHSO:MaintenanceInterval solution	Maximum interval of time for performance characteristics to remain within a predefined range without external servicing.
OntoHSO:Manpower solution	The power of human physical strength.
OntoHSO:Requirement solution	Need or expectation that is stated, generally implied or obligatory.
OntoHSO:Tool solution	External device, including keys and coins, used to aid a person to perform a mechanical function.
OntoHSO:Equipment_component	An element of a tool or equipment assembled for a specific purpose.

3.6. Relationships

Within HSO, there are two types of relationships to connect classes and individuals together: object and data properties. Object properties connect individuals by predicates. Data properties are predicates that associate individuals to a certain form of attribute data. Normally, both object and data properties are used to define classes and their constraints. In our predictive maintenance task, object properties will describe the semantic relationships among data fields within relational data bases. While data properties will be mapped to these data fields, for queries to be executed for examining hydraulic system status. These processes will be introduced in Section 4. Table. 3 lists key relationships within HSO as well as their domain and range.

Table 3: Major property and their domain-range in the HSO

Property	**Domain**	**Range**	**Description**
OntoHSO:hasEquipment_component	System	Equipment_component	Describe System has Equipment_component
OntoHSO:hasFeedback	System	Behavior	Describe Hydraulic System has Behavior
OntoHSO:hasBehavior	Hydraulic System	Behavior	Describe Hydraulic System has Behavior
OntoHSO:hasFunction	Hydraulic System	Function	Describe Hydraulic System has Function
OntoHSO:hasStructure	Hydraulic System	Structure	Describe Hydraulic System has Structure
OntoHSO:hasIssue	System	Issue	Describe System has Issue
OntoHSO:isSolvedBy	Issue	Solution	Describe Issue can be solved by Solution
OntoHSO:isAssembleBy	Subassembly	Part	Describe Subassembly is assemble by Part
OntoHSO:isAttachedTo	Sensor	Device	Describe Sensor is attached to Device
OntoHSO:inheritFrom	Structure	Equipment_component	Describe Structure is inherited from Equipment_component

3.7. The virtual knowledge graph system for predictive maintenance

The development of HSO enables the construction of a VKG system for predictive maintenance. The constructed VKG system is able to structure heterogeneous system historical and operation data in the form of a unified knowledge graph. The unified knowledge graph virtualises relational databases by R2RML mappings between HSO and data sets. In this way, data sources can be reasoned and explored by standard query language SPAQRL. The VKG system frees end-users from working on complex structure of data sources. Instead, end-users can work on the high-level graph layer for flexible manipulation of data and queries. In Section. 4, we give a detailed introduction to the VKG system and its implementation on a real-world predictive maintenance task.

4. Case study: predictive maintenance of hydraulic systems

This section demonstrates a real-world case study using the constructed VKG. The goal of this case study is to perform condition-based and predictive maintenance on hydraulic systems. We use a real-world data set obtained with a hydraulic test rig. OBDA technologies are used to map our ontology to specific data fields. After that, the status of system components are detected and monitored by executing task-specific queries. The returned results of queries reveal the real-time conditions of hydraulic system components, which enables further predictive analytics.

4.1. The hydraulic system data set

A hydraulic system harnesses liquid fluid power to create powerful machines. Fig. 2 shows the architecture of a hydraulic system. Normally, such a system consists of the following main components:

- Hydraulic pumps. This type of components converts mechanical power into hydraulic energy using the flow and pressure of liquid fluid inside it. When a hydraulic pump is working, a vacuum at a pump inlet is created to force liquid from a reservoir into an inlet line, also to the pump itself. In this way, a pump takes suction from a low-pressure reservoir and transfers the high-pressure hydraulic fluid to a directional control valve. This process is normally controlled by an operator.

- Actuator (linear motion). An actuator generates a linear motion by concerting hydraulic energy into mechanical energy. The output force of an actuator is proportional to the hydraulic fluid pressure and the actuator piston area.

- Hydraulic motor (rotary motion). A hydraulic motor generates the required torque and rotational speed of a system by converting hydraulic energy into mechanical energy.

- Hydraulic valves. This type of components properly directs the flow of liquid through a hydraulic system. Hydraulic valves are subdivided into three main categories according to their functionalities: directional control valves, pressure control valves and flow control valves. These valves provide high-pressure hydraulic fluid to the desired port on the actuator or hydraulic motor with a return port for the low-pressure hydraulic fluid.

- Hydraulic accumulators. These are energy storage devices that allow hydraulic systems to operate instantly as required. The main objective of accumulators is to store energy and to smooth out pulsations. When storing energy, a hydraulic accumulator receives pressurised hydraulic fluid for later use. The installation of accumulators allows a hydraulic system to respond to extremes of demand using a less powerful pump.

- Hydraulic oil coolers. These are devices usually installed in hydraulic power packs. Hydraulic oil coolers are normally used for cooling hydraulic oil. They are often essential for designing temperature-optimized hydraulic systems that keep oil temperatures within their optimum working range.

