Results and Discussions from Aligning Ontologies in the Circular Economy Domain

Huanyu Li[1,*,†], Jana Vataščinová[2,†], Ondřej Zamazal[2,†], Ying Li[1,3], Patrick Lambrix[1,3] and Eva Blomqvist[1]

[1]*Department of Computer and Information Science, Linköping University, Linköping, Sweden*
[2]*Prague University of Economics and Business, Czech Republic*
[3]*Swedish e-Science Research Centre, Linköping, Sweden*

Abstract

The Circular Economy (CE) domain is increasingly leveraging ontologies to represent domain knowledge for data sharing and exchange. Several CE-related ontologies have been developed to model CE-specific knowledge for circular value networks. However, CE knowledge representation also relies heavily on existing ontologies from related domains, such as materials and manufacturing, due to the cross-industry nature of CE. Aligning CE-related ontologies is a key step toward enhancing interoperability and reusability. In this paper, we present alignment results and discussions on CE-related ontologies based on an extended ontology survey within the scope of the Onto-DESIDE project.

Keywords

Circular Economy, Ontology, Ontology Alignment

1. Introduction

In recent years, the Circular Economy (CE) domain has seen increased development of ontologies for knowledge representation, supporting applications such as data sharing and exchange. Onto-DESIDE is an ongoing project focused on developing CE ontologies, including the recent release of the Circular Economy Ontology Network (CEON) [1] with new updates on the topics of energy, value and location. Since multiple CE-related ontologies exist or are being developed, a systematic approach to aligning these ontologies is necessary to learn their differences. In our previous work [2], we established a pipeline (as shown in Figure 1) for aligning CE-related ontologies within the Onto-DESIDE project. The key goals of ontology alignment include: (1) enhancing interoperability and knowledge exchange among CE-related ontologies; (2) linking domain-specific knowledge to CE knowledge; (3) linking CE knowledge to universal knowledge in top-level ontologies. To further explore the capability of ontology matching tools in aligning CE-related ontologies, we introduced a CE track at the Ontology Alignment Evaluation Initiative (OAEI) 2024 [3] which organizes yearly evaluation campaigns for ontology matching technologies. As CEON continues to evolve, with its latest release[1] in December 2024, and new related ontologies emerge, we produce updated alignments following an improved version of the pipeline. In this paper, we present the latest results of aligning relevant ontologies, in the CE domain, based on an extended survey of [4]. The remainder of the paper is structured as follows. Section 2 provides background on ontology alignment for the CE domain. Section 3 describes the methodology for generating alignments in this paper. In Section 4, we present and discuss the alignment results.[2] Finally in Section 5, we summarize our findings and outline directions for future work.

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*Corresponding author.
†These authors contributed equally.
huanyu.li@liu.se (H. Li); jana.vatascinova@vse.cz (J. Vataščinová); ondrej.zamazal@vse.cz (O. Zamazal); ying.li@liu.se (Y. Li); patrick.lambrix@liu.se (P. Lambrix); eva.blomqvist@liu.se (E. Blomqvist)
0000-0003-1881-3969 (H. Li); 0000-0001-9656-5564 (J. Vataščinová); 0000-0002-7442-9016 (O. Zamazal); 0000-0002-1367-9679 (Y. Li); 0000-0002-9084-0470 (P. Lambrix); 0000-0003-0036-6662 (E. Blomqvist)

[1]CEON v0.3.0: https://github.com/LiUSemWeb/CEON/releases/tag/v0.3.0
[2]https://github.com/LiUSemWeb/Circular-Economy-Ontology-Catalogue/tree/main/alignments/KG4S2025

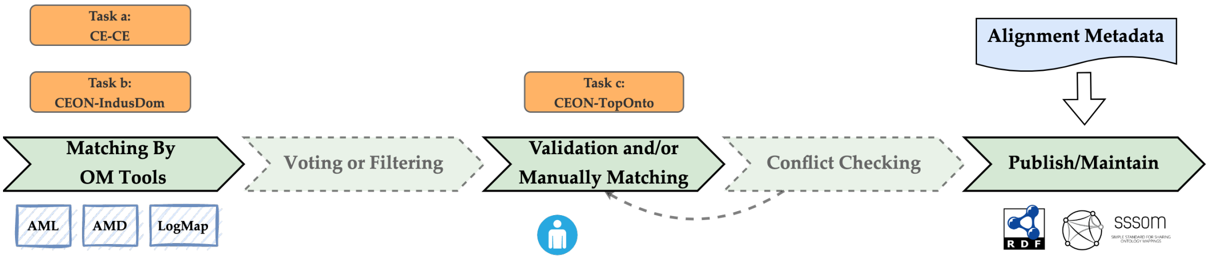

Figure 1: A pipeline of producing alignments [2] based on the general framework outlined in [5], which can be seen in many ontology matching tools.

