EUCISE-OWL: An Ontology-based Representation of the Common Information Sharing Environment for the Maritime Domain (CISE)

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Abstract. The timely and efficient cooperation across sectors and borders during maritime crises is paramount for the safety of human lives. Maritime monitoring authorities are now realizing the grave importance of cross-sector and cross-border information sharing. However, this cooperation is compromised by the diversity of existing systems and the vast volumes of heterogeneous data generated and exchanged during maritime operations. In order to address these challenges, the EU has been driving a number of initiatives, including several EU-funded projects, for facilitating information exchange across sectors and borders. A key outcome from these efforts is the Common Information Sharing Environment (CISE), which constitutes a collaborative initiative for promoting automated information sharing between maritime monitoring authorities. However, the adoption of CISE is substantially limited by its existing serialization as an XML Schema only, which facilitates information sharing and exchange to some extent, but fails to deliver the fundamental additional benefits provided by ontologies, like the richer semantics, enhanced semantic interoperability and semantic reasoning capabilities. Thus, this paper presents EUCISE-OWL, an ontology representation of the CISE data model that capitalizes on the benefits provided by ontologies and aims to encourage the adoption of CISE. EUCISE-OWL is an outcome from close collaboration in an EU-funded project with domain experts with extensive experience in deploying CISE in practice. The paper also presents a representative use case for handling information exchange during a maritime crisis, demonstrating thus the use of the proposed ontology in practice.

Keywords: Maritime Monitoring, CISE, EUCISE2020, Data Model, Ontology

1. Introduction

During maritime crises, human lives are constantly at stake, while the time to react to unforeseen events is extremely limited. Therefore, cooperation across sectors, and often across borders, is valuable in order to ensure the safety and efficiency of operations. Relevant studies indicate that authorities are indeed starting to realize the importance of cross-sector and cross-border information sharing [28].

Nevertheless, on a practical level, this cooperation is compromised by the vast diversity of systems that operate simultaneously but are not yet adequately interconnected. On top of that, one should also add the vast volumes of heterogeneous data generated during maritime operations, including sensor measurements, intelligence, and reporting, amongst others.

In order to address the above challenges, the EU launched in 2005 a number of initiatives for improving the interoperability between national authorities' systems. These efforts included published communications, roadmaps, and green and blue papers, and eventually resulted in EU's Integrated Maritime Policy (IMP) [7]. In parallel, there have been several EU-funded projects aimed at fostering information exchange across sectors and borders [27], with the participation of many EU maritime monitoring authorities.

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A key outcome from these EU-wide efforts is the *Common Information Sharing Environment* (*CISE*), representing an open, collaborative process within the EU for promoting automatic information sharing between authorities involved in maritime monitoring, across sectors and borders [6]. In order to support the authorities' continuously increasing needs, in conjunction with the constant decrease of operational personnel (operators), CISE aims to (a) increase the efficiency, quality, and responsiveness of surveillance and operations at sea, and, (b) ensure a safer, more secure, and environmentally protected EU maritime domain. The benefits of deploying a uniform model like CISE for maritime monitoring include the following: (a) minimizing the risk of human mistakes; (b) establishing a standard detection threshold, which can be dynamically adapted each time according to the needs and the occurring incidents; (c) expanding the human cognitive area; (d) reducing the need for highly experienced and specialized personnel; (e) reducing the adaptation and familiarization time for the users (operational personnel) with a minimal impact in their performance.

An important milestone in the roadmap for implementing CISE is represented by the FP7 project EUCISE2020 [5], which ran from 2014 to 2018 and promised to deliver an operational solution, built on a common service-based architecture and open information exchange. In order to facilitate the adoption of CISE by interested parties, EUCISE2020 openly published its CISE-based data model in 2015 [4] as an XML Schema specification accompanied by a set of UML diagrams.

However, the adoption of CISE is substantially compromised by the very serialization of the data model as an XML Schema. The latter does promote information sharing and exchange to an extent, but largely fails to deliver the fundamental additional benefits provided by ontologies, most prominently including a syntactically and semantically richer representation, enhanced semantic interoperability and semantic reasoning capabilities [13]. In order to capitalize on the critical benefits provided by ontologies, this paper presents a serialization of the EUCISE2020 data model as an ontology that will substantially encourage the extensive adoption of CISE. The proposed ontology is called *EUCISE-OWL* and aims to serve as a common representation framework for putting CISE in practical use. EUCISE-OWL is an outcome from the ROBORDER EU-funded project [20], after close collaboration with our end users who have extensive experience in deploying CISE in practice [14].