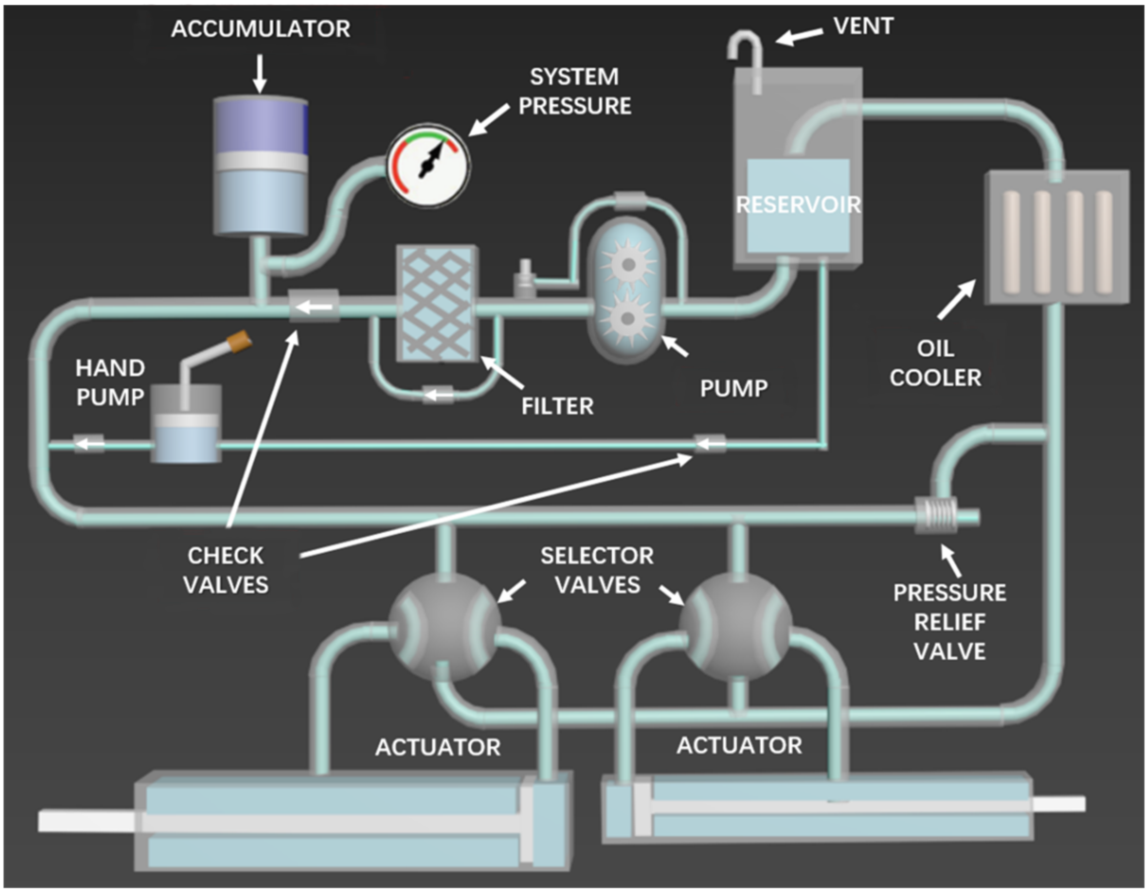

Figure 2: The architecture of a hydraulic system.

In this paper, we use public data sets[2] which is collected from the operation of a hydraulic system. The data sets address the condition assessment of a hydraulic test rig based on multivariate sensor data. The data sets were experimentally obtained with a hydraulic test rig. The test rig consists of two parts of system components:

[2]The data set can be found at: https://archive.ics.uci.edu/ml/datasets/Condition+monitoring+of+hydraulic+systems

a primary working and a secondary cooling-filtration circuit. The two components are connected via a oil tank. Operation of the system cyclically follows a repetitive constant load cycles and each cycle lasts for 60 seconds. During each operation cycle, process parameters such as pressure, motor power, volume flow, temperature, vibration, cooling efficiency, and cooling power are measured in real-time. The condition monitoring task is performed on four hydraulic components: hydraulic oil cooler, hydraulic valves, internal pump, and hydraulic accumulator.

The used data sets contain raw sensor data regarding the measurements mentioned above. Data is structured in the form of matrices (tab-delimited). The rows in the data set represents operation cycles of the system, and the columns contain the data recordings within a cycle. The sensors are installed at the valves, motors, internal pump, and oil coolers of the monitored hydraulic system. In total, there are 2205 recordings within the data set.

4.2. Ontology-based data access using HSO

To perform predictive maintenance on the hydraulic system of interest, we use HSO as the knowledge framework and map it to the hydraulic system data sets described in Section. 4.1. The data is stored in separate files, with each representing the conditions of system components, e.g. cooler, valve, internal pump, hydraulic accumulator. The predictive maintenance task is enabled by OBDA technologies, which aim to facilitate and automate the semantic data access and integration processes.

Normally, writing complex queries using a standard query language such as SQL can be time-consuming. Using SQL templates and manipulating query answers may be error prone, which leads to inappropriate decision results [44]. To cope with these challenges, OBDA offers a different solution for query formalisation and answering. Normally, an OBDA system automatically rewrites standard ontology queries (such as SPARQL queries) and map them to SQL queries over data sources. In this way, compared to traditional database technologies, an OBDA-based system enriches raw data with rich semantics incorporated in ontology models, by which the semantic relations between data files are established and explained. Moreover, using an OBDA system can avoid end-users being exposed to raw data sources. Instead, the access and manipulation of data is achieved by a VKG framework, where a high-level representation of the data is presented by ontology models. This provides a flexible and simplified way for ontology and knowledge graph-based predictive maintenance.

In this paper, we used Ontop [46] as the OBDA system. The main reason we choose Ontop is its support for compact mapping such as R2RML mappings. It also implements query optimisations for JOIN, UNION, and OPTIONAL Operators. Fig. 3 shows the query rewriting process in Ontop. In the figure, a SPARQL query q is

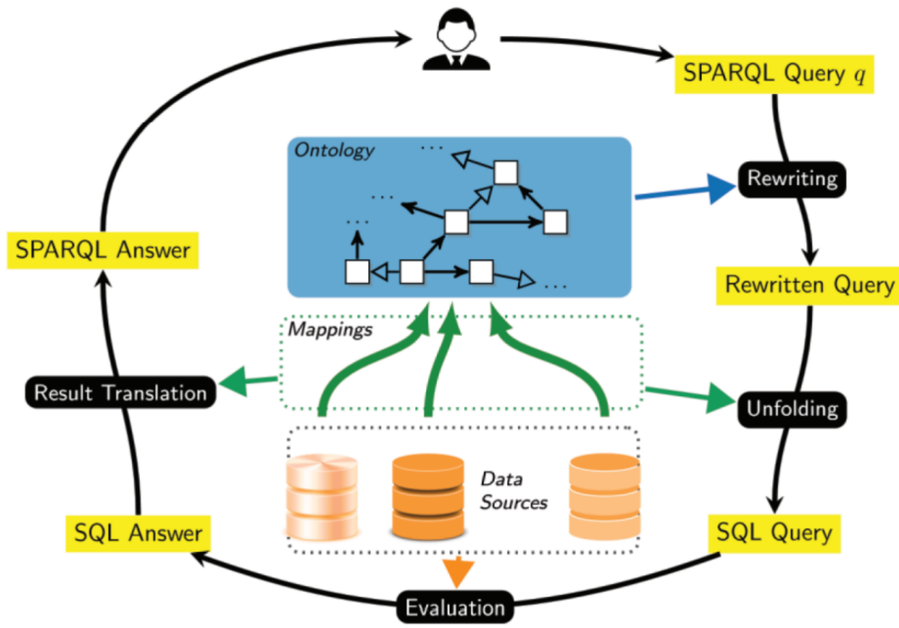

Figure 3: The query rewriting and formalisation process in Ontop [45].

