Highlights

A core reference ontology for steelmaking process knowledge modelling and information management

Qiushi Cao, Sadeer Beden, Arnold Beckmann

- A novel Core Reference Ontology for Steelmaking (CROS) has been introduced.
- CROS formally describes essential steelmaking manufacturing processes, facilities, resources, machines, machine tools, equipment, and system functionalities.
- We demonstrate the systematic ontology development process for CROS, which includes specification, knowledge acquisition, conceptualisation, integration, implementation, and evaluation.
- We evaluate the functionality and usefulness of the proposed ontology by demonstrating a real-world case study on a condition-based maintenance task of cold rolling mills in the steel industry.

A core reference ontology for steelmaking process knowledge modelling and information management

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Abstract

Following the trend of Industry 4.0, the business model of steel manufacturing is transforming from a historical inwardly focused supplier/customer relationship to one that embraces the wider end-to-end supply chain and improves productivity more holistically. However, the data and information required for supply chain planning and steelmaking process modelling are normally distributed over scattered sources across organisation boundaries and research communities. This leads to a major problem concerning semantic interoperability. To address this issue, this paper introduces a Common Reference Ontology for Steelmaking (CROS). CROS serves as a shared steelmaking resource and capability model that aims to facilitate knowledge modelling, knowledge sharing and information management. In contrast to most of the existing steelmaking ontologies which merely focus on conceptual modelling, our work pays special attention to the real-world implementation and utilisation aspects of CROS. The functionality and usefulness of CROS is evaluated and tested on a real-world condition-based monitoring and maintenance task for cold rolling mills at Tata Steel in the United Kingdom.

Keywords:
Industry 4.0, Steelmaking, Knowledge graph, Ontology, Ontology-based data access, Condition-based maintenance

1. Introduction

Within manufacturing activities, steelmaking is the process of producing steel from iron ore and scrap. Normally, steelmaking involves consecutive

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high-temperature chemical processes where liquid steel is refined for obtaining a narrow chemical composition for specified steel grades [1]. Within these chemical processes, impurities such as excess carbon, sulfur, nitrogen, and silicon are removed from iron. Alloying elements such as carbon, chromium, nickel, manganese, and vanadium are incorporated to iron for improving mechanical properties and maintaining high strength and ductility. The produced steel is a versatile material that is pervasively used across different industries such as buildings, infrastructure, cars, ships, trains, electrical appliances, and weapons. Statistics show that the global crude steel production reached just over 1.8 billion tons in 2018 [2].

Following the trend of Industry 4.0, the business model of steel manufacturing is transforming from a historical inwardly focused supplier/customer relationship to one that embraces the wider end-to-end supply chain and improves productivity more holistically. However, the data and information required for supply chain planning and steelmaking process modelling are normally distributed over scattered sources across organisation boundaries and research communities [3]. This leads to a major problem concerning *semantic interoperability*. By definition, semantic interoperability ensures the information requester and provider have a common understanding of the "meanings" of the exchanged data and information [4]. As computational resources are developed by different languages and vocabularies, they may use their own proprietary data structures, which leads to the encoding of vague data semantics [5]. Moreover, as humans and organisations involved in steelmaking may have different levels of experience and expertise, the interaction processes among these different stakeholders may suffer from different understanding of the used terminology and standards. The lack of semantic interoperability hinders the smooth exchange of data and information, thus is detrimental to the productivity and availability of manufacturing production systems [6]. These challenges highlight the requirement for semantic interoperability during steelmaking processes.

To address the semantic interoperability issue, ontologies appear to be a promising solution [3, 7, 8, 9]. In computer science, an ontology is defined as *"an explicit specification of a conceptualisation for a domain of interest"* [10]. Normally, the conceptualisation within an ontology is formalised by a logic theory that is written in a certain language. Also, ontologies provide reasoning capabilities by which new knowledge can be inferred. Since ontologies incorporate a formal representation of concepts, individuals, and relationships among these concepts, data and entities, they contain explicit and unambiguous data semantics thus enable semantic interoperability [11].

In the context of the Engineering and Physical Sciences Research Council (EPSRC) funded research project SUSTAIN[1], this paper presents a common formal ontological framework for steelmaking process knowledge modelling and information management. The proposed ontological framework serves as a shared steelmaking resource and capability model that aims to facilitate knowledge sharing and information management. The contributions of this paper are trifold:

1. In this paper, we propose a Core Reference Ontology for Steelmaking (CROS) that formally describes essential steelmaking manufacturing processes, facilities, resources, machines, machine tools, equipment, and system functionalities. The developed CROS serves as an ontological framework and aims to provide rich semantics to heterogeneous steel manufacturing data, thus enabling semantic interoperability. Compared to other existing steelmaking ontologies where the focus is solely on either steel products or resources, the distinguishing novelty of the proposed ontology is its wider modelling of domain knowledge with regard to steelmaking processes, resources, facilities, and system functionalities. Also, in contrast to most of the existing steelmaking ontologies which merely focus on conceptual modelling, our work pays special attention to the real-world implementation and utilisation aspects of ontologies. These two aspects of work are often overlooked in the literature.
2. We demonstrate the systematic ontology development process which includes specification, knowledge acquisition, conceptualisation, integration, implementation, and evaluation. The development process is enhanced by mature industry standards and terminology and yet retains an actionable level of flexibility for knowledge management and reuse. The incorporation of industry standards and terminology ensures rigorous conceptualisation of the ontology.
3. We evaluate the functionality and usefulness of the proposed ontology by demonstrating a real-world case study. The case study is performed on several real-world data sets collected from cold rolling processes at Tata Steel[2]. The aim is to use CROS for a condition-based maintenance

[1]https://www.sustainsteel.ac.uk/
[2]https://www.tatasteeleurope.com/ts/

task of cold rolling mills at a Tata Steel plant in Port Talbot. Results have shown that CROS is feasible and flexible to be implemented for knowledge reuse, knowledge modelling, data access, and data integration tasks within steelmaking. The utilisation of CROS can mitigate the pain points of traditional predictive maintenance/condition-based maintenance methods for which the reuse of domain knowledge is often overlooked.

The remainder of this paper is organised as follows: Section 2 gives a comprehensive review of the literature and highlights the open challenges that motivate the proposed work. Section 3 introduces the proposed ontology where the main classes and relationships of CROS are introduced. Section 4 presents a real-world case study within which CROS is used as a uniform knowledge model to query and reason on heterogeneous data sources for the goal of condition-based maintenance of cold rolling mills. Section 5 concludes the paper and outlines future directions of research.

2. Related work

Ontologies play a key role in knowledge modelling and information management for manufacturing systems [12]. By providing a formal description of terms and relationships within a domain of interest, ontologies enable interpretable and interoperable knowledge sharing and reuse among stakeholders. In this section, we first give a comprehensive review of the existing ontologies developed for the smart manufacturing domain. Then we focus on those ontologies specially designed for steelmaking processes.