The rest of this paper is structured as follows: Section 2 presents the EUCISE2020 data model in more detail, while section 3 describes the process we adopted for converting the EUCISE2020 UML diagrams into an ontology. Section 4 presents our EUCISE-OWL ontology, followed by a use case for handling information exchange during a maritime crisis demonstrating the use of the proposed ontology in practice. Section 6 evaluates the EUCISE-OWL ontology, while section 7 presents other relevant models with a similar scope to CISE. Finally, section 8 concludes the paper with a discussion and key directions for future work.

2. The EUCISE2020 data model

The EUCISE2020 data model is based on the CISE Data Model v1.0 [1], which was defined in FP7 project CoopP (Cooperation Project Maritime Surveillance). The key ambition behind the CISE model is to provide a common European cross-sector format to share information across countries and sectors. Towards this direction, and in order to facilitate the adaptation of existing maritime monitoring systems in Europe, the CISE data model takes into account the corresponding data standards and identifies the most useful aspects for maritime monitoring authorities. Those were identified and validated by experts who participated in the CoopP project and represented all relevant sectors at EU and national level.

The main design principles behind CISE's implementation included sector neutrality, flexibility, extensibility, simplicity and understandability. In a nutshell, the CISE data model identifies seven core data entities (*Agent*, *Object*, *Location*, *Document*, *Event*, *Risk* and *Period*) and eleven auxiliary ones (*Vessel*, *Cargo*, *Operational Asset*, *Person*, *Organization*, *Movement*, *Incident*, *Anomaly*, *Action*, *Unique Identifier* and *Metadata*). Fig. 1 illustrates the core concepts of the CISE v1.0 data model.

Without extending the scope of the CISE data model, EUCISE2020 maintains the original concepts, but also defines some additional attributes, in order to take into account additional data sources and to ensure that EUCISE2020 services can be implemented in practice. As already mentioned in the introduction, the EUCISE2020 data model is available as an XML Schema specification and as a set of UML diagrams.

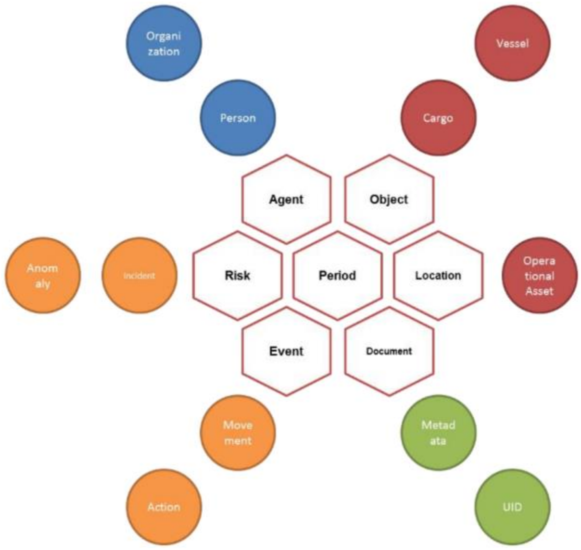

Fig. 1. CISE v1.0 core concepts [1].

3. Ontology creation

The Unified Modelling Language (UML) [21] and the Web Ontology Language (OWL 2) [32] are both established conceptual modelling languages that, despite being created on the basis of different contexts, they present significant similarities. A comparative overview of UML and OWL is presented in [10], [35]. Both language definitions are referred to comparable meta-models that follow the "object-property" modelling pattern. However, in contrast to UML, OWL 2 is fully built upon formal logic, which enables the application of logical reasoning in ontologies, a characteristic that can be used to discover inconsistencies in conceptual models and new knowledge that lies behind the asserted concepts and relations.

