Int. j. inf. tecnol. (January 2024) 16(1):507–515
https://doi.org/10.1007/s41870-023-01640-w

ORIGINAL RESEARCH

A real-time semantic based approach for modeling and reasoning in Industry 4.0

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Received: 18 June 2023 / Accepted: 25 September 2023 / Published online: 14 December 2023

Abstract In the rapidly evolving landscape of Industry 4.0, the transformation of manufacturing processes is driven by the seamless integration and intelligent utilization of data. The concept of semantic interoperability is central to this paradigm evolution, as it holds the key to unleashing unparalleled efficiency, productivity, and innovation. It enables machines, systems, and humans to communicate accurately and make informed decisions by promoting a deeper understanding and interpretation of data from disparate sources. This manuscript proposes a real-time semantic based framework using Semantic Web technologies for Industry 4.0. The framework allows real-time data annotation for semantic data enrichment and building an ontology (I4.0-Onto) for knowledge representation. In addition, semantic reasoning and querying on enriched data, and the publication of the developed model and data as Linked Data on the Web. This research advances and solves the issue of semantic interoperability, giving solutions for developing real-time industrial applications.

Keywords Internet of Things · Ontology · Semantic web technologies · Industry 4.0

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1 Introduction

Due to the noticeable expansion of the internet and smart technologies, Internet of Things (IoT) are increasingly expanding, providing considerable challenges and opportunities. The deployment of the IoT paradigm has triggered an epic wave of innovation as the most significant emerging technology trend [1]. The advancement of IoT revolutionized the industry, driving the field of Industry 4.0 (I4.0), which is analogous to the initial industrial revolution. Cyber-Physical System (CPS) represents the core of I4.0 in the concept's implementation and can self-monitor and generate information as data streams via the internet. Composing subsystems manufacture modern IoT systems that continually boost interactions between diverse systems that generate sensed streaming data with a high level of pervasiveness.The IoT has transformed modern lifestyles by bridging the physical and virtual worlds [2]. Recent statistics estimated that the number IoT devices exceeding 25.4 billion in 2030. So the output data generated will have hit 73.1 zettabytes by 2025.[1]

IoT is expected to play a critical role in the I4.0 vision with the birth of the Industrial Internet of Things (IIoT), which is a collection of smart sensor and object sets that are integrated with real-time industrial application setup [3]. It necessitates intelligent human-to-machine and machine-to-machine communication. Components such as actuators, sensors, CPS and their data are used to achieve this goal. The ubiquitous nature of the components that continuously generated data via the Internet and communicating with other associated entities, accumulating a massive amount of raw data on the web raise several issues, such as low interoperability, heterogeneity, and high development complexity. The heterogeneous nature of different

1 https://dataprot.net/statistics/iot-statistics/.

devices, and the variety of data generated, pose challenges to the efficient use of I4.0 production. Emphasizes that interoperability across "Things" on the IoT is one of the essential criteria for supporting object addressing, tracking, and discovery, along with information representation, storage, and exchange [4]. Modern manufacturing companies strive for digitalization to manage physical assets, processes, people, and locations. Since massive amounts of raw data have been generated and collected in this environment, integrating and managing various data sources is vital. Hence, providing semantic interoperability for IoT systems has emerged as a critical field of study. Interoperability issues arise when heterogeneous devices and systems are linked in an IIoT system [5].

Semantic interoperability ensures that information and services are shared to preserve the semantic flow. No matter how heterogeneous, each system must be able to identify data, represent it, and provide it with context to understand shared data in a meaningful manner. Since the communication is primarily intended to be interpreted by a machine and will only be transmitted to a human user once transformed, rich and expressive models appear especially appropriate in the case of connected objects. Many attempts have been made to tackle the problem presenting a variety of approaches based on the Semantic Web, defined by Berners-Lee [6] for merging Semantic Web technologies with the IoT. In the IoT sector, semantic Web technologies are also applied for other objectives such as the description and search of things and IoT services, the composition of services, models, and reasoning over IoT resources [7] leading to the framework of the Semantic Web of Things (SWoT). However, they still have some problems and limitations since the SWoT is not a real-time framework application since the raw data is stored first on the web. Real-time data transmission of applications and devices via the internet has been identified as one of the key performance indicators [8]. Interoperable standards, protocols, and networking technologies facilitate the adoption of I4.0 technology by companies. So, there is an increasing demand for developing a real-time semantic based approach.