2. Background

In this section, we introduce our previous work of aligning[3] CE-related ontologies.

2.1. Ontology Alignment in Onto-DESIDE

The Onto-DESIDE project defines three key tasks [2] for producing alignments among relevant ontologies: (1) aligning CE-specific ontologies (Task a in Figure 1); (2) aligning CEON with industry domain-specific ontologies (Task b in Figure 1); and (3) aligning CEON with top-level ontologies (Task c in Figure 1). To finish these three tasks, a pipeline for generating alignments is set up [2]. The pipeline as shown in Figure 1 is built upon general ontology matching frameworks (e.g., [5]) that many ontology matching tools are developed based on such a framework. This pipeline includes five essential steps which are *Matching By OM Tools*, *Voting or Filtering*, *Validation and Manual Matching*, *Conflict Checking* and *Publishing and Maintaining Alignments*. In this work, we extend the previous methodology by incorporating additional ontology matching tools and refining voting, filtering, validation and conflict checking steps. Further details on these updates are provided in Section 3.1.

2.2. Initial Alignment Results for Onto-DESIDE and OAEI2024

In [2], we presented initial alignment results[4] for six ontologies including CEON, Circular Exchange Ontology (CEO) [6], Circular Materials and Activities Ontology (CAMO) [6], Sustainable Bioeconomy and Bioproducts Ontology (BiOnto) [7], Building Circularity Assessment (BCAO) [8] and Digital Product Passport Ontology (DPPO) [9] that were pairwise matched in Task a. Following the pipeline outlined in Figure 1, we manually validated the mappings and identified key equivalence mappings for essential CE concepts such as *Product*, *Material*, *Manufacturer*, and *Manufacturing* concepts. These efforts led to the creation of a new CE track at Ontology Alignment Evaluation Initiative (OAEI)[5] in 2024. One central aim of OAEI is to evaluate how systems perform in different matching tasks (e.g., T-Box matching and instance matching). In addition, within the context of the Onto-DESIDE project, we matched CEON and other cross-industry domain-related ontologies over the topics of sustainability, materials, manufacturing, product and logistics (Task b). While the initial ontology alignment work provided a strong foundation, two steps in the pipeline (Voting/Filtering and Conflict Checking) were not used, and validation involved only one domain expert. In this work, we involve more domain experts for validation.

3. Methodology

As described in Section 2.2, within the Onto-DESIDE project, we have formulated three basic tasks for producing alignments among related ontologies. In this work, we focus on Task a, and Task b for

[3]We use "aligning" and "matching" interchangeably, both referring to the process of finding alignments which are sets of "mappings" or "correspondences" among ontologies.
[4]https://github.com/LiUSemWeb/Circular-Economy-Ontology-Catalogue/tree/main/alignments
[5]https://oaei.ontologymatching.org/2024/ce/index.html

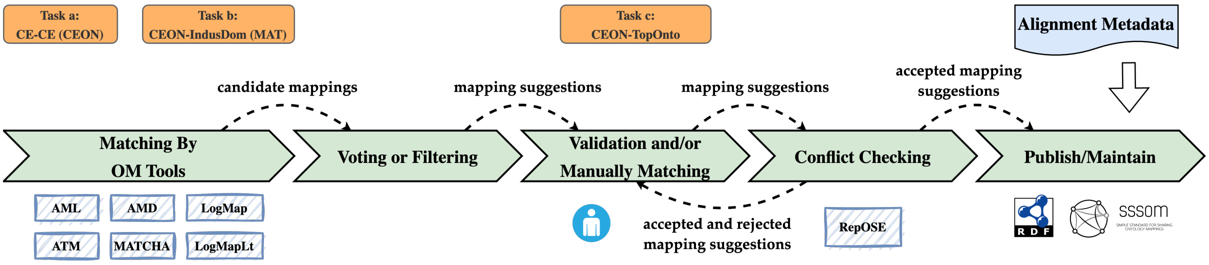

Figure 2: An updated pipeline of producing alignments.

materials-related ontologies. Additionally, we update the original pipeline for producing alignments.

3.1. Updated Pipeline for Producing Alignment

To enhance alignment quality, we introduce the following updates (as shown in Figure 2):

- *Integration of additional matching tools*: we incorporate more ontology matching tools that have demonstrated state-of-the-art performance in TBox matching. Such an update has a potential to obtain more candidate mappings. More details are presented in Section 3.3.
- *Voting or filtering step included*: for Task b, mappings generated by fewer than three tools are excluded to improve precision.
- *Expanded validation step*: additional domain experts and ontology engineers participate in two validation sessions, each lasting 1-2 hours.
- *Conflict checking with RepOSE*: the latest RepOSE system [10], which leverages the HermiT reasoner [11], is used to check coherence and repair ontology networks.