2.1. Ontologies for smart manufacturing

Over recent years, ontologies have emerged as promising solutions for addressing the semantic interoperability issue in smart manufacturing. The Manufacturing Service Description Language (MSDL) ontology is an upper-level ontology for the formal representation of manufacturing entities, services, and capabilities [13, 14]. Initially developed for automatic supplier discovery in distributed environments, MSDL was then extended and applied in several domain tasks such as mechanical machining capability description. Within MSDL, manufacturing capabilities are categorised into *Technological Capabilities*, *Operational Capabilities*, *Geometric Capabilities*, *Quality Capabilities*, *Relational Capabilities*, and *Stochastic Capabilities*. This ontology has been applied in several manufacturing activities, such as metal casting and manufacturing service description. MASON is another ontology that aims to propose a common semantic net for the manufacturing domain [15]. MASON ontology is built upon three super classes: *Entities*, *Operations*, and *Resources*. Among them, *Entities* are modelled to provide an abstract description of manufacturing produces. The *Operations* class is related to manufacturing process description. For applications, MASON is implemented for automatic cost estimation, and the construction of multi-agent systems for manufacturing [15].

Besides the above ontologies that model the manufacturing entities from a high level, there are ontologies specially developed for the manufacturing product domain. The consensus-based Additive Manufacturing Ontology (AMO) was developed to address the low degree of interoperability issue among dentistry product manufacturing systems [16]. The focus of AMO is to formally represent different components and phases within the Product Life Cycle (PLC) of additive manufacturing. The ontology introduced in [17] is another example of product knowledge and information modelling. This ontology was proposed to facilitate manufacturing knowledge reuse regarding effective product design and manufacturing processes. It incorporates domain knowledge relevant to Design Failure Mode and Effects Analysis (DFMEA) and Process Failure Mode and Effects Analysis (PFMEA). Other representative ontologies include the reference ontology for PLC management [18], Building Product Ontology (BPO) [19], Product-driven ONTOlogy for Product Data Management (ONTO-PDM) [20], and the ontology for product version management [21].

The domain ontology for smart condition monitoring is another example ontology for predictive maintenance [9]. For this ontology, the ontology modularisation design methodology is adopted to structure the big ontology into small ontological sub-models. This method eases the manipulation and management of knowledge components. As results, the ontology is organised into the *Manufacturing Module*, the *Context Module*, and the *Condition Monitoring Module*. A case study on a conditional maintenance task of bearings in rotating machinery is performed to evaluate the ontology. This ontology was extended in [22], where a more informative and expressive ontology named Manufacturing Predictive Maintenance Ontology (MPMO) was proposed. MPMO was used together with a pattern mining approach called chronicle mining [23] to propose a hybrid semantic approach for predictive maintenance. The hybrid semantic approach aims to automate and facilitate predictive maintenance tasks and has been evaluated on a real-world data set collected from a semi-conductor manufacturing process. Experimental results show that the ontology together with chronicle mining could achieve over 83% Precision regarding failure prediction.

2.2. Ontologies for steelmaking

Ontologies are also used in the steelmaking domain to facilitate knowledge sharing and information management. To cope with the challenges in the dynamic and heterogeneous global steelmaking supply chain, a rule-based ontology reasoning method is proposed in [24]. In [24], a shared domain ontology is developed to formalise both internal and external decision knowledge regarding global steelmaking supply chain and dynamic business market. Ontology matching and integration methods are also used to build a semantic interoperable decision environment within the global steel supply chain. In this way, interpretable multi-source knowledge is provided in a timely manner to facilitate decision making. To help with knowledge acquisition, an ontology for modelling steel manufacturing processes was jointly used with big data analysis techniques to proposes a big data knowledge management system (BDAKMS) [25]. Within their work, ontologies are used to model domain knowledge of steelmaking and enhance the usability and interoperability of BDAKMS. In [26], ontologies and logic rules are used to develop a steel semantic model (named STSM). The objective of STSM is to unify steel knowledge and discover new knowledge by performing rule-based reasoning. The proposed ontology covers basic concepts in the steel domain such as steel materials, steel types, steel properties, and the organisation structure of steel. In [27], a semantic model has been introduced to facilitate the seamless and agile cooperation and information exchange for the steel industry. The semantic model describes data and data sources related to steel products, production, and process information. In this way, it supports intelligent integration and reasoning over distributed system components.

Besides the aforementioned ontologies that model the steelmaking domain from a general point of view, there exist other works that focus on a specific sub-field of the steel industry. These works include the ontology-based intelligent diagnostic system for steel corrosion protection [28], the ontological approach for steel production scheduling and planning [29], steel reverse supply chain service modelling [30], and the ontology for the collaborative design of steel frame structures [31], etc.

We use Table 1 to compare the existing steelmaking ontologies with CROS. We summarise 7 core concepts that a core reference ontology should capture: *Steelmaking product*, *Steelmaking process*, *Steelmaking material*, *Steelmaking facility*, *Steelmaking tool*, *Steelmaking byproduct*, *Human*. If the concept is covered by the listed ontology, a check mark is assigned in the table. Otherwise, a cross mark is assigned. From the table we observe that the existing ontologies in the literature fail to cover all the essential concepts for describing the steelmaking industry. We aim to fill this gap by developing CROS.

Table 1: A comparison between the proposed CROS and the existing steelmaking ontologies with respect to their domain coverage.

Ontologies	Steelmaking product	Steelmaking process	Steelmaking material	Steelmaking facility	Steelmaking tool	Steelmaking byproduct	Human
[26]	✓	✓	✓	✗	✗	✓	✗
[28]	✓	✓	✓	✗	✓	✗	✗
[28]	✓	✓	✓	✗	✓	✗	✓
[30]	✓	✓	✗	✗	✓	✗	✗
[27]	✓	✓	✗	✓	✗	✗	✗
CROS	✓	✓	✓	✓	✓	✓	✓

2.3. Open challenges

The literature review exposes two main challenges concerning ontologies for steelmaking. Firstly, most of the existing ontologies merely cover a limited proportion of the steelmaking domain knowledge. Some of them are domain-specific and only focus on specific tasks within steelmaking processes such as steel resource planning, steel corrosion protection, and steel organisational structure, etc. This highlights the need for a core reference ontology for modelling steelmaking processes. The required ontology should be able to capture core concepts and relationships and be considered as a key component of future steelmaking manufacturing systems. Secondly, most of the works in the literature focus on the conceptual modelling work for the steelmaking domain while lacks the utilisation and implementation aspects of ontologies (on real-world scenarios). These two aspects of activities are often overlooked within the existing ontology-based approaches. In this context, we aim to address these two main challenges by developing a core reference ontology for steelmaking process knowledge modelling and information management. As developing large ontologies from scratch is time-consuming and work-intensive, our core reference ontology aims to form a unified semantic model that captures common concepts and relations within the steelmaking domain. In this way, it could be reused or specialised (for specific tasks) by others, which minimises their effort in developing similar ontological models for steelmaking.