The presented framework will enable achieving automatization, personalization, information retrieval, data reuse, and knowledge discovery throw the development of an innovative real-time semantic based framework providing a set of stages for real-time semantic data annotation, reasoning, and querying over semantically annotated data streams and publishing the data as Linked Data. This contribution in this research article is given as follows:

- Real-Time data annotation, providing a real-time integration of semantics into heterogeneous sensor stream data.
- Builds the I4.0-Onto for knowledge representation.

Table 1 Comparison of our framework with recent works of literature

Publication	RT DA	Ontology	SR	SQ	LD
[12]	–	+	–	–	–
[13]	–	+	–	–	–
[14]	–	+	–	–	–
[15]	–	+	–	–	–
[16]	–	+	–	+	-
[17]	–	+	–	+	–
[18]	–	+	+	+	+
[20]	–	+	–	–	–
[21]	–	+	–	–	+
[19]	–	+	–	+	–
Proposed approach	+	+	+	+	+

- Provide querying and reasoning engines to infer and acquire new knowledge to answer complex queries.
- Publish structured data as Linked Data to allow for structured data to be retrievable from different sources.

The remainder of this article is structured as follows: Sect. 2 represents similar works relating to semantic interoperability in I4.0 withing the literature review to discuss the background studies of the research area. Section 3 introduces the framework with the prototype implementation in the I4.0 use case. Section 4 summarizes and concludes the article with future work directions.

2 Motivation and related work

Semantic modeling of smart factories, manufacturing production lines, and interoperability within manufacturing systems are critical features established in Industry 4.0 production [9]. This involves connecting physical assets, such as systems, devices, and sensors, via the internet. The networking of these items and their semantic interoperability poses its most significant challenge. Indeed, IoT devices are heterogeneous, as they are built on various hardware platforms and networks [10], resulting in physically connected but semantically disconnected items. The evolution of the Semantic Web of Things has led to the convergence of various heterogeneous devices, allowing them to infer hidden relationships and providing a solution to interoperability [11]. Dealing with the heterogeneity of IoT data streams in Industry 4.0, semantic technologies have emerged as vital for ensuring data interoperability due to their capacity to harmonize concepts, extend knowledge, and facilitate the sharing of machine-readable data representations.

Below, we present some research papers relevant to the research area covering semantic interoperability issues in

Industry 4.0 (I4.0). Table 1 includes recent publications from related work, and we have compared them based on their key contributions in the realm of semantics. We use semantic concepts, including Real-Time Data Annotation (RT DA), Ontology, Semantic Reasoning (SR), Semantic Querying (SQ), and Linked Data (LD), as criteria.

The AutomationML ontology (AMLO) was presented in [12], which covers the AutomationML data exchange standard in the industrial engineering domain. The semantic model serves as a means for data exchange among various CPSs and improves engineering processes in I4.0.

Teslya et al. proposed an ontology-based approach to describe the industrial components merged from four different scenarios to form an upper-level ontology [13]. To increase product customization for customers while reducing costs for its producers.

Wan et al. in [14] proposed a resource configuration-based ontology describing domain knowledge of sensible manufacturing resource reconfiguration using web ontology language (OWL).

In [15], Ramírez-Durán et al. developed ExtruOnt, that is a development effort to create an ontology for describing a type of manufacturing machine, precisely one that performs an extrusion process (extruder). The ExtruOnt ontology terms provide various types of information related to an extruder, which is reflected in distinct modules that comprise the ontology.

Kalayci et al. in [16] demonstrates how the data integration challenge can be addressed using semantic data integration and the Virtual Knowledge Graph approach. They proposed the SIB Framework to semantically integrate Bosch manufacturing data, specifically the data required to analyze the Surface Mounting Process (SMT) pipeline.

Berges et al. in [17] present a proposal materialized in a semantic-based visual query system designed for a real-world I4.0scenario, allowing domain experts to formulate queries to deal with a customized digital representation of the machine and on-the-fly generated forms.

The issue of standard interoperability across different standardization frameworks is addressed in [18]; researchers developed a knowledge-driven approach that enables the description of standards and standardization frameworks into an I4.0knowledge graph (I40KG).

To address heterogeneity issues in the IIoT, Ren, et al. [19] proposed a novel concept based on the standardized W3C TD, semantic modeling of artefacts, and KG. They also presented two lightweight semantic model examples.