Moreover, we publish the alignment results following the Simple Standard for Sharing Ontological Mappings (SSSOM) [12, 13], which adhere the FAIR principles (Findable, Accessible, Interoperable and Reusable) [14].

3.2. Related Ontologies

In our previous work, we conducted a comprehensive survey [4] of related ontologies for the circular economy domain identifying 37 ontologies in total across 6 topics, of which 4 for circular economy, 6 for sustainability, 9 for materials, 15 for manufacturing, 10 for products, 8 for logistics, and EMMO (Elementary Multiperspective Material Ontology) [15] as a general top-level ontology. As mentioned in Section 3.1, in this paper, our focus is on ontologies related the core CE domain and materials domain. Therefore, we extend our previous survey to include new ontologies and provide more analysis which can contribute to analyze ontology alignment results. For instance, we utilize the tool, ROBOT [16], to get more detailed statistics on ontology characteristics as shown in Table 1 and Table 2, including metrics of basic ontology entity counts (i.e., number of classes, individuals, properties), counts of various axioms (i.e., subsumption axioms of classes, properties, equivalent classes and disjoint classes).

3.2.1. CE-related Ontologies

We noted that not many ontologies for CE can be found when we conducted the ontology survey [4]. Most target very specific use cases in specific industry domains. The four CE-related ontologies are Circular Materials and Activities Ontology (CAMO) [6], Circular Exchange Ontology (CEO) [6], Building Circularity Assessment Ontology (BCAO) [8], Sustainable Bioeconomy and Bioproducts Ontology (BiOnto) [7]. Recently, the Digital Product Passport Ontology (DPPO) [9] was developed which is relevant to CE domain. As shown in Table 1, BCAO, CAMO and DPPO are relatively small ontologies considering the number of classes and axioms. Among them, BCAO has a more detailed taxonomy (i.e., 48 *SubClassOf* axioms) as well as more properties. For the three bigger ontologies (i.e., BiOnto, CEO

Table 1
Ontology Characteristics for CE-related Ontologies.

	BCAO [8]	BiOnto [7]	CAMO [6]	CEO [6]	DPPO [9]	CEON v0.3.0
coherence (for TBox)	✓	✓	✓	✓	✓	✓
consistency	✓	✓	✓	✓	✓	✓
# of classes	37	780	86	62	15	147
# of individuals	0	0	0	2	0	71
# of object properties	19	64	1	78	5	87
# of data properties	17	5	7	25	3	34
# of axioms	212	2636	239	880	103	3215
# of SubClassOf axioms	48	804	88	124	13	159
# of SubObjectPropertyOf axioms	16	1	0	57	2	34
# of SubDataPropertyOf axioms	1	0	0	0	2	4
# of EquivalentClasses axioms	0	106	0	16	4	14
# of DisjointClasses axioms	10	0	1	1	0	0

and CEON), we see that (1): all three have detailed taxonomies (considering the number of classes and number of *SubClassOf* axioms); (2): all three have a number of property definitions while CEON and CEO also have hierarchies of properties (i.e., number of *SubObjectPropertyOf* axioms). In addition, all six ontologies shown in Table 1 have coherent TBoxes, as they do not contain any unsatisfiable concept names in their TBoxes. They are also consistent, as each has a model.

3.2.2. Materials-related Ontologies

The materials module in CEON reuses material-related concepts from the top-level ontology EMMO. This allows for modeling of materials at various levels of granularity. The previous survey [4] includes nine materials-related ontologies. In this work, seven more related ontologies are included. We note that although these ontologies have a general focus on materials, they still can be categorized into specific sub-topics such as, **t1:** *materials related to manufacturing processes focusing on more specific domain implementation (i.e., building materials)*; **t2:** *computational or theoretical materials science*; **t3:** *mechanical analysis on materials (i.e., mechanical testing)* and **t4:** *general data representation for material science and engineering domain.* For instance, AMO (Additive Manufacturing Ontology) [17] and BWMD-Domain ontology [18] share a similar industrial focus on modeling materials in the context of manufacturing (AMO for additive manufacturing specifically). On the other hand, Industrial Ontology Foundry Core ontology (IOF-core) [19] defines general materials which can be inputs of manufacturing processes. IOF-core ontology is also reused by some ontologies mentioned below (i.e., MSEO and MECH). About the more specific domain implementation, there are related ontologies, BUILDMAT (Building Material Ontology) [20], MPO (Material Properties Ontology) [21], and DEB (Devices, Experimental scaffolds and Biomaterials Ontology) [22]. Both BUILDMAT and MPO share the same focus on construction or building-related materials. Additionally, MPO focuses on representing material properties in the building context. DEB has a more general focus on representing and organizing information in the domain of biomaterials through the processes of designing, manufacturing and testing.

As mentioned above, one characteristic of materials-related ontologies is their focus on knowledge representation for computational or theoretical materials science (**t2**). For instance, MDO (Materials Design Ontology) [23], enables computational materials design-based data integration through representing structures and properties of materials. This is expanded by MAMBO [24], which integrates the chemical entity concept of ChEBI[6] with MDO for molecular material modeling. Similar to MPO, MATONTO (MatOnto ontology) [25] focuses on modeling material properties. MSEO (Material Science and Engineering Ontology) [26], extending a number of concepts from IOF-core and BFO,[7] focus on representing material structures on both meso and micro levels. Z-BRE4K [27] has an industrial focus

[6]Chemical Entities of Biological Interest: https://www.ebi.ac.uk/chebi/
[7]Basic Formal Ontology: https://basic-formal-ontology.org

Table 2
Ontology Characteristics for Materials-related Ontologies.

	AMO [17]	BUILDMAT [20]	BWMD-Domain [18]	DEB [22]	IOF-core [19]	MAMBO [24]	MATONTO [25]	MDO [23]	MECH [29]	MPO [21]	MSEO [26]	MTO [28]	MWO [30]	NMRRVOCAB [31]	PMDco [32]	Z-BRE4K [27]	CEON v0.3.0
surveyed in [4]	✓	✓	✓		✓		✓	✓		✓				✓		✓	
coherence (for TBox)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
consistency	✓	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
# of classes	293	27	772	601	93	57	848	37	450	140	239	421	116	3	239	56	147
# of individuals	139	12	0	0	0	21	131	2	0	0	2	2	5	994	20	0	71
# of object properties	19	56	24	12	103	35	83	32	26	13	129	158	74	0	113	53	87
# of data properties	5	7	11	109	0	63	13	32	0	8	3	3	29	0	15	26	34
# of axioms	1475	411	4664	2138	1764	632	5249	458	1746	549	3618	4352	1122	5503	2957	517	3215
# of SubClassOf axioms	520	26	771	666	172	43	1190	49	521	173	334	501	93	2	234	55	159
# of SubObjectPropertyOf axioms	4	47	21	0	68	17	74	0	17	0	92	107	8	0	51	0	34
# of SubDataPropertyOf axioms	3	5	10	63	0	42	3	0	0	0	2	2	6	0	8	0	4
# of EquivalentClasses axioms	19	0	0	8	21	0	282	0	12	0	35	35	7	0	22	0	14
# of DisjointClasses axioms	6	4	20	0	10	20	163	1	0	0	12	12	0	0	11	0	0

representing materials-related properties and measurements.

In terms of the mechanical testing perspective, there are related ontologies, MTO (Mechanical Testing Ontology) [28] and MECH (Materials Mechanics Ontology) [29] which focus on representing mechanical testing methods while MECH has a specific application aim for named entity recognition tasks. For the last characteristic of materials-related ontologies in general data representation, the examples are MWO (The MatWerk Ontology) [30], NMRRVOCAB (Materials Data Vocabulary) [31] and PMDco (Platform Material Digital Core Ontology) [32]. MWO and PMDco have a similar focus on data representation. MWO focuses on representing data of both scientific research and infrastructural status in the materials science and engineering community. PMDco [32] is a general ontology focusing on improving semantic interoperability in materials science and engineering domain, which is also reused by MECH. NMRRVOCAB aims to provide a vocabulary describing how NIST Materials Resource Registry[8] register records of material science.

In terms of coherence, as shown in Table 2, all ontologies have coherent TBoxes since none contain unsatisfiable concepts. However, MAMBO and MATONTO are inconsistent because they include instance assertions over data properties that conflict with the range definitions of the corresponding data properties.

3.3. Selected Ontology Matching and Reasoning Tools

We selected six ontology matching tools, which were successful participants in the previous OAEI editions and showed state-of-the-art performance. These tools are available using the Matching EvaLuation Toolkit (MELT) client [33], and we always use the latest version available for OAEI and run them with their default settings. Table 3 illustrates matching strategies used by these tools.

AMD [34]. AgreementMakerDeep (AMD) is a deep learning matching tool. It applies BERT-like pre-train language models and knowledge graph embedding methods. Its architecture includes textual matching with BERT-like pre-train language models, knowledge graph embedding, and candidate selection. For textual matching, AMD uses sentence-BERT [39] to compute the cosine similarity

[8] https://materials.registry.nist.gov/

Table 3
Characteristics of Ontology Matching Tools.

Tool	Matching Strategies
AMD [34]	Sentence-BERT model (textual aspect), TransL (structural aspect)
AML [35]	string equivalence, Jaccard, WordNet, structural similarity propagation, logical repair
ATM [36]	string equivalence, Levenshtein, English Wiktionary synonyms, reliance on instance
MATCHA [37]	AML's strategies + Sentence-BERT model (textual aspect)
LogMap [38]	lexical and structural indexation, unsatisfiability detection and repair, ISUB
LogMapLight [38]	string matching techniques only

between two concepts based on their labels and annotations. These are textual candidate mappings. For knowledge graph embedding, AMD uses a modified TransL model [40], which translates concepts and relations into concept and relation-specify spaces. Matching candidates are based on the plausibility of the triples using modified TransL.

AML [35]. AgreementMakerLight (AML) is an ontology matching tool focusing on matching very large ontologies. Its architecture includes lexical matching, structural matching, application of background knowledge, and logical repair algorithms. External background knowledge is automatically identified based on any given matching task. Lexical matching is based on baseline weighted string-equivalence algorithm, Jaccard measure and many others used in AgreementMaker [41]. WordNet synonyms, close hypernyms, and acronyms are also considered for small ontologies. Structural matching is based on similarity propagation based on matched ancestors and descendants. The logical repair algorithm ensures that the ontology network, including matched ontologies and their alignments, is coherent.

ATM [36]. ATBox (ATM) is an ontology matching tool focusing on knowledge graph matching. Its architecture includes string matching and structural matching techniques. String matching techniques include equality matching as well as Levenshtein distance. During string matching, synonyms extracted from the English Wiktionary are also considered. The string matching step is followed by filters to increase the precision of candidate mappings, such as similar neighbors (based on shared instances), cosine similarity (based on comparing text from their instances), and type filters (based on type overlapping of shared instances). Structural matching includes matching classes that are between two already matched classes in a hierarchy.

MATCHA [37]. MATCHA is an ontology matching tool based on AML's lexical and structural matching and background knowledge matching strategies. Its architecture further includes exploiting a language model to represent entity labels and synonyms as embeddings for subsequent measuring of cosine similarity. As a language model, sentence-BERT [39] without fine-tuning is employed.

LogMap and LogMapLight [38]. LogMap is an ontology matching tool focusing on scalability. Its scalability capability is based on lexical and structural indexation. LogMap was one of the first ontology matching tools allowing unsatisfiability detection and repair by exploiting modularization techniques. Initial mappings are computed based on the lexical indexes. Further mappings are found using ISUB [42] string matching of classes from contexts of initial mappings. LogMapLight (LogMapLt) is a variant of LogMap applying only string matching techniques.

RepOSE [10] and HermiT Reasoner [11]. RepOSE is a tool for detecting modeling defects and in particular detecting and repairing of the missing and wrong is-a structure within ontologies, and the missing and wrong mappings in alignments. RepOSE is used in the pipeline (Figure 2) for conflict checking. Its implementation is based on the HermiT reasoner which is an ontology reasoner supporting all OWL 2 ontology language features. Compared with other ontology reasoners, HermiT is enhanced

Table 4
Results of tools for Task a.

Tool	All Found Mappings	TPs	FPs	FNs	Precision	Recall	F1
AMD	31	21	10	19	0.677	0.525	0.591
AML	57	32	25	16	0.561	0.667	0.609
ATM	57	29	28	17	0.509	0.630	0.563
LogMap	58	36	22	13	0.621	0.735	0.673
LogMapLt	69	36	33	13	0.522	0.735	0.610
MATCHA	153	39	114	13	0.255	0.750	0.381

Table 5
Results of tools for Task b on material ontologies.

Tool	All Found Mappings	Evaluated Mappings	TPs	FPs	Precision
AMD	55	0	-	-	-
AML	91	32	14	18	0.437
ATM	827	154	89	65	0.577
LogMap	147	76	40	36	0.526
LogMapLt	234	141	81	60	0.574
MATCHA	827	153	88	63	0.575

by hypertableau calculus [43]. It supports common reasoning tasks such as classification, consistency checking, and entailment checking.

4. Alignment Results and Discussions

In this section, we analyze alignment results from both perspective of matching tool performance and perspective of detailed validated mappings.

4.1. Analysis of Matching Tool Performance

Table 4 and Table 5 provide evaluation of the tools which were used for the matching tasks. For both tasks, we show the numbers of all the mappings provided by the tools, the numbers of True Positives, False Positives, and the precisions.

Tool performance of Task a. Due to our previous manual matching of the ontologies in Task a [3], we were able to additionally provide the numbers of False Negatives, recalls, and F1-measures. Regarding precision, AMD achieved the highest score. However, its recall was the lowest. Similarly, MATCHA's recall was the highest while its precision was noticeably the lowest. Overall, LogMap achieved the highest F1-measure, and MATCHA was the only tool with a significantly lower F1-measure.

Tool performance of Task b. Regarding Task b on materials-related ontologies, a large number of mappings were received. To narrow the number of mappings before manual evaluation, we created a criterion for the mappings to proceed to the manual evaluation phase. We took into consideration only those mappings that were returned by at least three tools. In many cases, ATM, LogMapLt and MATCHA were the deciding tools. Table 5 provides the number of both found and evaluated mappings. ATM, LogMap and MATCHA achieved the close higher precisions.

4.2. Analysis of Validated Mappings

The resulting alignments of Task a can be seen in Table 6. The results reveal strong dependencies on ontology scope and design. Narrow-scope ontologies such as CAMO (e.g., 86 classes and 8 properties),

Table 6
Mapping results for Task a.

summary	subject_source	object_source	subject_id	object_id	relationship
CEON-CAMO (1 mapping), coherent	ceon	camo	ceon:Actor	camo:actor	=
CEON-CEO (5 mappings), coherent	ceon	ceo	ceon:duringTime	owl-time:hasTime	<=
	ceon	ceo	ceon:TimeInterval	owl-time:Interval	<=
	ceon	ceo	ceon:Product	ceo:Product	>=
	ceon	ceo	ceon:Resource	ceo:Resource	=
	ceon	ceo	opengis:Geometry	opengis:Geometry	=
CEON-BiOnto (32 mappings), incoherent	ceon	bionto	qudt:Quantity	bionto:Quantity	=
	ceon	bionto	ceon:Organisation	bionto:Organization	=
	ceon	bionto	ceon:Person	bionto:Person	=
	ceon	bionto	ceon:Biofuel	bionto:Biofuel	=
	ceon	bionto	ceon:Biogas	bionto:Biogas	=
	ceon	bionto	ceon:Biomass	bionto:Biomas	=
	ceon	bionto	ceon:Coal	bionto:Coal	=
	ceon	bionto	ceon:Energy	bionto:Energy	=
	ceon	bionto	ceon:EnergySource	bionto:EnergySource	=
	ceon	bionto	ceon:FossilFuel	bionto:FossilFuel	=
	ceon	bionto	ceon:NaturalGas	bionto:NaturalGas	=
	ceon	bionto	ceon:Petroleum	bionto:Petroleum	=
	ceon	bionto	ceon:RenewableEnergy	bionto:RenewableEnergy	=
	ceon	bionto	ceon:Celulose	bionto:Cellulose	=
	ceon	bionto	ceon:ChemicalElement	bionto:ChemicalElement	=
	ceon	bionto	ceon:Iron	bionto:Iron	=
	ceon	bionto	ceon:Material	bionto:Material	=
	ceon	bionto	ceon:Nickel	bionto:Nickel	=
	ceon	bionto	ceon:Catalyst	bionto:Catalyst	=
	ceon	bionto	ceon:ManufacturingProcess	bionto:Manufacturing	=
	ceon	bionto	ceon:ProductionProcess	bionto:Production	=
	ceon	bionto	ceon:RecycleProcess	bionto:Recycling	=
	ceon	bionto	ceon:ServiceProcess	bionto:Service	=
	ceon	bionto	ceon:Event	bionto:Event	=
	ceon	bionto	ceon:hasPart	bionto:hasPart	=
	ceon	bionto	ceon:Plan	bionto:Plan	=
	ceon	bionto	ceon:Process	bionto:Proces	=
	ceon	bionto	ceon:hasPart	bionto:hasPart	=
	ceon	bionto	ceon:Information	bionto:Information	=
	ceon	bionto	ceon:Resource	bionto:Resource	=
	ceon	bionto	ceon:ValueProposition	bionto:ValueProposition	=
	ceon	bionto	prov:Entity	bionto:Entity	=
CEON-DPPO (9 mappings), coherent	ceon	dppo	qudt:Unit	dppo:Unit	=
	ceon	dppo	ceon:Actor	dppo:Actor	=
	ceon	dppo	ceon:endTime	dppo:endTime	=
	ceon	dppo	ceon:hasPart	dppo:hasPart	=
	ceon	dppo	ceon:startTime	dppo:startTime	=
	ceon	dppo	ceon:Product	dppo:Product	=
	ceon	dppo	ceon:containsInformation	dppo:containsInformation	=
	ceon	dppo	ceon:hasPart	dppo:hasPart	=
	ceon	dppo	ceon:isAbout	dppo:isAbout	=

DPPO (15 classes, 8 properties) and CEO (62 classes, 103 properties) produced less mappings. CEON-CAMO yielded only one equivalence mapping on *Actor*. The main reason is that CAMO's model is narrower than that in CEON where CAMO has a specific scope such as that resources can be either materials or products while energy can also be a type of resource in CEON. Similarly, there are not so many mappings between CEON and CEO. There are three mappings on classes, *Product*, *Resource* and *Geometry* as well as two mappings on object properties. DPPO's focus on digital product passports limited its overlap with CEON to basic concepts like *Actor* and *Product*. In contrast, BiOnto's rich hierarchy enabled 32 mappings with CEON, including *Material*, *Process*, and *Energy* concepts. However, the ontology network, including CEON, BiOnto and their mappings has an incoherent TBox even though CEON and BiOnto have coherent TBoxes. For instance, the class *Biofuel* in BiOnto is unsatisfiable due to the following axioms (1) $ceon\colon FossilFuel \sqsubseteq bionto\colon FossilFuel$, (2) $bionto\colon NaturalGas \equiv bionto\colon Fertilizer \sqcup bionto\colon Fuel$, (3) $ceon\colon NaturalGas \sqsubseteq ceon\colon FossilFuel$, (4) $bionto\colon Fuel \equiv bionto\colon Biofuel \sqcup bionto\colon FossilFuel$, (5) $bionto\colon Biofuel \sqcap bionto\colon FossilFuel \sqsubseteq \bot$, (6) $bionto\colon NaturalGas \sqsubseteq ceon\colon NaturalGas$. After further examining the ontology network, including CEON, BiOnto, and their alignments, as well as reviewing energy domain knowledge, we find that the aforementioned axiom (2) represents a potential modeling defect, given that natural gas is a type of fossil fuel, which in turn is a type of fuel.

The resulting alignments of Task b can be seen in Table 7. CEON-MATONTO exhibits the most mappings (16), primarily chemical elements (e.g., *Boron*, *Chromium*), reflecting a shared focus on representing material composition on the level of chemical elements. CEON-MDO also aligns well (5 mappings) on representing structural information of materials, including chemical formulas like (e.g., *ReducedFormula*, *HillFormula*), due to CEON's adoption of MDO's data property design for using various chemical formulas to represent material compositions. Some other materials related ontologies also focus on representing materials and compositions but on a general level including BUILDMAT (*Material* and *Constituent*), IOF-core (*MaterialComponent*), MAMBO (*Material*), MECH (*Composition*), MSEO (*MaterialComponent* and *ChemicalEntity*), MWO (*Material*), and PMDco (*ChemicalEntity*). Another key observation is that we find quite a number of mappings on general concepts such as *Person* (IOF-core, MSEO, PMDco), *Organization* (MWO, PMDco). This is because many such materials domain ontologies reuse general concepts from existing ontologies such as the Provenance Ontology[9] or the schema of Schema.org.[10] In addition, several ontologies contain a focus on representing processes and corresponding inputs or outputs that result in mappings on classes such as *Process* and *ManufacturingProcess* and object properties such as *hasInput* and *hasOutput*.

5. Concluding Remarks and Future Work

Building on our prior survey of circular economy (CE)-related ontologies [4] and alignment framework [2], we enhance our methodology to investigate CE-related ontology interoperability through three key updates: (1) integrating additional ontology matching tools to expand candidate mapping generation, (2) involving more domain experts for systematic validation, and (3) employing tools to detect conflicts. These refinements produce updated CE ontology alignment results, analyzed both for tool performance and semantic granularity of mappings.

Future work will focus on completing three alignment tasks in Onto-DESIDE. For Task a, we will finalize mappings for remaining ontology pairs to strengthen benchmarking for the CE track in Ontology Alignment Evaluation Initiative (OAEI). Task b targets cross-domain alignment between CEON and cross-industry domain ontologies (manufacturing, sustainability, logistics). Task c involves collaborative development with the Elementary Multiperspective Material Ontology (EMMO) team to establish mappings.

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[9]https://www.w3.org/TR/prov-o/
[10]https://schema.org

Table 7
Mapping results for Task b on materials ontologies.

summary	subject_source	object_source	subject_id	object_id	relationship
CEON-BUILDMAT (3 mappings), coherent	ceon	buildmat	qudt:Unit	qudt:Unit	=
	ceon	buildmat	ceon:Material	buildmat:Material	=
	ceon	buildmat	ceon:Constituent	buildmat:Constituent	=
	ceon	buildmat	qudt:hasUnit	buildmat:hasUnit	=
CEON-DEB (2 mappings), coherent	ceon	deb	ceon:Titanium	deb:Titanium	=
	ceon	deb	opengis:Geometry	deb:Geometry	=
CEON-IOF-core (6 mappings), coherent	ceon	iof-core	ceon:Person	iof-core:Person	=
	ceon	iof-core	ceon:Capability	iof-core:Capability	=
	ceon	iof-core	ceon:MaterialComponent	iof-core:MaterialComponent	=
	ceon	iof-core	ceon:ManufacturingProcess	iof-core:ManufacturingProcess	=
	ceon	iof-core	ceon:hasInput	iof-core:hasInput	=
	ceon	iof-core	ceon:hasOutput	iof-core:hasOutput	=
CEON-MAMBO (1 mapping), incoherent	ceon	mambo	ceon:Material	mambo:Material	=
CEON-MATONTO (16 mappings), coherent	ceon	matonto	ceon:Boron	matonto:Boron	=
	ceon	matonto	ceon:Chromium	matonto:Chromium	=
	ceon	matonto	ceon:Copper	matonto:Copper	=
	ceon	matonto	ceon:Dysprosium	matonto:Dysprosium	=
	ceon	matonto	ceon:Iron	matonto:Iron	=
	ceon	matonto	ceon:Magnesium	matonto:Magnesium	=
	ceon	matonto	ceon:Manganese	matonto:Manganese	=
	ceon	matonto	ceon:Neodymium	matonto:Neodymium	=
	ceon	matonto	ceon:Nickel	matonto:Nickel	=
	ceon	matonto	ceon:Niobium	matonto:Niobium	=
	ceon	matonto	ceon:Silicon	matonto:Silicon	=
	ceon	matonto	ceon:Titanium	matonto:Titanium	=
	ceon	matonto	ceon:Zinc	matonto:Zinc	=
	ceon	matonto	ceon:Catalyst	matonto:Catalyst	=
	ceon	matonto	ceon:hasPart	matonto:hasPart	=
	ceon	matonto	prov:Role	bfo:Role	=
CEON-MDO (5 mappings), coherent	ceon	mdo	ceon:Material	mdo:Material	=
	ceon	mdo	ceon:AnonymousFormula	mdo:AnonymousFormula	=
	ceon	mdo	ceon:HillFormula	mdo:HillFormula	=
	ceon	mdo	ceon:ReducedChemicalFormula	mdo:ReducedFormula	=
	ceon	mdo	ceon:DescriptiveFormula	mdo:DescriptiveFormula	=
CEON-MECH (5 mappings), coherent	ceon	mech	ceon:Location	pmdco:Location	=
	ceon	mech	ceon:Location	mech:Location	=
	ceon	mech	ceon:Composition	mech:Composition	=
	ceon	mech	ceon:Process	pmdco:Process	=
	ceon	mech	ceon:hasInput	pmdco:input	=
CEON-MPO (1 mapping), coherent	ceon	mpo	ceon:Material	mpo:Material	=
CEON-MSEO (7 mappings), coherent	ceon	mseo	ceon:Person	iof-core:Person	=
	ceon	mseo	ceon:Capability	iof-core:Capability	=
	ceon	mseo	ceon:MaterialComponent	iof-core:MaterialComponent	=
	ceon	mseo	ceon:ChemicalEntity	chebi:ChemicalEntity	=
	ceon	mseo	ceon:ManufacturingProcess	iof-core:ManufacturingProcess	=
	ceon	mseo	ceon:hasInput	iof-core:hasInput	=
	ceon	mseo	ceon:hasOutput	iof-core:hasOutput	=
CEON-MTO (4 mappings), coherent	ceon	mto	ceon:Organisation	commoncore:Organization	=
	ceon	mto	ceon:Energy	mto:Energy	=
	ceon	mto	ceon:ManufacturingProcess	iofcore:ManufacturingProcess	=
	ceon	mto	ceon:hasPart	obo:has_part	=
CEON-MWO (9 mappings), coherent	ceon	mwo	ceon:Organisation	mwo:Organization	=
	ceon	mwo	ceon:Person	schema-org:Person	=
	ceon	mwo	ceon:Person	mwo:Person	=
	ceon	mwo	ceon:Material	emmo:Material	=
	ceon	mwo	ceon:Material	mwo:Material	=
	ceon	mwo	ceon:Material	mdo:Material	=
	ceon	mwo	ceon:hasPart	mwo:hasPart	=
	ceon	mwo	ceon:hasPostalCode	mwo:hasPostalCode	=
	ceon	mwo	ceon:ChemicalElement	mwo:ChemicalElement	=
CEON-PMDco (8 mappings), coherent	ceon	pmdco	ceon:Organisation	prov:Organization	=
	ceon	pmdco	ceon:Person	prov:Person	=
	ceon	pmdco	ceon:ChemicalEntity	chebi:CHEBI_24431	=
	ceon	pmdco	ceon:Description	pmdco:Description	=
	ceon	pmdco	ceon:Plan	prov:Plan	=
	ceon	pmdco	ceon:Process	pmdco:Process	=
	ceon	pmdco	ceon:hasInput	pmdco:input	=
	ceon	pmdco	ceon:hasOutput	pmdco:output	=

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