3. The Core Reference Ontology for Steelmaking

In this section, we first introduce ontology development methodology and development environment. We then list the reused ontologies for developing CROS. After that, we introduce the key classes and relationships of CROS in detail[3].

3.1. Ontology development methodology

There are several ontology development methodoloiges in the literature. These methodoloiges address the design and development aspects of ontology engineering and provide guidelines for constructing ontologies classes, relationships, and logic formalism. The most popular ontology development methodoloiges include Common-KADS [32], TOVE [33], the the Enterprise Model Approach [34], Ontology Description Capture Method (IDEF5) [35], and METHONTOLOGY [36]. In this work, we employ the IDEF5 methodology [35] for developing CROS. The reason we choose IDEF5 is its consideration of a gradual refinement process during ontology development. This refinement process allows us to develop CROS as an evolving prototype model, which ensures the ontology to progressively capture high-level domain concepts as well as low-level industrial data. Both knowledge acquisition and data integration processes help to enrich CROS while following its original conceptual structure.

Based on IDEF5, CROS is developed according to the following five steps: i) *Scope domain and collect raw data.* This step involves tasks regarding domain scoping and data collection. To obtain required domain knowledge and structure it in a systematic way, we refer to several international and industrial standards. The considered standards and their description are listed in Table 2. Also, to gain more granular domain knowledge, we have consulted domain experts who had years of experience in the steel industry; ii) *Develop initial proto-kinds.* This step is to use the captured knowledge and collected data to generate a tentative relation-poor ontology of proto-kinds, proto-concepts, and proto-types [35]; iii) *Refine initial analysis.* This step

[3]The ontology files can be found at: https://github.com/caoppg/CROS

focuses on generating a more stable version of ontology from the tentative ontology developed in step 2; iv) *Add relationships*. This step aims to system-essential relationships to the ontology; v) *Validate stable ontology using raw data*. Within this step, the stable ontology is to be validated using real-world data.

Table 2: International standards used for developing CROS.

International standard	Description
ISO 14649	Industrial Automation Systems and Integration
ISO 17359	Condition Monitoring and Diagnostics of Machines
ISO 23495	Industrial Furnaces and Associated Processing Equipment
ISO 204	Metallic Materials
A322 - 13	Standard Specification for Steel Bars, Alloy, Standard Grades
A108 - 18	Standard Specification for Steel Bar, Carbon and Alloy, Cold-Finished
A370	Test Methods and Definitions for Mechanical Testing of Steel Products
A109/A109M	Specification for Steel, Strip, Carbon (0.25 Maximum Percent)
A751	Test Methods and Practices for Chemical Analysis of Steel Products
IEC 62264	Enterprise-control System Integration
IEC 60050	International Electrotechnical Vocabulary
SAE J1739	Potential Failure Mode and Effects Analysis in Design

3.2. Ontology encoding and development environment

To develop CROS, we choose Web Ontology Language (OWL) [37] as the ontology encoding language. By providing rich and formal semantics to web contents, OWL supports a wide range of web data format such as XML, RDF, and RDF Schema (RDF-S). We also use Protégé 5.5.0[4] as the ontology editor to structure and modify our ontology. Protégé is an open-source knowledge acquisition and ontology development tool that includes deductive classifiers to validate that models are consistent and to infer new information based on the analysis of an ontology.

3.3. Ontology reuse

Ontology reuse is an important process where existing ontological resources are adapted or added to CROS. This step aims to leverage existing resources for the purpose of specifying and formally describing steelmaking-related activities. In this paper, several ontologies are considered important and reused during the development of CROS. These ontologies are listed in Table 3.

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

Table 3: Reused ontologies during the development of CROS.

Reused Ontologies	Ontology description
UFO [38]	A top-level ontology of universals.
MSDL [14]	An upper-level ontology for describing manufacturing services.
MASON [15]	An OWL-based ontology to facilitate knowledge sharing in manufacturing.
OntoProg [39]	An ontology for the predictive maintenance aspect of manufacturing activities.
DOSCM [9]	A domain ontology for smart condition monitoring.
MPMO [22]	An ontology for failure prediction in Industry 4.0.
Time Ontology [40]	An ontology to formalise temporal properties of resources in the world.
STSM [26]	A semantic model to unify steel knowledge.

3.4. Main classes

Within CROS, *SteelmakingProcess*, *SteelManufacturingResource*, *SteelProduct*, *SteelmakingTool*, *SteelmakingMaterial*, and *SteelmakingFacility* are the main/super classes. The *SteelmakingProcess* superclass describes a set of manufacturing processes that are involved in producing steel from iron ore and scrap. We define 30 subclasses under this superclass. The *SteelmakingFacility* class represents the equipment of places where a specific steelmaking activity is performed. We create 14 subclasses under this superclass. Other superclasses are defined around the *SteelmakingProcess* and *SteelmakingFacility* classes. Fig. 1 shows the class hierarchy of CROS as well as the subclasses of *SteelmakingProcess* and *SteelmakingFacility*. Table 4 gives a more detailed class description. Since the ontology contains a large number of 276 classes, for the reason of clarity, we only list a subset of important classes in the table.

For the construction of main classes, we reused concepts from other ontologies. The reuse and alignment to other ontologies bring a formal structure to CROS and enable reasoning in a general manner. The alignments of CROS classes with other ontologies are defined as below:

$$CROS : SteelmakingProcess \sqsubseteq MASON : Process$$
$$CROS : SteelManufacturingResource \sqsubseteq MASON : Resource$$
$$CROS : SteelProduct \sqsubseteq MPMO : Product$$
$$CROS : SteelmakingTool \sqsubseteq MASON : Tool$$
$$CROS : SteelmakingMaterial \sqsubseteq MASON : RawMaterial$$
$$CROS : SteelmakingFacility \sqsubseteq MSDL : ManufacturingFacility$$