May el al. in [20] address interoperability in smart manufacturing and the challenge of efficiently federating diverse data formats using semantic technologies in the context of maintenance in this study, and they present a semantic model in the form of an ontology for mapping pertinent data.

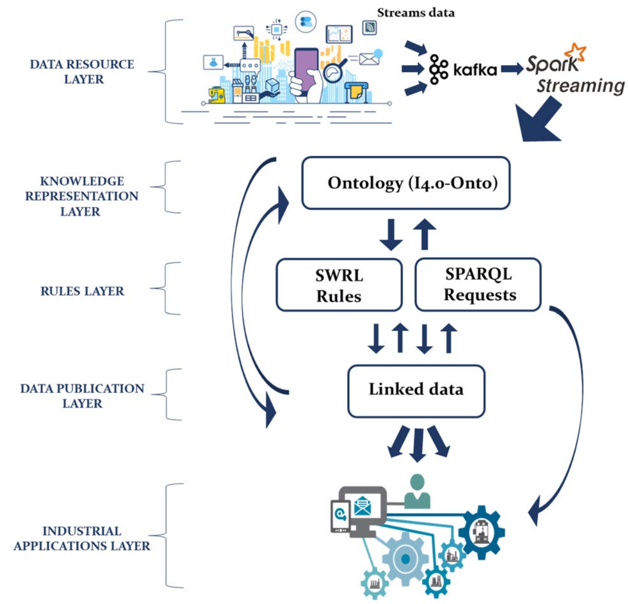

Fig. 1 Proposed framework for modeling and reasoning over IoT sStream data in I4.0

The authors of [21] present a Common Reference Ontology for Steelmaking (CROS). CROS is a shared steelmaking resource and capability model that aims to simplify knowledge modeling, knowledge sharing, and information management. To address the semantic interoperability issue caused by the data and information needed for supply chain planning and steel production.

To meet the requests of I4.0, focusing heavily on real-time data processing, which refers to machines abilities to continuously and automatically process data and provide real-time outputs Which is the main contribution of this research. This article proposed a Real-Time Semantic-Based Approach consisting of stages for real-time data annotation, building an ontology for knowledge representation, reasoning, and querying over semantically annotated data streams. Then the data is published as Linked Data so it can be reused by queering data streams for knowledge discovery, enriching them with other datasets to gain additional information, and facilitating data retrieval.

3 Proposed framework and implementation

The general vision of the framework and the data flows depicted in Fig. 1. Each layer with its functionality are described in detail in the section bellow.

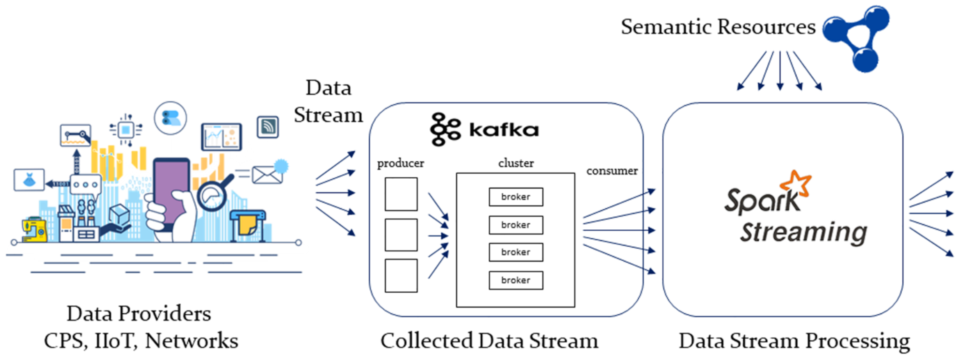

Fig. 2 Data resources and processing layer

3.1 Data resource and processing layer

The present layer holds two parts: data providers and the streaming system.

At the factory, the physical resource layer, is responsible for implementing the available manufacturing service and can be initiated by the user. CPSs, the IIoT, and the Internet of Services are the umbrella terms for these technologies. A massive amount data gathered from various distributed information sources for real-time data streams we use Apache Kafka[2] and Spark Streaming[3] to build a streaming and data annotation system, detailed description is shown in Fig. 2.