Table 1

Mapping between UML and OWL elements

UML Definitions	*OWL definitions*
UML package name	The namespace of `owl:Ontology` that corresponds to the UML package
Class	`owl:Class`
Association class	`owl:Class`
Enumeration class	`owl:oneOf`
Instance	Individual (`ex:instance rdf:type owl:Class`)
Attribute	`owl:DatatypeProperty`
Binary association	Pair or properties (relation `owl:inverseOf`)
Generalization (Class)	`rdfs:subClassOf`
Generalization (Association)	`rdfs:subPropertyOf`
Set of subclass	`owl:unionOf`
Multiplicity	`owl:cardinality`, `owl:minCardninality`, `owl:maxCardinality`, `owl:FunctionalProperty`, `owl:InverseFunctionalProperty`
Navigable association	`rdfs:domain` `rdfs:range`
Inheritance (default annotation: {incomplete[1], disjoint})	`ex:ClassB rdfs:subClassOf ex:ClassA .` `ex:ClassC rdfs:subClassOf ex:ClassA .` `ex:ClassB owl:disjointWith ex:ClassC`
Inheritance (annotation: {complete[2], disjoint})	`ex:ClassB rdfs:subClassOf ex:ClassA .` `ex:ClassC rdfs:subClassOf ex:ClassA .` `ex:ClassB owl:disjointWith ex:ClassC .` `ex:ClassA owl:disjointUnionOf(ex:ClassB ex:ClassC)`
Inheritance (annotation: {incomplete, overlapping[3]})	`ex:ClassB rdfs:subClassOf ex:ClassA .` `ex:ClassC rdfs:subClassOf ex:ClassA` (Only inheritance is declared through the `rdfs:subClassOf` property)

Many research approaches already address the problem of reusing knowledge from existing UML class diagrams to develop ontologies, in automated or semi-automated procedures [10], [18], [34]. Regardless the degree of automation or the adopted technologies (XML, XSLT, translation algorithms, etc.), a precise conceptual correspondence between UML and OWL elements is defined, through a semantics-preserving schema translation [18], [34]. The model-conversion from UML to OWL follows simple conversion rules, the most common of which are presented in Table 1.

These mappings formed the groundwork in creating the EUCISE-OWL, an ontological representation

[1] *Incomplete* means that there are instances of the upper class `ClassA` which are neither of type `ClassB` nor `ClassC`.

[2] *Complete* means that each instance of the upper class `ClassA` is either of type `ClassB` or `ClassC`.

[3] *Overlapping* means that instances of the upper class `ClassA` may be both of type `ClassB` and of type `ClassC`.

model of the domain of discourse that is fully compliant to the available, well-established UML definitions presented in the EUCISE2020 data model [4]. The conversion rules applied from the existing EUCISE2020 notions to OWL triples are indicated below, presented in Turtle format [33].

Classes. Any core entity or class described in the EUCISE2020 data model is defined in EUCISE-OWL as an `owl:Class`, which is a subclass of `eucise:Entity` (subclass of `owl:Thing`).

```
eucise:ClassC rdf:type owl:Class;
       rdfs:subClassOf eucise:Entity .
eucise:Entity rdfs:subClassOf
owl:Thing .
```

Attributes. In the EUCISE2020 data model, classes are connected with other data types (either classes or literal values) through the declaration of attributes. In ontologies, object and data properties undertake such a representation; the former describes how classes and their individuals are related to each other, while the latter assigns literal values (e.g. `xsd:string`, `xsd:double`, `xsd:boolean`) to populated individuals.

```
eucise:propertyP1 rdf:type
owl:ObjectProperty ;
       rdfs:domain eucise:ClassD1 ;
       rdfs:range eucise:ClassR1 .
```

```
eucise:propertyP2 rdf:type
owl:DatatypeProperty ;
       rdfs:domain eucise:ClassD2 ;
       rdfs:range xsd:string .
```

Enumerations and Enumeration Types. Enumerations in the EUCISE2020 data model usually present the possible types of specific entities. In EUCISE-OWL, enumerations are represented as classes (`rdf:type owl:Class`) that additionally have a predefined list of asserted instances. All enumerations of the EUCISE2020 data model are grouped together under a top-level class named `eucise:EnumerationType` (subclass of `owl:Thing`).

```
eucise:EnumerationE rdf:type
owl:Class ;
       rdfs:subClassOf eu-
cise:EnumerationType .
eucise:EnumerationType rdfs:subClassOf
owl:Thing .
```

```
eucise:enumeration_value_EV rdf:type
eucise:EnumerationE ;
       rdf:type owl:NamedIndividual .
```