firstly rewritten according to domain ontologies and then unfolded through R2RML mappings. The rewritten query Q is formalised in SQL language and evaluated by data sources. This step is realised at the data federation layer in Ontop. The results of SQL queries are then translated to RDF terms that are compatible with ontology languages. During this result translation process, a set of optimisation methods are used to reduce query answer time and to improve the performance.

4.3. R2RML mappings between HSO and data sets

In this work, R2RML mappings are used to link HSO classes and properties to the data fields is relational data sources. The generated mappings allow performing predictive analytics on hydraulic system components. Each mapping consists of a set of assertions, which each assertion corresponding to a class or property in HSO. After building the links between ontoloy entities and data sources, queries can be executed over data sources, by which HSO is populated with data of interest. In this way, we obtain a VKG encoded in RDF language. The predictive or condition-based maintenance tasks are then realised by performing task-specific SPAQRL queries to retrieve useful information. The retrieved information reflects the status of the hydraulic system and may indicate potential anomalies that may lead to future system failures.

In this work, we use Protégé to generate mappings. The following codes give some of the example R2RML mappings that connect HSO to data sources. Fig. 4 shows the screenshot of the mappings generated in Protégé Mapping Editor.

```
[PrefixDeclaration]
HSO:            http://www.semanticweb.org/ontologies/hso#
owl:            http://www.w3.org/2002/07/owl#
rdf:            http://www.w3.org/1999/02/22-rdf-syntax-ns#
xml:            http://www.w3.org/XML/1998/namespace
xsd:            http://www.w3.org/2001/XMLSchema#
obda:           https://w3id.org/obda/vocabulary#
rdfs:           http://www.w3.org/2000/01/rdf-schema#

[MappingDeclaration] @collection [[
mappingId       Mapping Cooler_3
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/cooler_close_to_total_failure> ;
                :hasCooler_condition_value {COOLER_CONDITION}^^xsd:int .
source          SELECT * FROM status WHERE "COOLER_CONDITION" = 3

mappingId       Mapping Cooler_20
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/reduced_efficiency> ;
                :hasCooler_condition_value {COOLER_CONDITION}^^xsd:int .
source          SELECT * FROM status WHERE "COOLER_CONDITION" = 20

mappingId       Mapping Cooler_100
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/full_efficiency> ;
                :hasCooler_condition_value {COOLER_CONDITION}^^xsd:int .
source          SELECT * FROM status WHERE "COOLER_CONDITION" = 100

mappingId       Mapping Valve_100
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/optimal_switching_behavior> ;
                :hasValve_condition_value {VALVE_CONDITION}^^xsd:int .
source          SELECT * FROM status WHERE "VALVE_CONDITION" = 100

mappingId       Mapping Valve_90
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/small_lag> ;
                :hasValve_condition_value {VALVE_CONDITION}^^xsd:int .
source          SELECT * FROM status WHERE "VALVE_CONDITION" = 90

mappingId       Mapping Valve_80
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/severe_lag> ;
                :hasValve_condition_value {VALVE_CONDITION}^^xsd:int .
source          SELECT * FROM status WHERE "VALVE_CONDITION" = 80

mappingId       Mapping Valve_73
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/valve_close_to_total_failure> ;
                :hasValve_condition_value {VALVE_CONDITION}^^xsd:int .
source          SELECT * FROM status WHERE "VALVE_CONDITION" = 73

mappingId       Mapping Pump_0
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/no_leakage> ;
                :hasInternal_pump_leakage_value {INTERNAL_PUMP_LEAKAGE}^^xsd:int .
source          SELECT * FROM status WHERE "INTERNAL_PUMP_LEAKAGE"=0

mappingId       Mapping Pump_1
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/weak_leakage> ;
                :hasInternal_pump_leakage_value {INTERNAL_PUMP_LEAKAGE}^^xsd:int .
```

```
source          SELECT * FROM status WHERE "INTERNAL_PUMP_LEAKAGE"= 1

mappingId       Mapping Pump_2
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/severe_leakage> ;
                :hasInternal_pump_leakage_value {INTERNAL_PUMP_LEAKAGE}^^xsd:int .
source          SELECT * FROM status WHERE "INTERNAL_PUMP_LEAKAGE"= 2

mappingId       Mapping  Accumulator_130
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/optimal_pressure> ;
                :hasHydraulic_accumulator_value {HYDRAULIC_ACCUMULATOR}^^xsd:int .
source          SELECT *  FROM status WHERE "HYDRAULIC_ACCUMULATOR"= 130

mappingId       Mapping Accumulator_115
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/slightly_reduced_pressure> ;
                :hasHydraulic_accumulator_value {HYDRAULIC_ACCUMULATOR}^^xsd:int .
source          SELECT * FROM status WHERE "HYDRAULIC_ACCUMULATOR" = 115

mappingId       Mapping Accumulator_100
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/severely_reduced_pressure> ;
                :hasHydraulic_accumulator_value {HYDRAULIC_ACCUMULATOR}^^xsd:int .
source          SELECT * FROM status WHERE "HYDRAULIC_ACCUMULATOR"= 100

mappingId       Mapping Accumulator_90
target          :status/{SEQ_ID} a <http://www.semanticweb.org/ontologies/hso/accumulator_close_to_total_failure> ;
                :hasHydraulic_accumulator_value {HYDRAULIC_ACCUMULATOR}^^xsd:int .
source          SELECT * FROM status WHERE "HYDRAULIC_ACCUMULATOR"= 90

mappingId       Mapping flag_0
target          :status/{SEQ_ID} :hasStableFlag "conditions_were_stable"^^xsd:string .
source          SELECT "SEQ_ID" FROM status WHERE "STABLEFLAG"= 0

mappingId       Mapping flag_1
target          :status/{SEQ_ID} :hasStableFlag "static conditions might not have been reached yet"^^xsd:string .
source          SELECT "SEQ_ID" FROM status WHERE "STABLEFLAG"= 1
]]
```