Kafka is a streaming transport that receives various sensor data streams and transforms them into a specific format that Spark Streaming can process. The heterogeneous sensor stream data is transmitted from CPS, IIoT, and networks serve as the producer for the Kafka server. A producer represents a system or process that generates and transmits sensed data. Then the data is distributed across cluster brokers, that is a node transferring a message from a process producer to a consumer application employing topics. Which is a virtual repository of messages with the same or similar content from which a consumer application retrieves the information it requires. Apache Spark Streaming processes the data streams published by Kafka in parallel and in real time.

Enabling a real-time integration of semantics into heterogeneous sensor stream data with the use of semantic sources, allowing the understanding of transmitted data. The enriched sensor stream data with the results of the semantic annotation will be stored in a developed ontology by means of a Resource Description Framework (RDF).

Implementation: I4.0 factories real-time monitoring visualizes sensor stream data and their semantic annotations using CPS and IIoT sensor data. The system receives raw sensor stream data from different types of sensors. Figure 3 shows a part of the received raw data streams displayed in JSON format. Different semantic annotations for sensor stream data are developed in our system, such as:

Temperature: Temperature monitoring controls and regulates the temperature of a specific environment. Temperature monitoring is an important part of industry; it is acceptable in the range of 40° to 85°C.

Humidity: detecting changes that affect electrical currents or air temperature The normal relative humidity ranges between 40 and 60%. However, each industrial application has its own optimal level of humidity to achieve the best productivity results.

```
{
    "sensor_1": {
        "id": "senh1",
        "type": "humidity_sen",
        "location": "workstation_w54",
        "observes": "humidity",
        "value": 60,
        "measurment_unit": "percent"
    },
    "cps": {
        "uri": "http://cps256.org/",
        "state": {"available": true},
        "operation": "post",
        "configuration": {
            "parameter": {
                "ip_adress": "255.154.129.1",
                "port_number": 6 }
        },
        "information": {
            "location": "factory_fw10",
            "sensors": [
                {"id": "senh1"},
                {"id": "seng31"}
            ],
            "actuators": [
                {"id": "act_a31"},
                {"id": "act_a20"}
            ]
        },
        "function": {
            "midlleware": "data_collecting"
        }
    },
```


Fig. 3 Streams data in JSON format

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[2] https://kafka.apache.org.

[3] https://spark.apache.org.

Gas_emission: for gas Detection Systems, monitor and control levels of gases that are either poisonous or flammable to trigger an alert.

Industrial_noise: detected by a noise level sensor or sound sensor, a module used to detect the intensity of sound in order to monitor changes in the noise level in the industry.

The annotations described above are being developed into I4.0-Onto. So, the process of semantic annotations is presented after a description of the various types of semantic annotations for sensor stream data. Sensor stream data may arrive in various formats to the Kafka server, transforming it into a specific format (JSON Fig. 3) that Spark Streaming will process. The sensor data stream will then be semantically annotated using Spark Streaming.

The outcomes enriched data will be saved as RDF[4] triples in the developed ontology, which will be used for the industrial systems.

3.2 Knowledge representation layer

We opt for developing an ontological model to represent knowledge in the proposed framework. Ontology is essential in the creation of the semantic web [22]. It can be viewed as a significant step toward more effective management of heterogeneous data.

After determining the domain I4.0and its scope, we built the ontology (I4.0-Onto), the ontology is regarded as an important factor in data integration and relation between concepts[23]. Our system needs to interact with other applications that already use specific ontologies in the domain we want to represent. Hence, reusing existing ontologies may be required. To annotate data into enriched Resource Description Framework (RDF) triples while accounting for heterogeneity, volume, and frequency, we will develop and implement a semantic ontology model (I4.0-Onto) extending the SOSA standard ontology. The knowledge is expressed in an ontology by means of RDF annotation. In addition to representing concepts that characterize information, the next layer must store the enriched data transmitted by the previous layer. It's required to model the physical concepts and describe knowledge of CPS, IIoT, and network specifications.

Implementation: The ontology I4.0-Onto is built to represent knowledge in a standard process that identifies the tasks that must be completed when it is built. It enables the transformation of raw data into an ontological model represented in the OWL[5] language.

Determine domain and scope of the ontology: The representation of I4.0 and data gathered in factory area was identified as a domain to represent to use this ontology to boost the digitization of modern manufacturing companies.