Association Classes and Association Roles. In the EUCISE2020 data model, an association class is a specific type of class that defines the connection between the core entities of the model, through the use of specific attributes named “association roles”. Association classes can have an enriched definition, with additional properties and datatypes asserted. In ontology terms, association classes are presented as notions of type `owl:Class`, whereas association roles define their related object properties. All association classes of the EUCISE2020 data model are grouped together under a top-level class named `eucise:AssociationClass` (subclass of `owl:Thing`).

```
eucise:ClassC1_ClassC2 rdf:type
owl:Class ;
       rdfs:subClassOf eu-
cise:AssociationClass .
eucise:AssociationClass
rdfs:subClassOf owl:Thing .
eucise:ClassC1 eucise:associationRole
eucise:ClassC2 .
eucise:associationRole rdf:type
owl:ObjectProperty .
```

Metadata. The EUCISE2020 data model contains metadata descriptions in each defined component, so as to enrich their comprehensibility and facilitate their reuse. Those data were completely integrated into the ontological model, through the adoption of well-known object, datatype and annotation properties (e.g. `rdfs:comment`, `skos:example`, `rdfs:seeAlso` and `rdfs:label`). Indicative initialisations are presented in triples below.

```
eucise:ClassC rdfs:comment "Description
text"^^xsd:string ;
       skos:example "Example
text"^^xsd:string ;
       rdfs:seeAlso <source_URL> ;
       rdfs:label "example label" .
```

To better illustrate the EUCISE2020 UML notions and efficiently elaborate their relevant OWL mappings, an excerpt UML diagram of an EUCISE2020 core class named `Agent` is presented (Fig. 2).

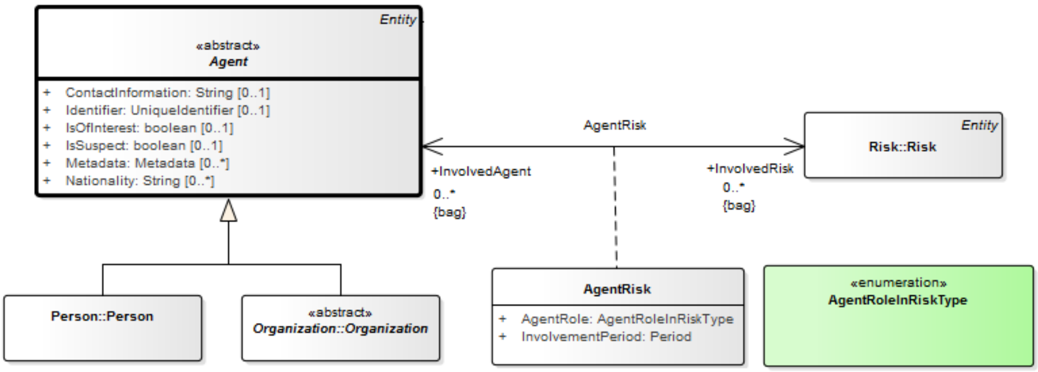

Fig. 2. An excerpt UML diagram of the core class `Agent`.

As seen in the figure, class `Agent`, which is a subclass of `Entity`, is assigned with six specific attributes: the `Identifier` and `Metadata` are attributes that associate class `Agent` with other EUCISE2020 classes namely `UniqueIdentifier` and `Metadata`; in the ontology they are considered as object properties. Also, the `ContactInformation`, `IsOfInterest`, `IsSuspect` and `Nationality` are attributes that associate class `Agent` with common data types (string, boolean, etc.); in the ontological model they are defined as data type properties. Moreover, a connection between the core classes `Agent` and `Risk` (subclasses of `Entity`) is identified through an association class `AgentRisk` (subclass of `eucise:AssociationClass`). Its asserted association roles `involvedAgent` and `involvedRisk` correlate the `AgentRisk` with classes `Agent` and `Risk` correspondingly, thus they are of type `owl:ObjectProperty`. It is also indicated in the UML diagram that class `Agent` is further specialised into class `Person` and class `Organization` while the default inheritance annotation (*incomplete*, *disjoint*) is implied. Such an hierarchy is seamlessly represented in the ontological schema through the assertion of the relations `rdfs:subClassOf` and `owl:disjointWith`. Finally, the `AgentRoleInRiskType` enumeration presents the role of an `Agent` in relation to a reported `Risk`; in the ontology, this enumeration is defined as a subclass of `eucise:EnumerationType`, including also a specific set of instances populated under this concept.