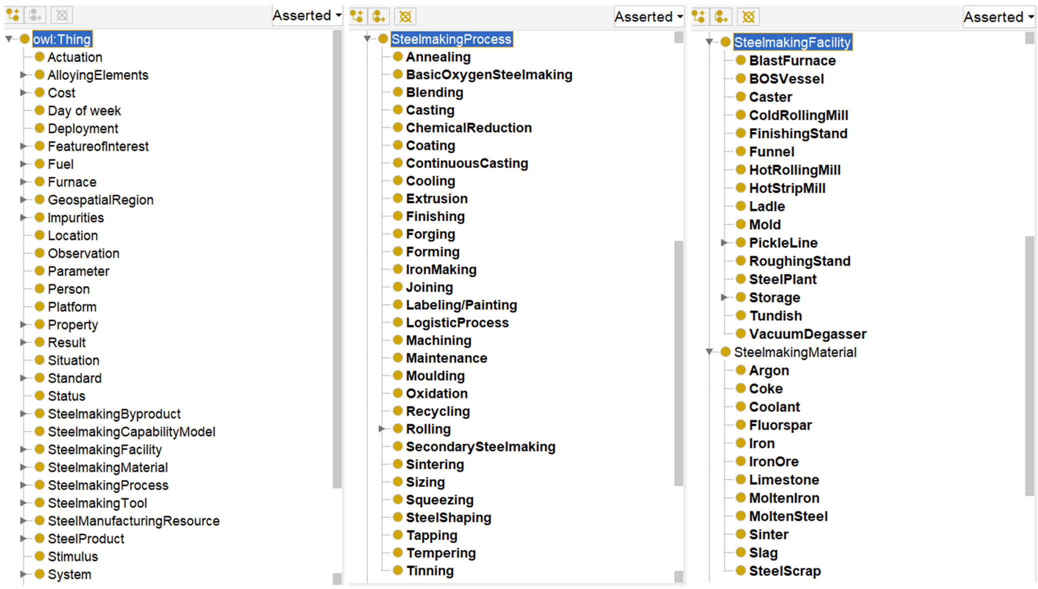

Figure 1: The class hierarchy of CROS: i) main classes; ii) The *SteelmakingProcess* class; iii) The *SteelmakingFacility* and *SteelmakingMaterial* classes.

3.5. Relationships

For OWL ontoloiges, object and data properties are the two important relationships that connect classes. Object properties are used to link individuals and data properties link an individual to an XML Schema Datatype value or an rdf literal [41]. Fig. 2 gives an overview of the created object and data properties for CROS. In Fig. 2, the left column shows main object properties, and the right side column presents data properties.

3.6. Ontology evaluation

Ontology evaluation refers to the processing of accessing the expressiveness, accuracy, and quality of an ontology from the knowledge representation perspective. The aim of ontology evaluation is to avoid logical inconsistencies or undesired inferences [42]. To make sure CROS is free of modelling errors and anomalies, we use the web-based ontology evaluation tool OOPS! (OntOlogy Pitfall Scanner!) [42] to access the quality of CROS. As an automatic ontology pitfall detector, OOPS! helps to detect the most common pitfalls that appear during the ontology development process.

In OOPS!, ontology pitfalls are classified into three importance levels: *critical*, *important*, and *minor*. *Critical* pitfalls may affect the ontology con-

Table 4: Description of CROS main classes and their subclasses.

CROS ontology classes	Class description
CROS:SteelmakingProcess	**Describes a set of processes for producing steel from iron ore and scrap.**
CROS:BasicOxygenSteelmaking	Primary steelmaking where carbon-rich molten pig iron is made into steel.
CROS:Blending	Mix substances together so as to make a steel product of the desired quality.
CROS:Casting	Shape (metal or other material) by pouring it into a mold while molten.
CROS:ChemicalReduction	A type of chemical reaction in which the oxidation states of atoms are changed.
CROS:Coating	A covering process that is applied to the surface of an object.
CROS:Extrusion	A forming process to reduce the cross section of metal or convert it into desire shape.
CROS:IronMaking	A smelting process to turn the ore into a form from which products can be fashioned.
CROS:Rolling	A metal forming process where steel plate is passed through rolls to reduce thickness.
CROS:ColdRolling	A process of strengthening steel by changing its shape without using heat.
CROS:HotRolling	A process of strengthening steel by changing its shape using heat.
CROS:Sintering	Make coalesce into a solid or porous mass by heating it without liquefaction.
CROS:Squeezing	A method combining die casting and forging to create stronger metal alloys.
CROS:SecondarySteelmaking	A process using an electric arc to melt scrap iron.
CROS:Tempering	To improve the hardness and elasticity of steel by reheating and then cooling it.
CROS:SteelmakingFacility	**Describes the equipment of places that perform steelmaking activities.**
CROS:ColdRollingMill	Used to pass hot-rolled coils and produce products of the desired thickness.
CROS:HotRollingMill	Produces sections of steel at various dimensions from billets of steel at high temperature.
CROS:BlastFurnace	A type of metallurgical furnace used for smelting to produce industrial metals.
CROS:BlastFurnace	A type of metallurgical furnace used for smelting to produce industrial metals.
CROS:BOSVessel	It takes a combined charge of scrap and liquid iron and convert this into steel.
CROS:Mold	A hollow container used to give shape to molten or hot liquid material.
CROS:PickleLine	The place where metal surface treatment is performed to remove impurities.
CROS:RoughingStand	The first rolling stand through which metal passes during hot rolling.
CROS:Tundish	An intermediate vessel placed between the ladle and the mold.
CROS:VacuumDegasser	Quickly removes gases entering the system for safe and reliable operation.
CROS:SteelmakingMaterial	**This class describes the materials needed for steelmaking.**
CROS:Coke	A solid fuel made by heating coal in the absence of air.
CROS:Coolant	A liquid or gas that is used to remove heat from something.
CROS:Fluorspar	A mineral consisting of calcium fluoride which typically occurs as cubic crystals.
CROS:IronOre	Rocks and minerals from which metallic iron can be economically extracted.
CROS:Limestone	Used to remove impurities from the blast furnace when making iron.
CROS:MoltenIron	A liquid material that is created by smelting iron ingots or other iron items.
CROS:Sinter	A mixture of iron ore and other materials prepared for smelting.
CROS:Slag	Stony waste matter separated from metals during the smelting or refining of ore.
CROS:SteelScrap	Discarded steel or steel products, generally segregated by composition.
CROS:SteelmakingTool	**This class describes the tools used for steelmaking.**
CROS:Choke	Used to reduce the amount of air in the fuel mixture.
CROS:GasBurner	A device producing a controlled flame by mixing fuel gas with oxidizer.
CROS:GraphiteElectrode	The main heating element used in an electric arc furnace.
CROS:Lance	A metal pipe supplying a jet of oxygen to a furnace or to a hot flame for cutting.
CROS:SteelMill	An industrial plant for the manufacture of steel.
CROS:SteelRoll	Equipment that performs steel rolling.
CROS:Roll_Grinding	Power grinding tools or machine tools used in the grinding process.
CROS:Roll_Refurbishment	Renovation and redecoration of steel rolls.
CROS:RollingMillStands	Used to reduce the thickness of steel and extend the overall length.
CROS:SteelTube	Can be used to make furniture, frameworks and for general construction.
CROS:SeamlessTube	Manufactured using the extrusion process.
CROS:WeldedTube	Produced either by hot forming and cold forming processes.
CROS:Tuyeres	A nozzle through which air is forced into a smelter, furnace, or forge.

sistency, reasoning and applicability. It is crucial to correct these pitfalls. *Important* pitfalls are not critical for ontology function but recommended to be corrected. *Minor* pitfalls are those that do not represent a real ontology engineering problem. However, removing *minor* pitfalls may help to better organise the ontology and improve its usability.

To evaluate the quality of CROS, we uploaded the source codes of the ontology to the web-based OOPS! platform[5]. As results, no ontology devel-

[5]http://oops.linkeddata.es/

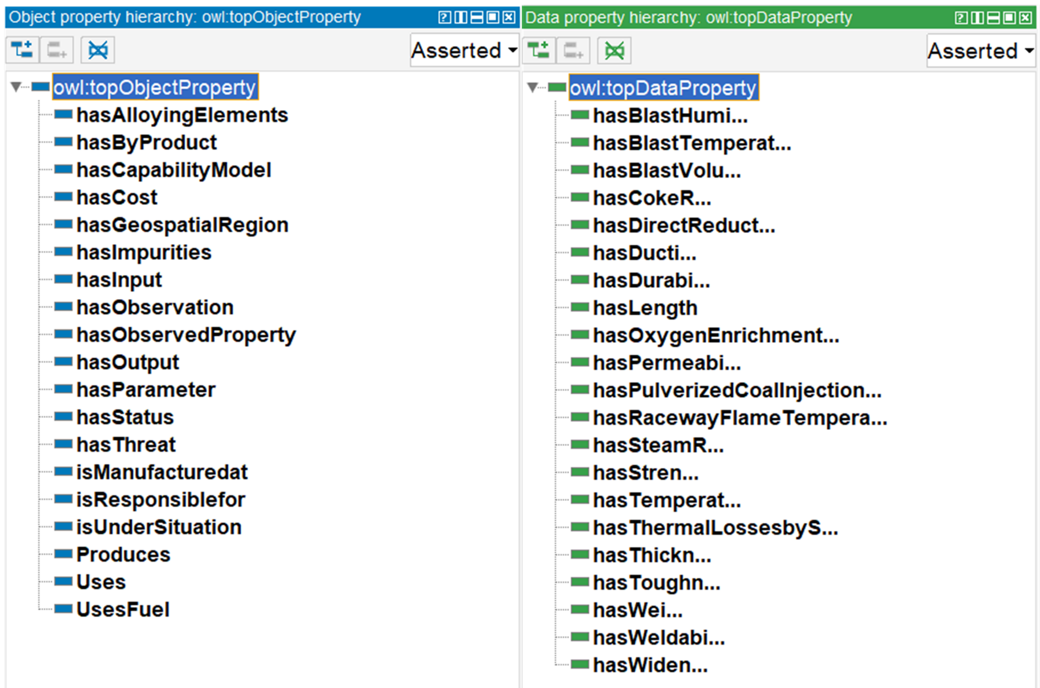

Figure 2: The main relationships of CROS: i) object properties; ii) data properties.

opment pitfalls have been detected, as shown in Fig. 3. This means our ontology is free of errors that are detrimental to logic consistency, reasoning and applicability.

4. Industrial application: a case study

This section demonstrates a real-world case study using CROS. This case study is about a condition-based maintenance task performed on a cold rolling process at a Tata Steel plant in Port Talbot. The aim of the case study is to evaluate the functionality and usefulness of CROS under real-world scenarios. We focus on the knowledge reuse and information management perspectives within this condition-based maintenance task. The obtained results prove that CROS and its related ontological modelling tools are easy to use for knowledge embedding, data access, and information retrieval within the steelmaking domain. The remainder of this section gives a detailed description of our experimental set-up, data collection, and ontology-based predictive maintenance process.

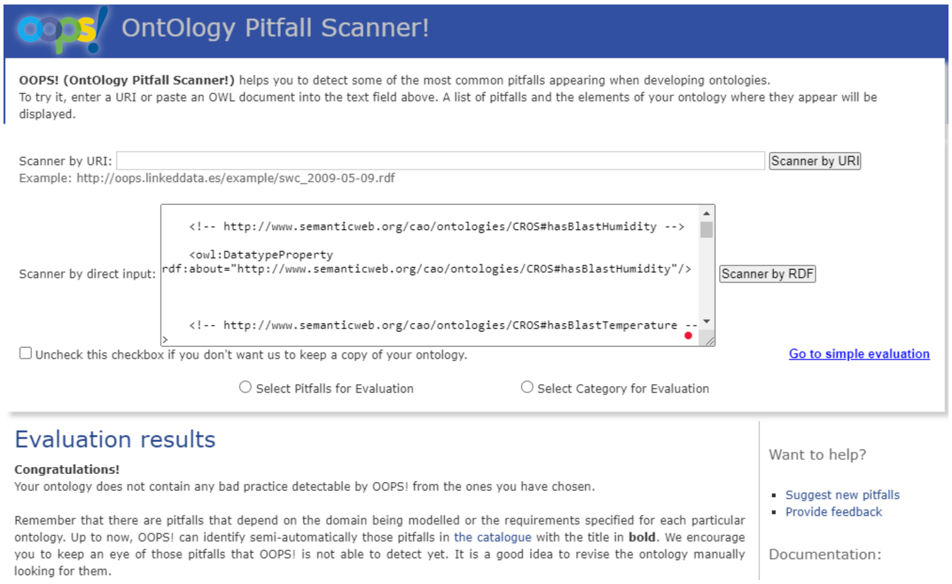

Figure 3: Ontology evaluation results by OOPS!.

4.1. Cold rolling at Tata Steel

In steel manufacturing, the cold-rolled strip is produced on a cold strip mill, where the work rolls flatten the strip to a deformed flat shape. Fig. 4 shows a graphical conceptualisation of the roll management procedure in the Port Talbot cold rolling mill at Tata Steel. In the figure, the rolls and chocks move from refurbishment which is carried out by refurbishment shops to the roll management system in a clockwise manner. The cold rolling mill has five stands, with each stand having a work and backup roll. There is also a top and bottom roll pair (i.e. work and backup). After doing a "fixed" amount of tonnage, the rolls are extracted and sent to refurbishment shops.

At present, Tata Steel adopts a heuristic approach towards estimating this "optimal" time of roll maintenance. However, this is complex, as the remaining useful life (RUL) of a roll depends on many factors, which need to be understood prior to developing an advanced predictive maintenance model. As integrating different data sets and providing convenient access to them are essential but work-intensive and expensive tasks, a flexible method for easy data access and management is required. This motivates us to use CROS to perform ontology-based data access (OBDA), which facilitates the condition-based maintenance task on cold rolling mills. Leveraging the rich semantics encoded in CROS, the targeted data sets are enriched by the

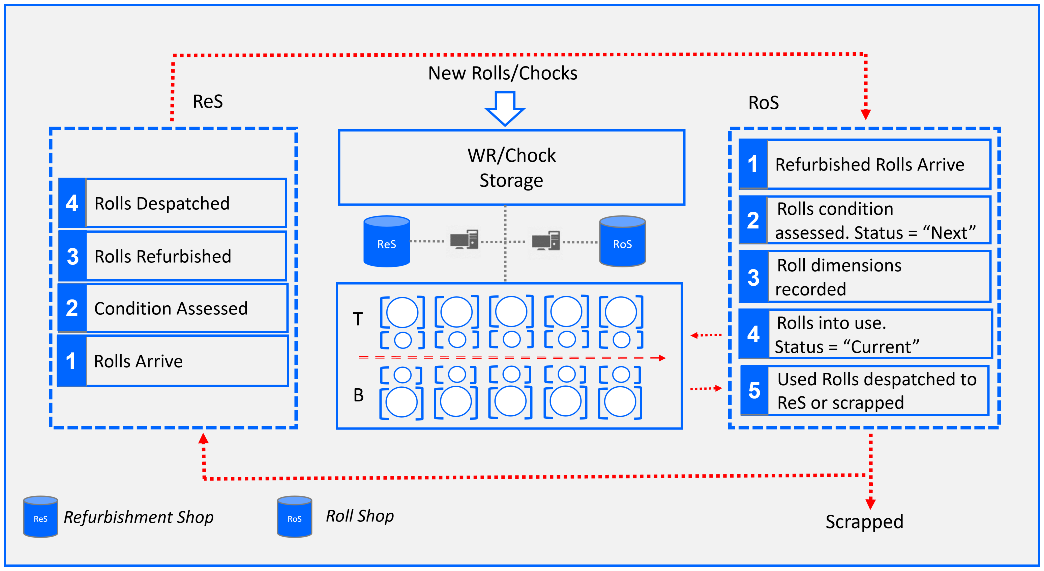

Figure 4: High-level visualisation of roll management system for cold rolling mills.

domain knowledge. This allows reasoning and inference to be performed over data and knowledge, which enhances the autonomous decision making process of the condition-based maintenance system.

4.2. Data collection

The data sets used in this case study are obtained from the cold rolling processes at Tata Steel. They contain static data related to the rolls, roll storage, and roll refurbishment. The data sets are stored in several tables in a database where the numeric values are dynamic because of the changes of conditions of the rolls. The changes of roll conditions are causes either by the continuous usage of rolls or the manual operation of machine operators (roll replacement, roll grinding, roll refurbishment, etc.). For this paper, we use three specific tables within the database: *ROLLS*, *ROLL_GRINDING*, and *ROLL_MILLS*. These tables contain data fields that are crucial for the predictive and condition-based maintenance of cold rolling mills. For example, in the *ROLLS* table, data fields such as *ROLL_ID*, *DIAMETER*, *INIT_DIAME-TER*, *LAST_LOC_DATA_TIME*, *SUPPLIER_ID*, *MILL_ID*, and *LAST_GRIND_NR* are considered important for determining the status of cold rolling mills. Table 5 shows the data sets used in our case study.

Table 5: Used data sets and their key data fields, data types, and data description.

Table and fields	Data type	Description
ROLLS	**Table**	**Contains static data relevant to the Rolls.**
ROLL_ID	Integer	Unique identifier of the roll. Primary Key.
DIAMETER	Double	Stores the value of the diameter of the roll.
POSITION	String	Top or Bottom to denote their position in mill.
PARTNER_ID	Integer	Unique identifier of the roll's partner.
WORK_BACKUP	String	Identifier to specify whether a roll is a work or backup roll.
LAST_LOC_DATE_TIME	Date	Timestamp of the date when the roll was last located.
Last_STAND_ID	Integer	The last stand this roll was placed in.
ROLL_GRINDING	**Table**	**Table that stores the previous grindings of each roll.**
ROLL_ID	Integer	Unique identifier to specify which roll.
DIAMETER	Double	Stores the value of the diameter of the roll.
GRIND_DATE	Date	Timestamp of the date when that roll was grinded.
STAND_ID	Integer	The last stand this roll was placed in.
ROLL_MILLS	**Table**	**Table that stores the data of mills for cold rolling.**
MILL_ID	Integer	Unique identifier of a mill.
MILL_ID	String	Unique string identifier of a mill.
MILL_RETIRE	Boolean	A boolean value indicating whether a mill is retired.
ACT_MILL_NAME	String	Unique string identifier for a mill in action.
UPDATE_DATETIME	Date	Timestamp of the mill status update.

4.3. Ontology-based data access using CROS

The predictive and condition-based maintenance task of Port Talbot cold rolling mills is carried out using OBDA techniques. In this work, we use the Virtual Knowledge Graph System Ontop[6]. Ontop can map domain ontologies to arbitrary relational databases using R2RML, Direct Mapping, and its own mapping language. The advantage of Ontop is its adoption of *Virtual Knowledge Graphs*. As the graphs (ontologies) are kept virtual, it avoids the manipulation of relational databases, which is normally considered as work-intensive and expensive. In this way, Ontop provides convenient access to databases and eases the task of data integration.

Some of the data tables introduced in Table 5 are not interconnected but contain fields that are semantically related. For example, *ROLL_ID* appears only in the table *ROLLS* but is linked to different data fields accross all the data sets. To effectively use the data, integration is required which could be manually costly and time consuming. To mitigate this data integration pain point, OBDA is a promising solution as it allows flexible integration through virtual knowledge graph. An ontology-based approach also enables the enrichment of domain knowledge, by which inference over data and knowledge could be carried out to derive new knowledge.

In this case study, we first upload the three data sets onto the H2 Data Base Engine[7]. H2 is a Java-based relational database management system

[6]https://ontop-vkg.org/

[7]https://www.h2database.com/html/main.html

that allows users to interact with relational databases in a client-server mode. Fig. 5 shows the H2 console and uploaded data sets.

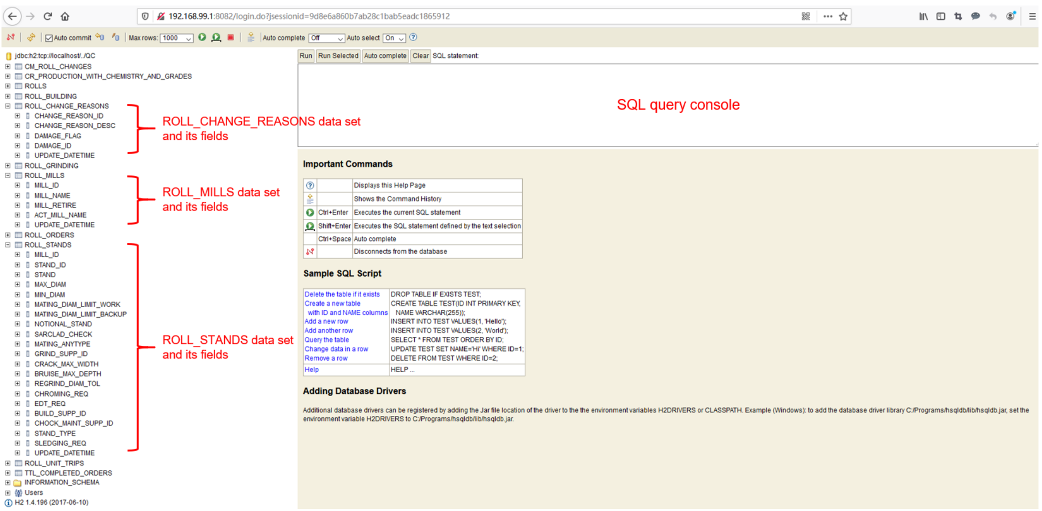

Figure 5: The H2 relational database management system and uploaded data sets.

We then use the software Protégé 5.5.0 to create mappings from CROS to cold rolling mill data sets. The aim of these mappings is to connect ontology vocabulary to data sources for collecting queries over original relational data sets. The collected queries are then used to construct ontology class and property assertions for CROS. The following codes show an example mapping we generated to connect CROS to data sets:

```
:roll_{roll_id} a :Work_Roll;
:hasPosition {_position};
:hasRollID {roll_id};
:hasDiameter {diameter};
:hasPartner {partner_id};
:isWorkOrBack {work_backup};
:isAssignedToStand {last_stand_id};
:hasTypeID {type_id};
:hasMillID {mill_id};
:hasLastSelectedGrinder {last_grinder};
:hasLastStand {stand_id};
:hasLastChokeNumber {last_chocking_nr}.
```

The mapping is written in Turtle syntax, which connects logic axioms in CROS to relational databases. Each Ontop mapping can be considered an RDF subject-predicate-object (SPO) graph, and they are separated by space followed by period. For the mapping shown above, relationships such as *:hasPosition*, *:hasRollID*, *:hasDiameter*, *:hasPartner*, *:hasMillID*, *:hasLastSelectedGrinder*, and *:hasLastChokeNumber* are data properties in CROS. Syntax in curly brackets are data fields/attributes in the data sets. They map from relational databases to ontology axioms. Similarly, two other mappings are created to connect CROS to the collected data sets. In this way, OBDA allows rich data semantics to be provided for information retrieval and management tasks. Compared to traditional data retrieval tasks, our approach helps to improve the explainability of data retrieval results and enrich the query answers with rich domain knowledge.

4.4. Condition-based maintenance of cold rolling mills

After creating the mappings, queries are created to reason and examine the status of cold rolling mills for the goal of condition-based maintenance. In this work, the W3C standard ontology query language SPARQL [43] is used for data and information retrieval. Once SPARQL queries are constructed, Ontop translates them to SQL queries over the H2 relational database management system. By this, we aim to use SPARQL-based ontology reasoning for the condition-based maintenance and monitoring task on cold rolling mills.

The first SPARQL query we execute is to reason about the diameter of those rolls that have at least one partner roll which can be used for replacement. In a real-world scenario, rolls may break due to constant usage. To avoid shut down of the whole steelmaking production line, a partner roll is needed for rapid replacement of the broken roll. To execute this replacement, it is required that both the broken and replacement partner roll have the same diameter. In this context, we propose the following SPARQL query to retrieve the diameter of the rolls, by which we can discover which rolls have partners for replacement once they are broken:

```
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 skos: <http://www.w3.org/2004/02/skos/core#>
PREFIX time: <http://www.w3.org/2006/time#>
PREFIX cros: <http://www.semanticweb.org/CROS#>

SELECT ?Diameter

WHERE {
   ?roll cros:hasRollID ?rollid .
   ?roll cros:hasDiameter ?Diameter .
   MINUS {
    ?roll cros:hasGrindRoll ?grind .
   }
}

GROUP BY ?Diameter
having (count(?Diameter) > 2)
```

The proposed query looks for all the subjects that contain the *:hasDiameter* variable of any diametric value, and then prints out those variables whose diametric value appears more than twice. This query does not include the subjects that also contain the *:hasGrindRoll* relatinoship as these diameter values are often historical of previous grind values. The SPARQL query results are shown in Fig. 6, where the diameter of the rolls are displayed.

In Fig. 6, the diameter of rolls that appears more than twice are printed in the Protégé Ontop SPARQL Tab. The SPARQL query reasoning results provide steel manufacturers with the diametric information of the rolls that have at least one partner roll. In case a roll breaks down under a specific diametric value, steel manufactures can execute this SPARQL query to discover whether one roll has a partner roll for rapid replacement. In this way, intelligent maintenance of the rolls is achieved.

Another proposed query for roll maintenance is to identify condition of the rolls with temporal information. The data sets we use contain temporal information of the rolls from the year 2015 to 2019. To retrieve the relevant information regarding rolls, roll partners, diameter, and temporal information, we executed the following SPARQL query:

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

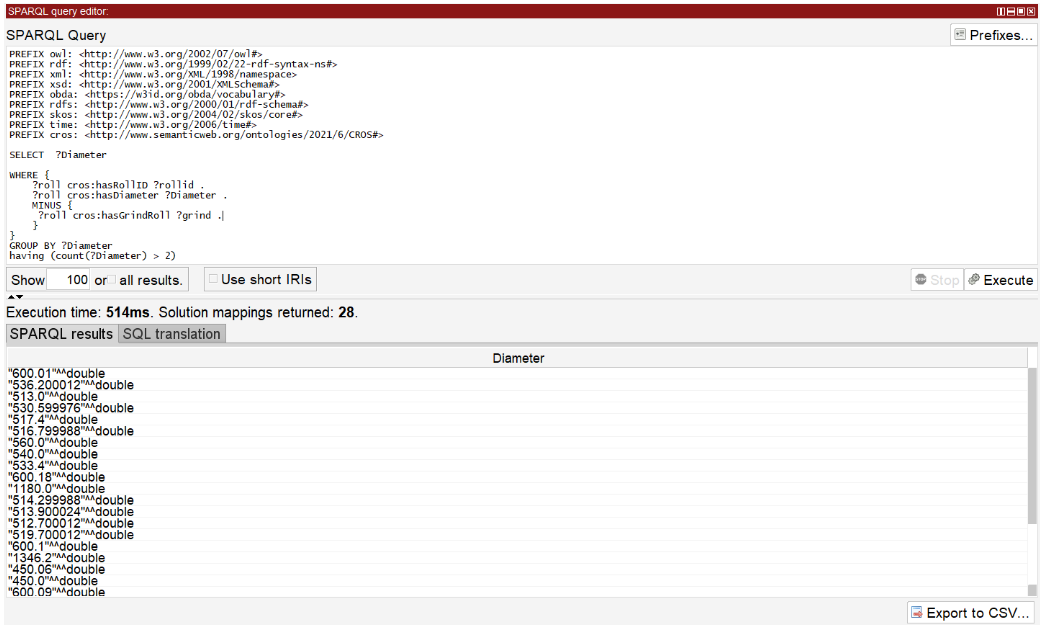

Figure 6: The SPARQL query for reasoning on diameter of roll partners and the query results.

```
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 skos: <http://www.w3.org/2004/02/skos/core#>
PREFIX time: <http://www.w3.org/2006/time#>
PREFIX cros: <http://www.semanticweb.org/CROS#>

SELECT ?Roll ?Partner ?Diameter ?LastLocatedDate

WHERE {
   ?Roll cros:hasRollID ?RollID .
   ?Roll cros:hasDiameter ?Diameter .
   ?Roll cros:lastLocatedDate ?LastLocatedDate .
   OPTIONAL {
    ?Roll cros:hasPartner ?Partner .
   }
   MINUS {
```

```
    ?Roll cros:hasGrindRoll ?GrindRoll .
   }
   FILTER (?LastLocatedDate
        > "2015-01-15T16:09:20.000Z"
        ^^xsd:dateTime && ?LastLocatedDate
        < "2019-05-15T16:09:20.000Z"
        ^^xsd:dateTime)
}

GROUP BY ?Roll ?Diameter ?Partner ?LastLocatedDate
ORDER BY ?Roll
```