Reuse existing ontologies: Ontologies represent the essential facts about a specific domain of interest in the form of concepts, relationships, instances, axioms, or rules. SOSA ontology [24], is based on the W3C Semantic Sensor Networks Incubator Group's SSN-XG[6] SSN Ontology, as well as considerations from the W3C/OGC[7] Spatial Data on the Web Working Group. It contains the basic concepts and relationships essential for building our ontology as Observation, Sensor, Observable property, etc. SOSA was modified by extending it with other classes and properties to develop I4.0-Onto.

List the important terms of the ontology: Ontology comprises various components such as classes, individuals, relations, attributes, functions and axioms [25]. A list should be made of all the existing terms since it would be nice to be able to make statements about manufacturers in order to explain technical facets in I4.0, regardless of the overlap between the classes that the terms represent, relationships between the terms, or properties that the classes may have. The modelled domain is capable of completing the following scopes: CPS, sensor, observation, feature of interest, actuator, HMI, function, network, operation, observable property, etc. Some classes of developed ontology are described below:

actuator: machine component in charge of moving and controlling a mechanism or system.

CPS: Cyber physical systems, incorporate sensing, computation, control, and networking into physical objects and infrastructure, and connect them to the Internet and to one another.

Observation: provides information about the entity being observed.

Observed_property: identifies which property is observed by a sensor (temperature, humidity, gas emmision, industrial noise, etc.).

feature_of_interest: represents a portrayal of the real world. Sensors detect stimulation and observe properties of features of interest.

information: gives information about CPS such as equipments contained (sensors, actuators, ets), location.

Define classes and class hierarchy: Defining the classes and their hierarchy, from top to bottom, to define the general concept (super-class) and then define the subclass. Class A is a super-class of class B if and only if every instance of B is also an instance of A, example, each type of sensor is

[4] https://www.w3.org/RDF/.

[5] https://www.w3.org/OWL/.

[6] https://www.w3.org/2005/Incubator/ssn/wiki/SSN-XG_Liaison_activities.

[7] https://www.w3.org/2015/01/spatial.