The mappings are written in Turtle syntax and used in the target of mapping axioms [47]. The execution of mapping points to the target triples in HSO, with each triple written as an RDF subject-predicate-object (SPO) graph. The triples are in the form of $< s, p, o >$, where s is a subject node standing for a URI reference or URI template. Each p is a predicate node that accepts URI references. o is an object node that is a Literal or Literal template. In this way, the classes and properties are connected to the important data fields in data sets, for the goal of predictive analytics.

4.4. Predictive analytics for the hydraulic system

To enable predictive analytics, we use SPARQL as the standard query language to retrieve useful information from the established OBDA system. Essentially, SPARQL is a graph-matching query language that is composed by three parts: *pattern matching part*, *solution modifiers*, and *output*. The *pattern matching part* includes features (operators) for graph pattern matching, such as optional parts, union of patterns,

Figure 4: The R2RML mappings generated in Protégé Mapping Editor.

nesting, and filtering values of possible matching [48]. Once the output of graph patterns (normally in the form of tables) are computed, the *solution modifiers* are used to modify the output by applying operators such as *group by*, *order by*, *distinct*, and *limit*. At last, the execution of a SPARQL query generates an output where different forms of variable bindings are produced.

In this work, the SPARQL queries are proposed to evaluate the status of the hydraulic system of interest. To do this, we use the SPARQL query editor of the Ontop system within the Protégé environment. As introduced in Section. 4.2, Ontop rewrites SPARQL queries over the relational data sources so that the source query engine can execute them. We leverage this mechanism to enable predictive analytics based on SPARQL queries.

4.4.1. The condition-based monitoring of hydraulic system components

We execute SPARQL queries to peform condition-based monitoring of hydraulic system components. The first type of SPARQL queries is used to identify the status of three main components of the hydraulic system: valve, internal pump, and accumulator. We are also interested in retrieving the system stable flag (boolean) to check whether the system is under stable conditions. To construct such a query, prefixes are first generated for the used ontologies. Besides standard schemas such as owl, rdf, xml, xsd, and obda, the IRI of HSO is also inserted as a new prefix for SPARQL queries. In this query, the *SELECT* clause is used to form and return variables of interest as well as their bindings. *DISTICT* is a solution modifier that eliminates duplicate solutions from the solution set. For the target hydraulic system, the cooler may experience three conditions: *close to total failure*, *reduced efficiency*, and *full efficiency*. Each condition is indexed with an integer number. Within the below example query, we would like to investigate when the cooler is under *full efficiency* status what are the conditions of other system components (valve, internal pump, hydraulic accumulator). To do this, we populate HSO with individuals, where each individual stands for a piece of record in the data set. These individuals are named as *SEQ_ID* in the result table. *?SEQ_ID a:full_efficiency* is a predicate to control the entry of cooler conditions. The remaining codes query the conditions of other components.

```
PREFIX : <http://www.semanticweb.org/lenovo/ontologies/2021/7/hso/>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX xml: <http://www.w3.org/XML/1998/namespace>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX obda: <https://w3id.org/obda/vocabulary#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX hso: <http://www.semanticweb.org/lenovo/ontologies/2021/7/hso#>

SELECT DISTINCT
?SEQ_ID ?Cooler_condition ?Valve_condition ?Internal_pump_leakage_condition
?Hydraulic_accumulator_condition ?Stable_flag {
    ?SEQ_ID a :full_efficiency ;
    hso:hasCooler_condition_value ?Cooler_condition;
    hso:hasValve_condition_value ?Valve_condition;
    hso:hasInternal_pump_leakage_value ?Internal_pump_leakage_condition;
    hso:hasHydraulic_accumulator_value ?Hydraulic_accumulator_condition;
    hso:hasStableFlag ?Stable_flag.
}
GROUP BY
?SEQ_ID ?Cooler_condition ?Valve_condition ?Internal_pump_leakage_condition
?Hydraulic_accumulator_condition ?Stable_flag
```

Results of the above query is shown in Fig. 5. The results clearly presents the status of valve, internal pump, and accumulator when hydraulic sysetm coolor works with *full efficiency*. For the valve component, *"90"*^^xsd:int stands for the *small lag* condition, *"100"*^^xsd:int means the *optimal switching behavior* of the valve. For the internal pump component, *"2"*^^xsd:int means it suffers from the *severe leakage* problem. *“1”*^^xsd:int indicates the *weak leakage* of it, and *“0”*^^xsd:int shows that this component has no leakage problem. For the accumulator component, *“130”*^^xsd:int gives the information that this system component works under optimal pressure. At the end of this query, *GROUP BY* keyword organises the presentation of results.