4. EUCISE-OWL

The EUCISE-OWL ontology has been implemented in OWL 2, a W3C Standard ontology language. Following the NeOn methodology [26] throughout the development process, we defined the main purpose of EUCISE-OWL; that is to specify a common information sharing environment, based in a widely accepted format apart from the UML, so as to enhance the usability and adaptability of the EUCISE2020 data model. Such an ontology-based representation can be easily integrated in an information or decision support system for supporting knowledge representation, event triggering, action inference, and information dissemination to the authorities. Moreover, as introduced in the previous section, in order to maximise the expressiveness and robustness of the ontological model, we adopt the SKOS schema [16], and specifically the `skos:example` property to incorporate examples and use cases in each represented concept.

In a nutshell, the proposed EUCISE-OWL ontology enumerates a total number of 153 classes, 116 object properties and 132 data properties. The key ontology metrics are summarised in Table 2.

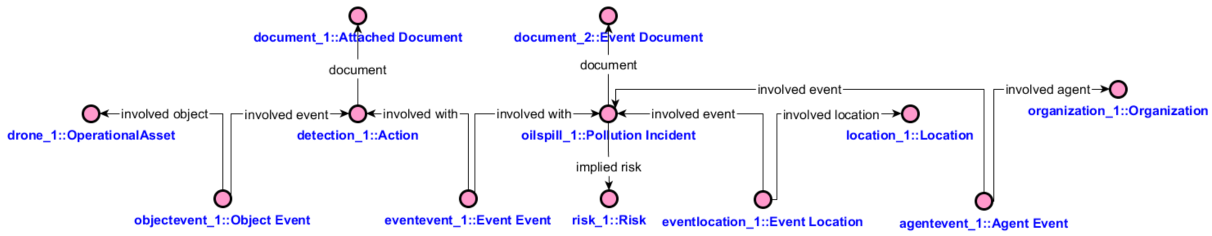

Fig. 3. Main instances in EUCISE-OWL for representing a sea pollution incident where an oil spill was detected.

Table 2

EUCISE-OWL ontology metrics

Metric	*Value*
Class count	153 (4)[4]
Object property count	127 (17)
Object property – Domain axioms count	116
Object property – Range axioms count	116
Data property count	135 (1)
Data property – Domain axioms count	132
Data property – Range axioms count	132
Individual count	869
DL expressivity	*SHIF*$^{(D)}$
Number of triples	6,209 (257)

In compliance with the original model provided in UML format, there are 8 core elements defined in the ontology, under class `Entity`; these are classes `Agent`, `Document`, `Event`, `Location`, `MeteoOceanographicCondition`, `Object`, `OperationalAsset` and `Risk`. Additional concepts are represented as subclasses of `owl:Thing`, as seen in Fig. 4.

Compared to the original data model, two additional concepts were introduced in the ontology schema: (i) the `AssociationClass` for representing classes that interconnect core classes, and (ii) the `EnumerationType` for representing sets of enumerated values that define different types of entities in specific concepts. In the EUCISE-OWL ontology, there are 10 association classes and 869 instantiations of enumerated values (see *individual count* in Table 2).

[4] The count of imported concepts is in parentheses.

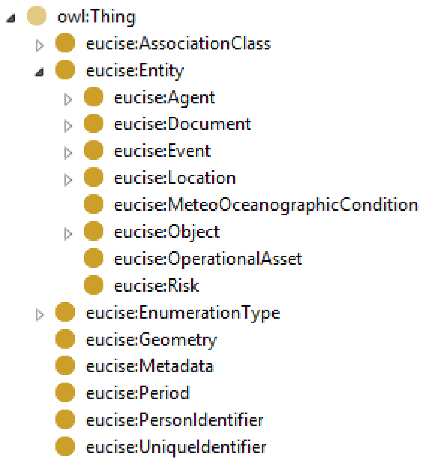

Fig. 4. Hierarchy of the EUCISE-OWL ontology's main notions.