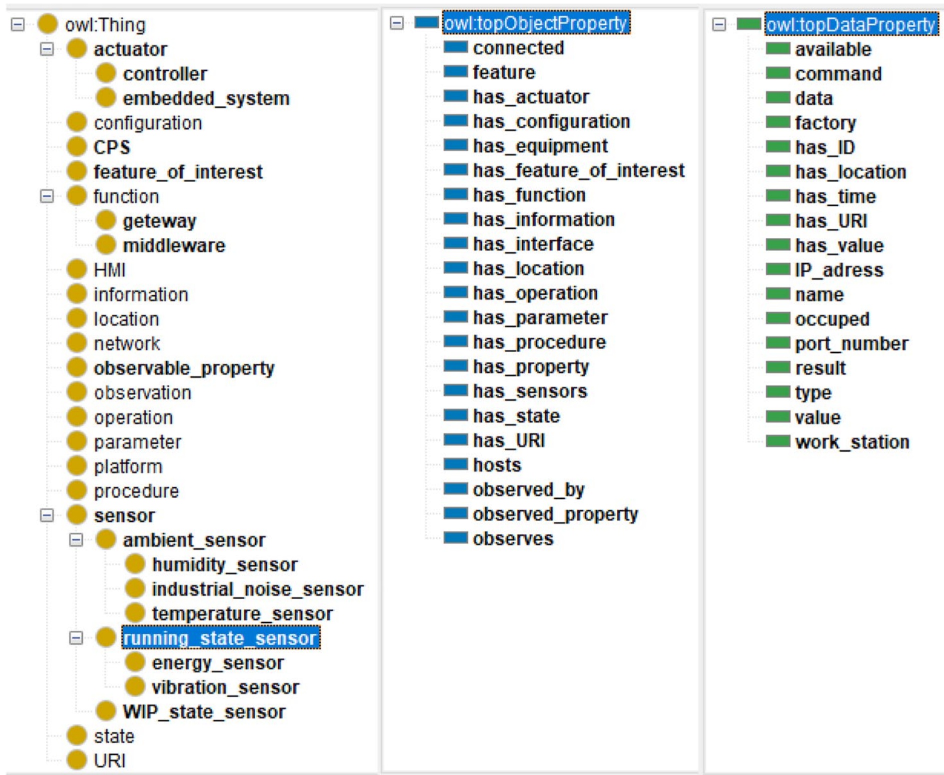


Fig. 4 Classes and data/objects properties of I4.0-Onto

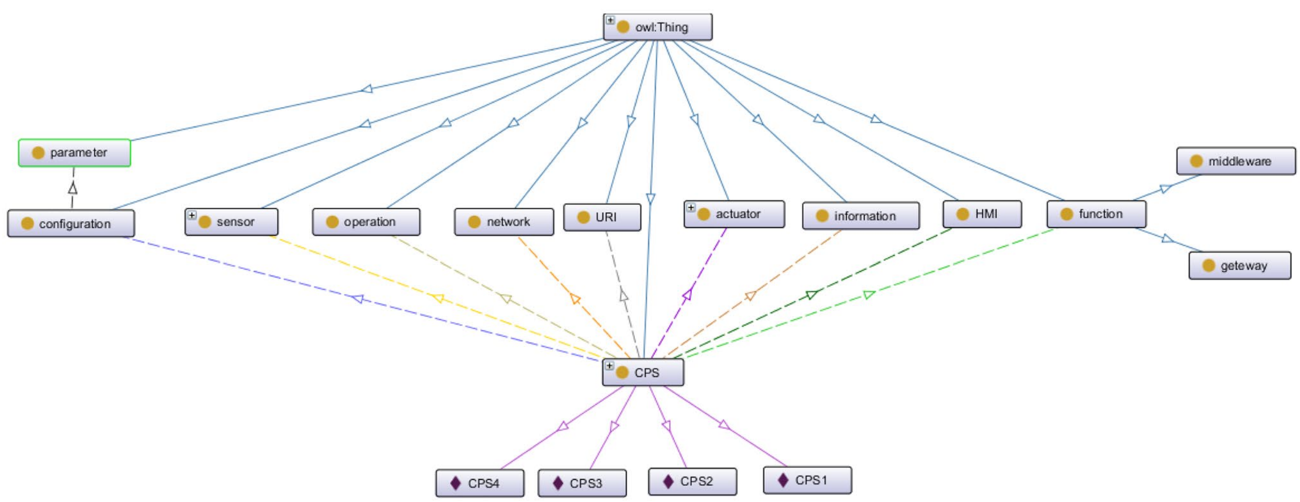


Fig. 5 A part of I4.0-Onto ontology represented with OntoGraph

necessarily a sensor. Therefore, class running_state_ sensor is a subclass of the class sensor (Fig. 4).

Set ontology properties: Each class has properties which are attached to this class. OWL was used to define relationships between previously presented classes defining object properties of classes. The related object properties were retained from the SOSA Ontology. Data properties link individuals with literals to define the type of data value. Figure 4 depicts the main ontological classes, and data/objects properties for I4.0-Onto represented in Protege 5.5.0. The resulting ontological model comprises the key concepts of I4.0 domain formalises the data sources and the generated data. The binary relations diagram is illustrated in Fig. 5 which is made with OntoGraph plug-in 2.0.3., representing a portion of the developed ontology graphically.

Tests results

Test	Result	Problem
feature_of_interest feature observation	Passed	None
gaz_emission type observable_property	Passed	None
hosts type Property	Passed	None
sensor disjointWith actuator	Passed	None
sensor type class	Passed	None
controller subclassOf actuator	Passed	None

Fig. 6 Tests and results

Ontology evaluation: Themis is a testing tool to assist ontology experts and users in validating ontologies based on functional requirements that define the knowledge that the ontology must represent [26]. For generating the tests the glossary of terms was used, each test in the ontology produced by Themis has four potential outcomes: Correct, undefined, Conflicting information, Missing relation. Figure 6 display the example of the evaluation of I4.0-Onto, showing some tests cases that have been run through this tool and all potential outcomes in the results section.

3.3 Semantic rules layer

The rules layer is divided into two parts:

3.3.1 Semantic reasoning

The ability to deduce logical consequences from a set of asserted facts or axioms is known as semantic reasoning. The proposed framework uses SWRL,[8] reasoning rules are in the form of an implication between an antecedent and a consequent. Applying SWRL rules in decision-making processes necessitates using a reasoning engine that can operate on OWL ontologies and SWRL rules. The reasoning rules were implemented in SWRL a rule language for the Semantic Web, which allows us to formalize in terms of the concepts defined in the model. The implementation was carried out in Protege, using a dedicated plug in (SWRLTab Plugin 2.0.11). An overview of two examples rules is bellowed.