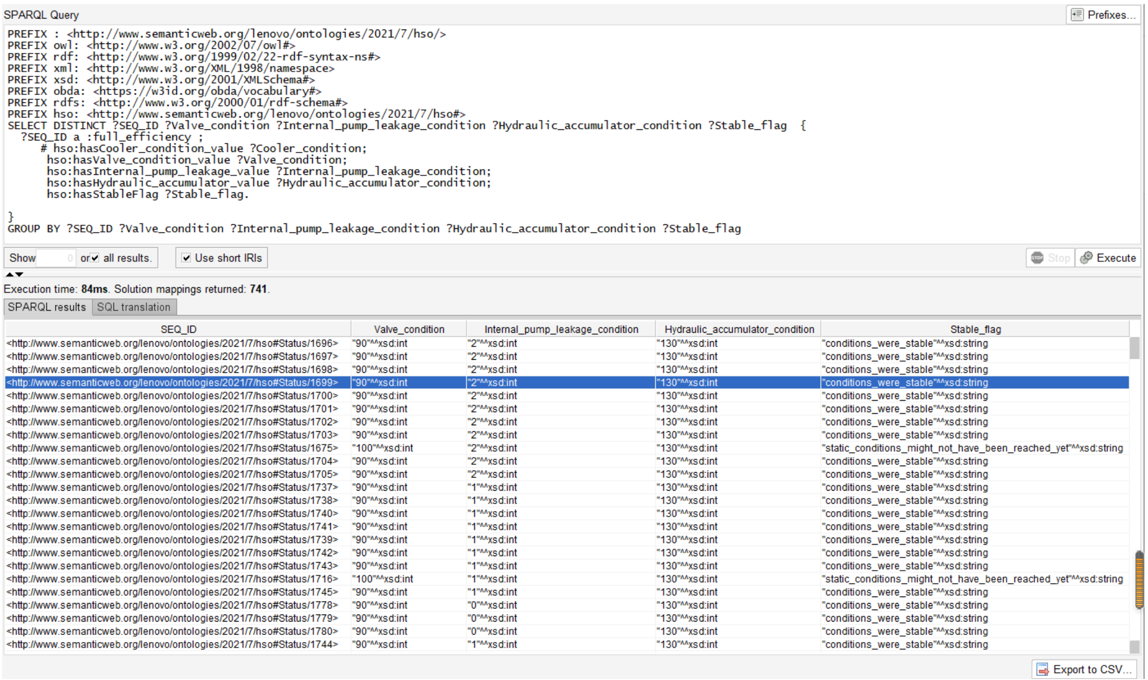

Figure 5: The SPARQL query for reasoning on the status of valve, internal pump, and hydraulic accumulator, when hydraulic system cooler works with full efficiency.

4.4.2. Early detection of hydraulic system anomalies

The second type of queries for predictive maintenance is retrieve the first data record when the system encountered a failure. During the life cycle of a hydraulic system, due to continuous usage, system components and tools may deteriorate according to time. Thus it is of vital importance to identify and detect early-stage anomalies as early as possible. Within this query, we also use *SELECT DISTINCT* clause. In the main body of the query, we specify the IRI of the first individual as *<http://www.semanticweb.org/ontologies/hsostatus/1>* . This individual is mapped from the first data record describing an anomaly in the data sets. *hso:hasCooler_condition_value ?Cooler_condition, hso:hasValve_condition_value ?Valve_condition, hso:hasInternal_pump_leakage_value ?Internal_Pump_Leakage, hso:hasHydraulic_accumulator_value ?Hydraulic_accumulator, hso:hasSt-*

ableFlag ?Stable_flag. are the predicates for binding variables variable values to the four system components and system stable flag. The codes for an example SPARQL query is given below. Query results are shown in Fig. 6

```
PREFIX : <http://www.semanticweb.org/ontologies/hso#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX xml: <http://www.w3.org/XML/1998/namespace>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX obda: <https://w3id.org/obda/vocabulary#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX hso: <http://www.semanticweb.org/ontologies/hso#>

#Example Query the status of an ID
SELECT DISTINCT ?Cooler_condition ?Valve_condition ?Internal_Pump_Leakage
?Hydraulic_accumulator ?Stable_flag{
   <http://www.semanticweb.org/ontologies/hso#status/1>
        hso:hasCooler_condition_value ?Cooler_condition;
        hso:hasValve_condition_value ?Valve_condition;
        hso:hasInternal_pump_leakage_value ?Internal_Pump_Leakage;
        hso:hasHydraulic_accumulator_value ?Hydraulic_accumulator;
   hso:hasStableFlag ?Stable_flag.
}

GROUP BY ?Cooler_condition ?Valve_condition ?Internal_Pump_Leakage
?Hydraulic_accumulator ?Stable_flag
```

In the returned results, the status of four hydraulic system components are shown as *"3"*^^xsd:int, *"100"*^^xsd:int, *"0"*^^xsd:int, *"130"*^^xsd:int respectively. This means the cooler is having a *close to total failure* problem, valve is having an *optimal switching behavior*, internal pump is working without *leakage* issues, and the pressure of system accumulator is under *optimal* status. Results in the last table column (stable flag) tell us *static system conditions might not have been reached yet.*

4.4.3. Detection of occurrences for specific type of anomalies

In real-world scenarios, it is important to know which types of system failures occur frequently. Also, for a certain type of failure, knowledge about how frequently it happens within a system is helpful to carry out appropriate maintenance strategies. To cope with such kind of issues, we propose the third type of queries for detecting the status of system components when experiencing a certain type of anomalies. The codes below show an example query.