Within this query, the *OPTIONAL* keyword is a binding that allows us to query for data but not to fail the query when that data does not exist. After query execution, both optional and non-optional information is returned. In this example, we retrieve the rolls without considering whether a specific roll has a partner of the same diameter. Same to the previous query, the *:hasGrindRoll* relationship is removed by the *MINUS* keyword. To restrict the scope of this query, *FILTER* keyword is used to select those rolls that last located from 15th January 2015 to 15th May 2019. The date in *xsd:dateTime* format.

Fig. 7 shows the results of the above SPARQL query. We group the results using the *GROUP BY* keyword and then use the *ORDER BY* clause to establish the order of a solution sequence. The results are ordered by the name of rolls. In total, 1866 results are returned from data sets.

The SPARQL-based query capability of CROS is a significant enhancement over traditional data access and retrieval methods. Leveraging the rich domain knowledge and data semantics incorporated in CROS, the search results do not only present the text field matching but also provide a more precise and richer ontological description of data. This enhancement is achieved by mapping the specific data fields to the pre-defined concepts and relationships in ontologies. In this way, data access, harmonisation and integration are easily performed at the knowledge layer where CROS serves as a virtual knowledge graph encoded with rich domain knowledge. The use of this ontology-based approach mitigates the pain points of traditional predictive maintenance/condition-based maintenance methods for which the reuse of domain knowledge is often overlooked. Moreover, compared to traditional information retrieval tasks where keyword searches in heterogeneous data

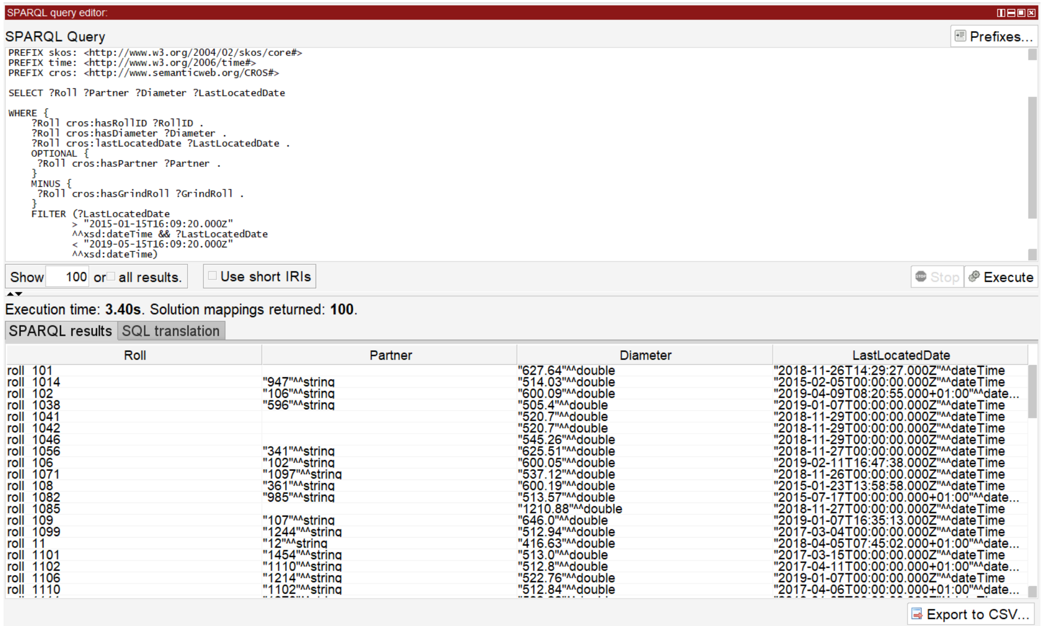

Figure 7: The SPARQL query for reasoning on the temporal information of rolls. Results are grouped by roll names, partner ID, diameter, and last located date.

files are work-intensive, our proposed ontology-based approach proves to have more flexibility regarding data access and integration. However, there are two main limitations for this work. Firstly, the proposed ontology-based predictive maintenance method does not perform well when dealing with real-time data. To address this issue, real-time data processing techniques such as stream reasoning [44] should be considered. Secondly, it is time-consuming for the Protégé-based Ontop system query large data sets. To improve the efficiency of data retrieval and integration, we aim to consider the source code version of Ontop in the future.

5. Conclusions and future work

In this paper, a core reference ontology for steelmaking named CROS is presented. The proposed ontology aims to facilitate steelmaking process modelling and information management and serves as a uniform knowledge model that can be used to query and reason on heterogeneous steelmaking data sources. To develop the ontology, we formalised the knowledge anchored in different steelmaking processes and applied this knowledge to facilitate decision making for solving complex tasks. During knowledge acquisition and formalisation, a set of international standards and domain ontologies were reused to ensure rigorous conceptualisation. The ontology development methodology IDEF5 was adopted for conceptualisation. The developed CROS was then evaluated by the ontology pitfall detection system OOPS!. Results have shown that CROS is free of critical development errors that may affect ontology consistency, reasoning and applicability. Unlike most of the existing steelmaking ontologies, we focus on the utilisation and implementation perspectives of ontologies. These two aspects of ontology usage are often overlooked in the literature. The functionality and usefulness of CROS were tested and validated by a real-world case study where a condition-based predictive maintenance task of cold rolling mills is performed.

For future work, we firstly will focus on investigating the ontology reasoning capability of CROS. We plan to implement rule-based reasoning on the important data attributes within cold rolling mill data sets, such as roll diameter, roll partner, roll damage, roll scrap reason, and roll supplier. This will help with the predictive analytics tasks such as roll refurbishment time prediction, roll partner selection, and intelligent supplier discovery. The second future direction of research is to combine statistical methods and ontology reasoning for the predictive maintenance of cold rolling mills. Machine learning and data mining will be used to derive and capture interesting patterns from data. Then a hybrid approach for cold rolling mill maintenance will be proposed. The hybrid approach will automatically generate IF-THEN-based logic rules from derived data patterns. By this, we aim to use ontology reasoning to automate and facilitate the decision making process regarding cold rolling mill refurbishment.

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