Rule 1: If the humidity sensor value from the defined workstation is greater than 60%, a rule-based reasoning infers that the humidity level is higher than normal, and the monitoring system will issue an alert.

Rule 2: If the temperature of a workstation measured by a temperature sensor is greater than 85 degrees Celsius. A rule-based reasoning engine detects a temperature problem that may affect factory equipment and alerts the monitoring system.

3.3.2 Semantic query

Ontologies can be implemented in information retrieval systems to define query types based on Semantic Web languages. SPARQL[9] Protocol and RDF Query Language are used in the presented work. SPARQL is a query language and protocol for searching, adding, modifying or deleting RDF data available on the web. The queries are applied to the triples that make up an RDF data graph (ontology). It allows users to query data from any data source that can be mapped to RDF. SPARQL queries can produce results sets or RDF graphs.

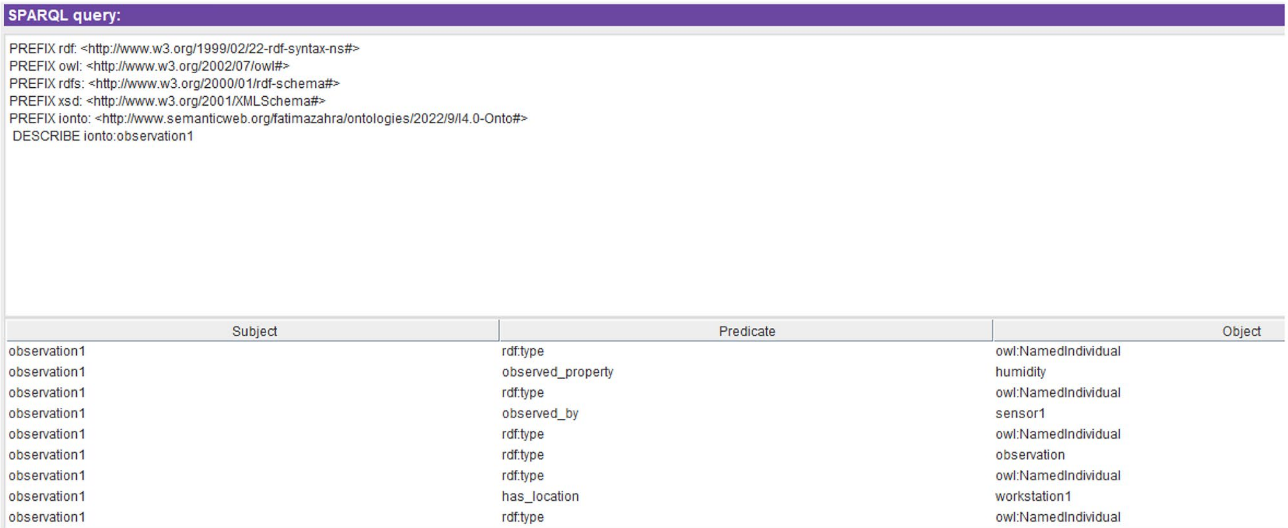
Any concept can be accessed by any of its attributes thanks to the concept and properties defined in our ontological model and RDF triples. The implementation was done in Protege with a dedicated plug in (SPARQL Query Plugin 3.0.0). Figure 7 depicts an outline of an example query that describe an observation.

3.4 Data Publication Layer

The semantic publication provides a way for computers to understand the structure and meaning of the published

[8] https://www.w3.org/Submission/SWRL/.

[9] https://www.w3.org/TR/2013/REC-sparql11-query-20130321/.