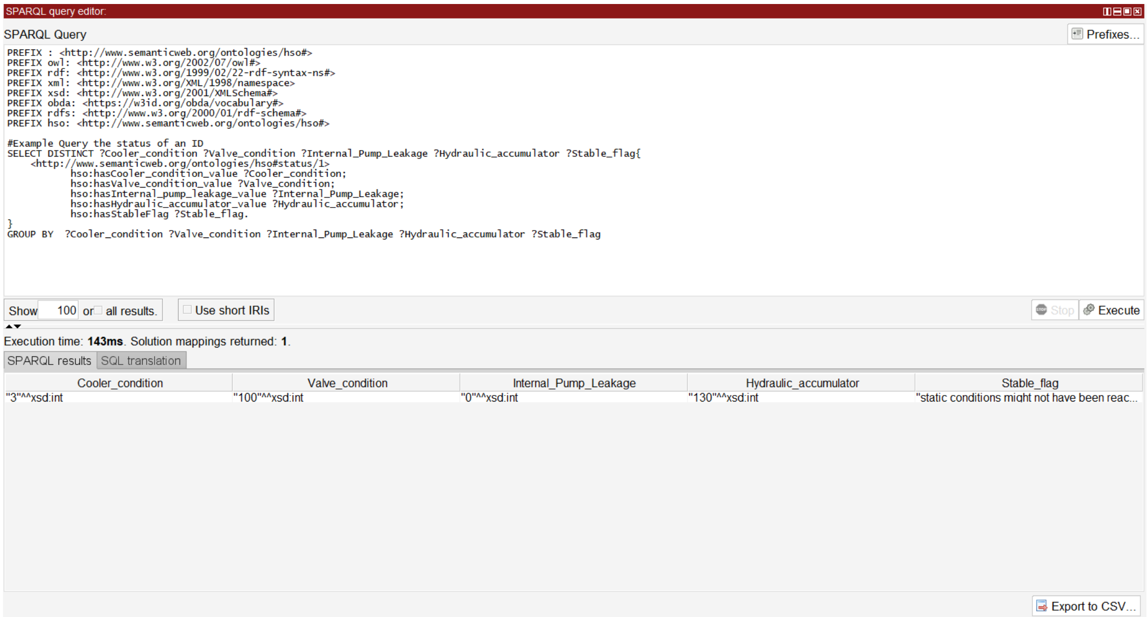

Figure 6: The SPARQL query to retrieve the first data record where the first system anomaly is detected.

```
PREFIX : <http://www.semanticweb.org/ontologies/hso/>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX xml: <http://www.w3.org/XML/1998/namespace>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX obda: <https://w3id.org/obda/vocabulary#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX hso: <http://www.semanticweb.org/ontologies/hso#>

SELECT (COUNT(DISTINCT ?SEQ_ID)AS ?COUNT)
WHERE{
  ?SEQ_ID a :optimal_pressure.
  ?SEQ_ID a :optimal_switching_behavior.
  {?SEQ_ID a :weak_leakage}
  UNION
  {?SEQ_ID a :severe_leakage}
  {?SEQ_ID a :cooler_close_to_total_failure}
  UNION
  {?SEQ_ID a :reduced_efficiency}

}
```

For this query, we use the *SELECT* clause to retrieve variables of interest with their value bindings. The *COUNT* function is used together with *DISTINCT* solution modifier for calculating the number of data records that follow a failure pattern. In the *WHERE* clause, three graph pattern alternatives are syntactically specified using the *UNION* keyword. With reference to the descriptions of data sets, this query calculate the number of occurrence for the specified failure pattern. Results of the query is displayed in Fig. 7, which shows there are 4 times of occurrence for this type of anomalies.

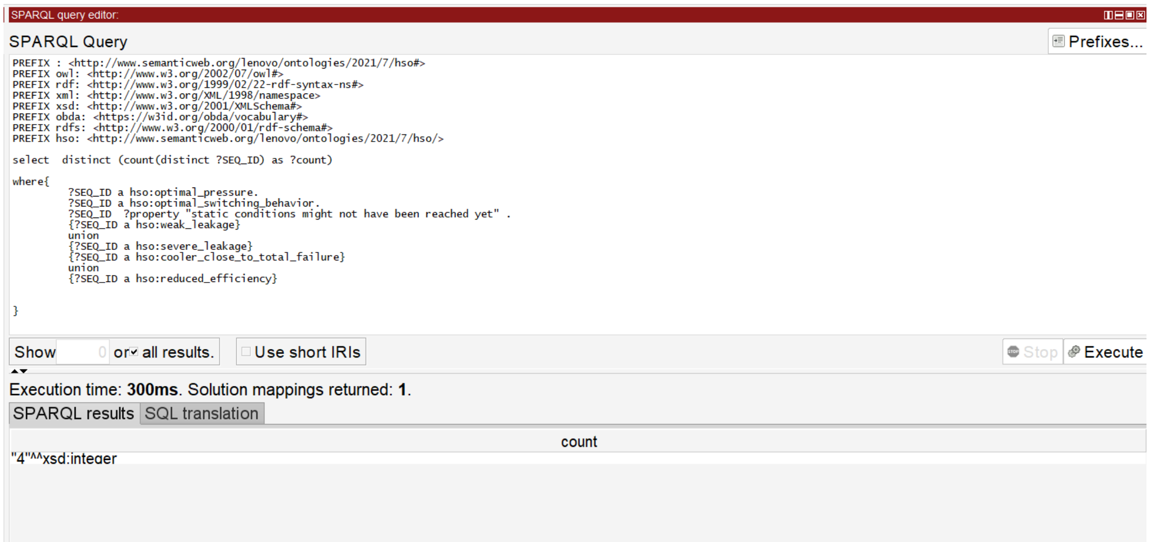

Figure 7: The SPARQL query to retrieve the first data record where the first system anomaly is detected.

The SPARQL-query based condition-based and predictive maintenance approach enable the monitoring of the hydraulic system by the use of a VKG system. Compared to traditional predictive maintenance systems where relational database technologies are used, HSO enables a more flexible approach for information retrieval where rich data semantics are incorporated into queries and query results. This approach is enabled by the generation of R2RML mappings that connect HSO classes and properties to important data fields. This eases the work for data integration, especially when semantic relations between data sets are hidden from heterogeneous data sets. The virtual knowledge layer of HSO facilitates data virtualisation, by which the end-users are prevented from being exposed to raw data sources. This significantly saves the efforts for data interpretation, access, retrieval, and integration.

5. Conclusions and future work

This paper introduces a knowledge graph-based approach for intelligent predictive maintenance of hydraulic systems. The main contribution of this paper is trifold. Firstly, we develop a domain ontology named HSO to structure and formalise domain knowledge related to hydraulic systems and predictive analytics. We demonstrate a systematic ontology development process where ISO and IEC standards are used for rigorous conceptualisation. Existing ontologies are also reused for cost-effective purposes. HSO is encoded in the standard language OWL, and it describes hydraulic systems according to the qualitative characterisation categories: function, behavior, and structure. Secondly, we propose an intelligent predictive maintenance approach based on a VKG system. Within the VKG system, the developed HSO is mapped to heterogeneous data sources by R2RML mappings. These mappings connect ontology classes and properties to important data fields, thus bringing rich semantics to the data. This approach allows semantic-enriched queries to be executed to identify and detect system conditions. Compared to traditional approaches that use relational data models, our approach is more flexible and interpretable because of the utilisation of a virtual knowledge layer on top of data sources. Thirdly, we demonstrate the effectiveness of our approach by applying it to a real-world case study. The case study aims to implement the developed VKG system for the predictive analytics of hydraulic system components. Results have shown that the developed system is able to query and reason on the data collected from a hydraulic test rig for the goal of early detection of anomalies. The early detection of potential failures helps to trigger essential maintenance actions to avoid downtime of the hydraulic system. Compared to most of the knowledge graph-based industrial systems, which merely focus on conceptual modelling work, we pay special attention to the real-world implementation aspect of HSO. By this, we aim to fill the gap where the real-world application of knowledge graphs and ontology-based systems is often overlooked.