5. Use case

To illustrate the efficiency and completeness of the implemented ontology, we present an operational scenario, inspired from [8] (*Use Case 25b: Investigation of antipollution situation (law enforcement)*). More specifically, the use case concerns a sea pollution incident reported when an oil spill was detected by a drone in its monitoring area. The main instances populated in the ontology as well as their interrelations are visualised in Fig. 3, with the use the Grafoo ontology visualization framework [9]. The circles indicate instances (real data), while their captions are written in the form of "`instance_XYZ::Class_ABC`", declaring the name and the type (class) of each instance correspondingly. All classes and relations mentioned in the diagram or the text below, belong to the EUCISE-OWL ontology, otherwise they are explicitly defined with their relevant prefixes.

As seen in Fig. 3, a drone (`drone_1`) is represented in the ontology as an `OperationalAsset` (`rdfs:subClassOf Object`), which is associated with an instance of *detection* event (`detection_1 rdf:type Action` and `Action rdfs:subClassOf Event`) via the `ObjectEvent` association class. Details of the detection event are included in `document_1` (`rdf:type AttachedDocument` and `AttachedDocument rdfs:subClassOf Document`). The aforementioned event actually concerns an oil spill (`oilspill_1`), spotted in an area (`location_1`) under observation. The oil spill is represented in the ontology as an instance of class `PollutionIncident` (`rdfs:subClassOf Event`). Both events (`detection_1` and `oilspill_1`) are associated with each other through an instance of the association class `EventEvent`. Details of the pollution incident (e.g. the analysis dataset) may be potentially described through asserted values in `document_2` (`rdf:type EventDocument` and `EventDocument rdfs:subClassOf Document`). The occurred pollution incident may imply direct risks to the ecosystem and human health, the degree or details of which can be encoded through the assertions of relevant properties/values in an instance of `Risk` type (`risk_1`). On the basis of the observed pollution incident, of its severity and its implied risks, the interested authorities could be informed, the details of which can be represented as an instance of `Organization` type (`organization_1`).

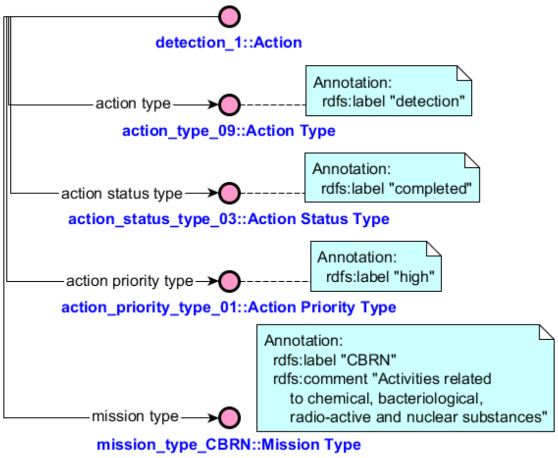

Fig. 5. Asserted instances to the `detection_1` instance of `Action` type.

Instances `detection_1` and `oilspill_1` represent events of different types (`Action` and `PollutionIncident`, respectively), and are thus associated with different properties and values. As seen in Fig. 5, an instance of `Action` type may be described through the assertion of relevant enumeration values that define the *mission type*, as well as the *type*, the *status* and the *priority* of the action. On the other hand, an instance of `PollutionIncident` may be described through the assertion of relevant enumeration values that define the *pollution type*, the *nature*, the *type*, the *severity* and *certainty* of the incident, as well as the *urgency* and *response type* of the event (Fig. 6). For example, in the specific use case, the severity of the incident was defined as *moderate*, i.e. possible threat to life or property (`severity_type_03`); considering this, responsive actions should be taken soon (`urgency_type_02`), according to the defined protocol (`response_type_04`).

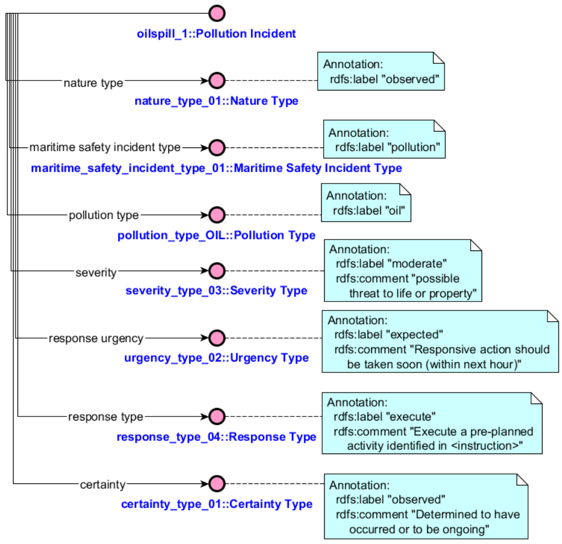

Fig. 6. Asserted instances to the `oilspill_1` instance of `PollutionIncident` type.

Details about the actual geographical location (latitude and longitude) of the pollution incident can be presented through the assertion of properties and values in an instance of type `Location`. Additional metadata can be represented through relevant instantiations attached to instance `eventlocation_1` of the association class `EventLocation`. For example, as seen in Fig. 7, the *date* and *time* at which the oil spill was detected is represented through an instance of type `Period`; the location where the oil spill was detected is where the event *started* (enumeration value location_role_in_event_type_01); and, the area where the event takes place is now considered as *dangerous* (enumeration value event_area_type_DGR).

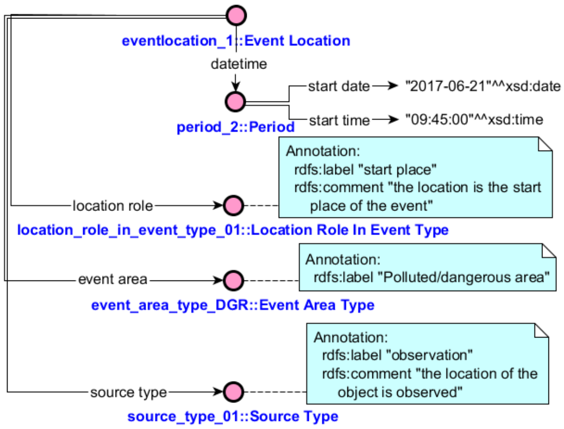

Fig. 7. Asserted instances to the eventlocation_1 instance of EventLocation type.

6. Ontology evaluation

For evaluating the EUCISE-OWL ontology, we followed the guidelines in [22]. Initially, we focused on evaluating its modelling quality and the first step was to validate the ontology's logical correctness through the use of reasoners. Indeed, FaCT++ [29], Pellet [25] and HermiT [17] all verified the consistency of the ontology[5], with the minor exception of FaCT++ indicating that it does not support data types xsd:base64Binary and xsd:date.

We then submitted EUCISE-OWL to OOPS! (OntOlogy Pitfall Scanner!), an online system for testing an ontology against the most common relevant pitfalls [19]. OOPS! also provides an indicator (critical, important, minor) for each pitfall, according to the respective possible negative consequences. In the case of EUCISE-OWL, OOPS! did not detect any pitfall.

On the other hand, although the development of the proposed ontology was heavily based on a UML-to-OWL conversion from an existing data model (see section 3), which was in turn designed with substantial contributions by domain experts (see section 2), it would be interesting to get some insight into the assessment of the ontology's domain coverage. We thus submitted EUCISE-OWL to OntoMetrics [15], an online platform for calculating more advanced ontology metrics. Table 3 includes a subset of the metrics calculated by OntoMetrics that present the most interesting aspects of the ontology with regards to its domain coverage.

Table 3

EUCISE-OWL advanced metrics

Metric	*Value*
Attribute richness	1.694805
Inheritance richness	0.967532
Relationship richness	0.464029
Average population	5.603896
Class richness	0.558442

As indicated in [12], the first three metrics refer to the ontology's accuracy, while the other two refer to its conciseness:

- *Attribute richness* is defined as the average number of attributes (slots) per class, giving an indication of both the ontology design quality and the amount of information pertaining to instance data. The more slots that are defined the more knowledge the ontology conveys. The value of 1.694805 demonstrates a high attribute richness for EUCISE-OWL, especially when taking into account the fact that a large subset of the classes in the ontology are enumeration types (see sections 3 and 4), which correspond simply to sets of instances.
- *Inheritance richness* is defined as the average number of subclasses per class and describes the distribution of information across different levels of the ontology's inheritance tree. It is a good indication of how well knowledge is grouped into different categories and subcategories in the ontology. This metric distinguishes a horizontal from a vertical ontology. The value of 0.967532 for EUCISE-OWL indicates that the ontology covers a wide range of concepts, without delving too deep into their specialisations.
- *Relationship richness* is defined as the ratio of the number of (non-inheritance) relationships divided by the total number of relationships in the ontology and reflects the diversity of the types of relations. An ontology containing only inheritance relationships conveys less information than an ontology that contains a diverse set of relationships. The value for EUCISE-

[5] With the minor exception of having FaCT++ indicate that it does not support data types xsd:base64Binary and xsd:date.

OWL in Table 3 indicates that the ontology has a mediocre richness of relationships, mostly due to the numerous enumeration types and association classes (see sections 3 and 4).

– *Average population* corresponds to the number of instances compared to the number of classes and is an indication of the ontology population quality. Since, as already mentioned, EUCISE-OWL is rich in enumeration types, the specific value is considered very high.
– *Class richness* is related to how instances are distributed across classes. The number of ontology classes that have instances is compared with the total number of classes, giving an overview of how well the knowledge base utilises the knowledge modelled by the schema classes. The low value of the specific metric in Table 3 indicates that the ontology does not contain data that exemplifies all the class knowledge existing in the schema. This is reasonable, since EUCISE-OWL does not contain sample data, like e.g. the instances discussed in the use case in section 5.

7. Related work

There is currently a great interest in automated, on-time maritime surveillance, with an increasing attention towards efficient data handling. Besides EUCISE2020, an indicative list of ongoing relevant maritime EU-funded projects includes MARISA[6], AtlantOS[7], MARSUR[8], EMODnet[9], RANGER[10] and datAcron[11]. From these projects, only RANGER is aimed at establishing compliance with the CISE framework, while a similar process is also underway for MARISA. On the other hand, only datAcron proposes an ontology-based solution for the representation of trajectories of moving objects' [23].

There are additional semantic approaches that model concepts relevant to the maritime domain, but usually they are targeted to a more narrowed scope. More specifically, in [31] an ontological representation of the different types of ships and relevant parameters is implemented, according to the AIS (Automatic Identification System), for maritime traffic analysis. Moreover, the detection ([2], [30]) or prediction [4] of abnormal ship behaviour is investigated, by analysing semantic trajectories and geographical localizations of the maritime objects. In [11], an ontology-based representation of maritime regulations is proposed, for formulating maritime decision support rules in a machine readable way.

To the best of our knowledge, CISE is the most concrete and complete model for implementing a common information sharing environment across countries and involved authorities, where all maritime surveillance operations can cooperate with one another and share data, following a common set of rules. Thus, its availability in an interoperable and easily adoptable form, as the proposed ontology-based representation in the current work, is of vital importance for operational use.

8. Conclusions and future work.

This paper presented EUCISE-OWL, an ontology representation of the CISE data model that constitutes an EU-wide collaborative initiative for facilitating information sharing between maritime monitoring authorities. EUCISE-OWL is an outcome from the ROBORDER EU-funded project, and we are currently deploying it as a common platform for semantically integrating analysed data from heterogeneous sensors and for performing semantic reasoning on top of this data, in order to facilitate decision support for authorities. Within ROBORDER, EUCISE-OWL is addressing the project's pilot use cases, which include addressing pollution incidents at sea (see section 5), tracking suspicious vessels, countering illegal activities etc. The upcoming pilot demonstrations will provide an excellent opportunity for evaluating the utility of the ontology in practice.

As for our future goals, ROBORDER serves as a good testbed for the wider adoption of our proposed ontology and its potential extensions in a wider variety of scenarios, like e.g. border trespassing in the sea or on the land, or in applying robotics for enhanced security [24]. A more long-term goal is to work towards including EUCISE-OWL in the EU's SEMIC action[12] for promoting semantic interoperability amongst the EU Member States.

[6] https://www.marisaproject.eu/
[7] https://www.atlantos-h2020.eu
[8] http://marsur.info/start.php
[9] http://www.emodnet.eu
[10] https://ranger-project.eu/
[11] http://datacron-project.eu/
[12] http://semic.eu/

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