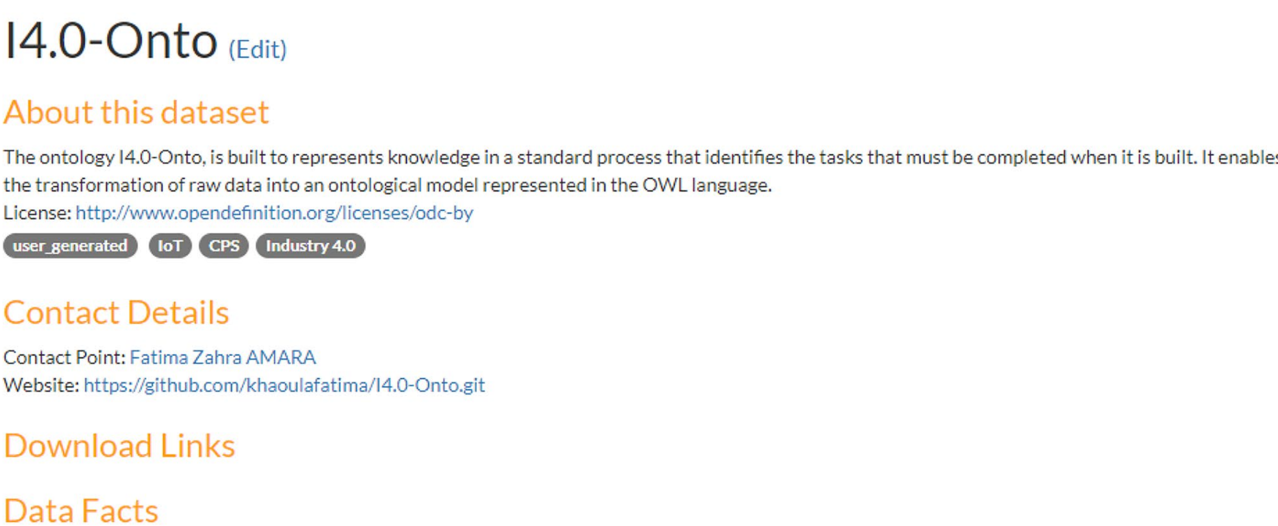


SPARQL query:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX ionto: <http://www.semanticweb.org/fatimazahra/ontologies/2022/9/I4.0-Onto#>
 DESCRIBE ionto:observation1
```

Subject	Predicate	Object
observation1	rdf:type	owl:NamedIndividual
observation1	observed_property	humidity
observation1	rdf:type	owl:NamedIndividual
observation1	observed_by	sensor1
observation1	rdf:type	owl:NamedIndividual
observation1	rdf:type	observation
observation1	rdf:type	owl:NamedIndividual
observation1	has_location	workstation1
observation1	rdf:type	owl:NamedIndividual

Fig. 7 Result of execution of the DESCRIBE query



I4.0-Onto (Edit)

About this dataset

The ontology I4.0-Onto, is built to represents knowledge in a standard process that identifies the tasks that must be completed when it is built. It enables the transformation of raw data into an ontological model represented in the OWL language.

License: http://www.opendefinition.org/licenses/odc-by

user_generated IoT CPS Industry 4.0

Contact Details

Contact Point: Fatima Zahra AMARA

Website: https://github.com/khaoulafatima/I4.0-Onto.git

Download Links

Data Facts

Fig. 8 Developed model on the LOD cloud

knowledge and be more discoverable and open to aggregation and reinterpretation due to semantic publishing.

Semantic Web languages such as RDF and OWL are used to publish information as data objects. To this end, W3C coined the term Linked Data which is a collection of design principles for exchanging machine readable, interconnected data over the Internet [27].The aim of this phase is to make the main products of the generation process, namely the ontology and the RDF dataset, available via the Web. To publish structured data RDF/XML on the web, the first procedure is to store the RDF data in a persistent RDF repository, which can be accessed and queried.

We publish the dataset on the LOD cloud (Fig. 8),[10] in a publicly accessible DNS, with the appropriate permissions set. The LOD Cloud is a Knowledge Graph that manifests as a Semantic Web of Linked Data. Our data set is accessible via the link.[11]

[10] https://lod-cloud.net.

[11] https://lod-cloud.net/dataset/fatimazahra.

4 Conclusion

This phase of our research is primarily motivated by the growing trend across industries to harness the potential of artificial intelligence (AI) in addressing challenges and transitioning to I4.0. The key contribution of this research is the development of a real-time framework for annotating heterogeneous data streams within the context of I4.0. This framework enhances timely decision-making, especially in scenarios where raw data poses challenges for humans and machines alike. The creation of the I4.0-Onto ontological model, an extension of the SOSA ontology, facilitates knowledge representation for data sources and raw stream data. By utilizing semantic rules, queries, and Linked Data publication, the framework supports knowledge inference and extraction. In future research, our goals include expanding the ontology, evaluating the framework's performance, exploring enhancements to semantic queries, and diversifying its application across domains.

Availability of data The data are available from the corresponding author.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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