The contributions of this paper indicate several future research directions. We first aim to address the dynamic characteristic of industrial knowledge graphs. As the manufacturing domain is highly dynamic, knowledge graphs should be able to adapt themselves for making rapid and accurate decisions. This also requires knowledge graph-based systems to be equipped with capabilities for dynamic data access, integration and reasoning with low latency. To address this challenge, dynamic knowledge graph construction technologies [49, 50] will be considered in the future. The second future research is to combine statistical AI methods with VKG systems. Deep learning technologies as such as Graph Neural Networks (GNNs) [51] will be considered to help with predictive analytics. In this way, deep learning and knowledge graph are jointly used to bridge the neural-symbolic gap in industrial contexts.

We aim to study how structured knowledge encoded in knowledge graphs may help with neural network architectures for pattern recognition, graph mining, job shop scheduling, and machine condition monitoring.

Acknowledgement

This work is supported by the National Natural Science Foundation of China (62002207, 62072290, 12075142, 62073201), the Natural Science Foundation of Shandong Province (ZR2020MA102) and Shandong Provincial Key Laboratory for Novel Distributed Computer Software Technology.

References

[1] A. G. Frank, L. S. Dalenogare, N. F. Ayala, Industry 4.0 technologies: Implementation patterns in manufacturing companies, International Journal of Production Economics 210 (2019) 15–26.

[2] K. Khan, M. Sohaib, A. Rashid, S. Ali, H. Akbar, A. Basit, T. Ahmad, Recent trends and challenges in predictive maintenance of aircraft's engine and hydraulic system, Journal of the Brazilian Society of Mechanical Sciences and Engineering 43 (2021) 1–17.

[3] T. Zonta, C. A. da Costa, R. da Rosa Righi, M. J. de Lima, E. S. da Trindade, G. P. Li, Predictive maintenance in the industry 4.0: A systematic literature review, Computers & Industrial Engineering 150 (2020) 106889.

[4] A. Mileo, D. Merico, R. Bisiani, Support for context-aware monitoring in home healthcare, Journal of Ambient Intelligence and Smart Environments 2 (2010) 49–66.

[5] X. Zhao, W. Ke, Z. Hu, C. Zhou, L. Zhao, Research on fault diagnosis knowledge representation method of hydraulic system based on ontology-production rule, THE CHINESE SOCIETY OF MECHANICAL ENGINEERS 36 (2015).

[6] M. Sabou, S. Biffl, A. Einfalt, L. Krammer, W. Kastner, F. J. Ekaputra, Semantics for cyber-physical systems: A cross-domain perspective, Semantic Web 11 (2020) 115–124.

[7] Q. Cao, S. Beden, A. Beckmann, A core reference ontology for steelmaking process knowledge modelling and information management, Computers in Industry 135 (2022) 103574.

[8] A. Gyrard, S. K. Datta, C. Bonnet, A survey and analysis of ontology-based software tools for semantic interoperability in iot and wot landscapes, in: 2018 IEEE 4th World Forum on Internet of Things (WF-IoT), IEEE, 2018, pp. 86–91.

[9] Q. Cao, F. Giustozzi, C. Zanni-Merk, F. de Bertrand de Beuvron, C. Reich, Smart condition monitoring for industry 4.0 manufacturing processes: An ontology-based approach, Cybernetics and Systems 50 (2019) 82–96.

[10] Y. Lin, X. Han, R. Xie, Z. Liu, M. Sun, Knowledge representation learning: A quantitative review, arXiv preprint arXiv:1812.10901 (2018).

[11] P. Patel, M. I. Ali, A. Sheth, From raw data to smart manufacturing: Ai and semantic web of things for industry 4.0, IEEE Intelligent Systems 33 (2018) 79–86.

[12] K. Zhou, T. Liu, L. Zhou, Industry 4.0: Towards future industrial opportunities and challenges, in: 2015 12th International conference on fuzzy systems and knowledge discovery (FSKD), IEEE, 2015, pp. 2147–2152.

[13] T. R. Gruber, Toward principles for the design of ontologies used for knowledge sharing?, International journal of human-computer studies 43 (1995) 907–928.

[14] V. R. S. Kumar, A. Khamis, S. Fiorini, J. L. Carbonera, A. O. Alarcos, M. Habib, P. Goncalves, H. Li, J. I. Olszewska, Ontologies for industry 4.0, The Knowledge Engineering Review 34 (2019).

[15] M. Hankel, B. Rexroth, The reference architectural model industrie 4.0 (rami 4.0), ZVEI 2 (2015) 4–9.

[16] S. Beden, Q. Cao, A. Beckmann, Scro: A domain ontology for describing steel cold rolling processes towards industry 4.0, Information 12 (2021) 304.

[17] C. Huang, H. Cai, L. Xu, B. Xu, Y. Gu, L. Jiang, Data-driven ontology generation and evolution towards intelligent service in manufacturing systems, Future Generation Computer Systems 101 (2019) 197–207.

[18] R. Jardim-Goncalves, J. Sarraipa, C. Agostinho, H. Panetto, Knowledge framework for intelligent manufacturing systems, Journal of Intelligent Manufacturing 22 (2011) 725–735.

[19] F. Giustozzi, J. Saunier, C. Zanni-Merk, Context modeling for industry 4.0: An ontology-based proposal, Procedia Computer Science 126 (2018) 675–684.

[20] H. Cheng, P. Zeng, L. Xue, Z. Shi, P. Wang, H. Yu, Manufacturing ontology development based on industry 4.0 demonstration production line, in: 2016 Third International Conference on Trustworthy Systems and their Applications (TSA), IEEE, 2016, pp. 42–47.

[21] H. Panetto, M. Dassisti, A. Tursi, Onto-pdm: Product-driven ontology for product data management interoperability within manufacturing process environment, Advanced Engineering Informatics 26 (2012) 334–348.

[22] Q. Cao, C. Zanni-Merk, A. Samet, C. Reich, F. d. B. de Beuvron, A. Beckmann, C. Giannetti, Kspmi: A knowledge-based system for predictive maintenance in industry 4.0, Robotics and Computer-Integrated Manufacturing 74 (2022) 102281.

[23] M. Grüninger, Using the psl ontology, in: Handbook on Ontologies, Springer, 2009, pp. 423–443.

[24] A. Eibeck, M. Q. Lim, M. Kraft, J-park simulator: An ontology-based platform for cross-domain scenarios in process industry, Computers & Chemical Engineering 131 (2019) 106586.

[25] A. Badri, B. Boudreau-Trudel, A. S. Souissi, Occupational health and safety in the industry 4.0 era: A cause for major concern?, Safety science 109 (2018) 403–411.

[26] D. Çelik, Foodwiki: Ontology-driven mobile safe food consumption system, The scientific World journal 2015 (2015).

[27] J. Wan, S. Tang, D. Li, M. Imran, C. Zhang, C. Liu, Z. Pang, Reconfigurable smart factory for drug packing in healthcare industry 4.0, IEEE transactions on industrial informatics 15 (2018) 507–516.

[28] J. Frysak, C. Kaar, C. Stary, Benefits and pitfalls applying rami4. 0, in: 2018 IEEE Industrial Cyber-Physical Systems (ICPS), IEEE, 2018, pp. 32–37.

[29] T. Porrmann, R. Essmann, A. W. Colombo, Development of an event-oriented, cloud-based scada system using a microservice architecture under the rami4. 0 specification: Lessons learned, in: IECON 2017-43rd Annual Conference of the IEEE Industrial Electronics Society, IEEE, 2017, pp. 3441–3448.

[30] M. Yahya, J. G. Breslin, M. I. Ali, Semantic web and knowledge graphs for industry 4.0, Applied Sciences 11 (2021) 5110.

[31] R. Peng, S. Renwang, Fault diagnosis method for hydraulic of concrete pump trucks based on ontology, Machine Tool & Hydraulics (2016).

[32] M. Klusch, A. Meshram, A. Schuetze, N. Helwig, icm-hydraulic: Semantics-empowered condition monitoring of hydraulic machines, in: Proceedings of the 11th international conference on semantic systems, 2015, pp. 81–88.

[33] Y. XING, X.-h. CHEN, W.-f. WU, Knowledge modeling and reasoning for hydraulic system fault diagnosis based on ontology, Computer Technology and Development (2013).

[34] K.-W. Chau, An ontology-based knowledge management system for flow and water quality modeling, Advances in Engineering Software 38 (2007) 172–181.

[35] M. El Ghosh, H. Naja, H. Abdulrab, M. Khalil, Towards a middle-out approach for building legal domain reference ontology, International Journal of Knowledge Engineering 2 (2016) 109–114.

[36] C. PERAKATH, C. MENZEL, R. MAYER, et al., The idef5 ontology description capture method overview, Knowledge Based Systems (1994).

[37] D. L. McGuinness, F. Van Harmelen, et al., Owl web ontology language overview, W3C recommendation 10 (2004) 2004.

[38] G. Guizzardi, R. de Almeida Falbo, R. S. Guizzardi, Grounding software domain ontologies in the unified foundational ontology (ufo): The case of the ode software process ontology., in: CIbSE, Citeseer, 2008, pp. 127–140.

[39] F. Ameri, D. Dutta, An upper ontology for manufacturing service description, in: International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, volume 42578, 2006, pp. 651–661.

[40] S. Lemaignan, A. Siadat, J.-Y. Dantan, A. Semenenko, Mason: A proposal for an ontology of manufacturing domain, in: IEEE Workshop on Distributed Intelligent Systems: Collective Intelligence and Its Applications (DIS'06), IEEE, 2006, pp. 195–200.

[41] D. L. Nuñez, M. Borsato, Ontoprog: An ontology-based model for implementing prognostics health management in mechanical machines, Advanced Engineering Informatics 38 (2018) 746–759.

[42] Q. Cao, A. Samet, C. Zanni-Merk, F. de Bertrand de Beuvron, C. Reich, Combining chronicle mining and semantics for predictive maintenance in manufacturing processes, Semantic Web (2020) 1–22.

[43] J. R. Hobbs, F. Pan, Time ontology in owl, W3C working draft 27 (2006) 133.

[44] G. Xiao, D. Calvanese, R. Kontchakov, D. Lembo, A. Poggi, R. Rosati, M. Zakharyaschev, Ontology-based data access: A survey, International Joint Conferences on Artificial Intelligence, 2018.

[45] G. Xiao, L. Ding, B. Cogrel, D. Calvanese, Virtual knowledge graphs: An overview of systems and use cases, Data Intelligence 1 (2019) 201–223.

[46] D. Calvanese, B. Cogrel, S. Komla-Ebri, R. Kontchakov, D. Lanti, M. Rezk, M. Rodriguez-Muro, G. Xiao, Ontop: Answering sparql queries over relational databases, Semantic Web 8 (2017) 471–487.

[47] M. Grabmüller, P. Hofstedt, Turtle: A constraint imperative programming language, in: International Conference on Innovative Techniques and Applications of Artificial Intelligence, Springer, 2003, pp. 185–198.

[48] J. Pérez, M. Arenas, C. Gutierrez, Semantics and complexity of sparql, ACM Transactions on Database Systems (TODS) 34 (2009) 1–45.

[49] A. Bosselut, Y. Choi, Dynamic knowledge graph construction for zero-shot commonsense question answering, arXiv preprint arXiv:1911.03876 3876 (2019) 1–9.

[50] S. Deng, H. Rangwala, Y. Ning, Dynamic knowledge graph based multi-event forecasting, in: Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2020, pp. 1585–1595.

[51] F. Scarselli, M. Gori, A. C. Tsoi, M. Hagenbuchner, G. Monfardini, The graph neural network model, IEEE transactions on neural networks 20 (2008) 61–80.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: