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MEP DOMAIN OBJECT CLASSIFICATION THROUGH INTERDOMAIN RULE-BASED SEMANTIC ENRICHMENT ON KNOWLEDGE GRAPHS

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Abstract

The data and information of objects in building information modelling (BIM) from different software are delivered with incomplete data and misclassified objects. This study focuses on classifying mechanical, electrical, and plumbing (MEP) objects based on interdomain topological relationships and geometry conditions through semantic web technologies and semantic enrichment with a rule-based inferencing technique. Four rule sets were developed and run over 32 knowledge graphs of building models with at least 90% accuracy. False positives and negatives arose from non-discrete geometry and topology features of the objects. To address this issue, future work will integrate the proposed method with image recognition.

Introduction

In the Architecture, Engineering, and Construction (AEC) industry, building information modelling (BIM) serves as an object-oriented model enriching objects' data and information with physical and functional properties, for visualizing three-dimensional (3D) and analyzing building analytical models. BIM allows the creation of complicated building shells and physical objects with encapsulate rich data and information during the design process. In addition, engineering integration of a single system or multiple systems based on shared data has become easier with the introduction of BIM workflows that share information between existing simulation and analysis tools (Howard and Björk, 2008; Sacks et al., 2018).

The Industry Foundation Classes (IFC) provide a common data schema and structured data model for BIM (International Organization for Standardization, 2018). Furthermore, Information Delivery Manuals (IDM) describe processes with the required information for BIM through IFC as an integrated reference. Model View Definitions (MVD) specify portions of the IFC Model Specification that are needed for information exchanges subject to different IDMs (See et al., 2012).

Although IDMs along with MVDs specify each information exchange scenario relevant to the IFC model (BuildingSMART, 2008), well-functioning information exchange among software and all stakeholders is difficult (Pauwels et al., 2014, 2017). BIM applications have native models (vendor-specific) with different aggregating, identifying, and parametrizing objects. When extracting data from the BIM model, oftentimes inaccurate, incomplete, or false information is generated (Bloch and Sacks, 2018).

Additionally, the IFC, as an open BIM standard, has insufficient definitions in its objects' libraries and associated standards, which leads to essential elements for objects being left out (Howard and Björk, 2008). For instance, IFC (even in the latest version IFC4) does not support the characterization of entire heating, ventilation, and air conditioning (HVAC) systems' elements (El Asmi et al., 2015). Therefore, as a distinctive feature of BIM, object classification commonly results in incorrect object classification, which prevents the full use of BIM models (Ma et al., 2018).

To solve the issues of data exchange and missing semantics in the BIM models, in terms of mapping functional properties or concepts in IFC models, semantic web technologies and semantic enrichment have been suggested. The semantic web consists of a set of technologies and standards to store, share, and reuse data on the Web (Sadeghineko et al., 2022). It allows setting logical assertions on classes, instances, and properties and relationships among not only instances but also instances' properties using axioms. Facts are deduced through a knowledge-based ontology in the semantic net, utilizing formalized sources of reasoning and inquiry. Thus, a deductive approach is achieved by querying and verifying the knowledge base and inserting new knowledge. Indeed, the semantic web provides the use of multiple and different abstraction levels and supports the interoperability of concepts (Simeone et al., 2019).

By following the advances in semantic nets, MVD has been developed for identification and specification of information requirements. Since the data requirements are dynamic and use-case specific, buildingSMART has developed Information Delivery Specifications (IDS) to determine information requirements and compliance with IFC (van Berlo et al., 2021). The main purpose is to author and validate nongeometrical information requirements in a simple but comprehensive way (Tomczak et al., 2022).

The IDS standard links objects' classes and properties through the building Smart Data Dictionary (bSDD) - an ontology-based-data dictionary- that includes IFC elements and the standard classification systems for construction work (e.g. UniClass and MasterFormat) (van Berlo et al., 2021; Son et al., 2022). However, in the current state of bSDD, it can not assure semantic correctness and automated semantic mapping (Son et al., 2022).

To summarize, the issues of data exchange and missing semantics in BIM models remain, which often results in incorrect object classification in extracted building models. This study aims to classify MEP domain objects based on interdomain topological relationships and exact geometry conditions through semantic web technologies and semantic enrichment with a rule-based inferencing technique.

Semantic Web Technologies

In the semantic web, semantics are characterized via web ontology language (OWL) and serialized to resource description framework (RDF). SPARQL is a query language over RDF triple data structure (Domingue et al., 2011). IfcOWL represents the IFC standard using OWL (Pauwels and Terkaj, 2016). Subsequently, the IFCtoRDF converter was proposed to enable sufficiently usable EXPRESS elements by OWL ontology by mapping each element onto its nearest equivalent in OWL (Pauwels and van Deursen, 2012). As a comprehensive monolithic ontology, IfcOWL has usability and performance limitations for querying and reasoning in industrial practice (Terkaj and Pauwels, 2017). The available ontologies that serve to present the building information in a semantic graph are integrated with the help of Linked Data technologies. Linked Building Data (LBD) conserves the building information in simple, extensible, and modular ontologies and links them. The modular ontologies include Building Topology Ontology (BOT) as a core; ontology for managing geometry (OMG); ontology for product (PRODUCT); ontology for building elements (BEO); ontology for distribution elements (MEP); ontology for properties (PROPS); ontology for managing properties (OPM) (Pauwels et al., 2022; Petrova et al., 2019). The IFCtoLBD converter was generated for the conversion of BIM models to LBD graphs (Oraskari et al., 2021). The current graph converters (IFCtoRDF and IFCtoLBD), as technical enablers of the semantic web in the AEC industry, have limitations due to either poor data/information quality in the original BIM models or the mapping quality of the converters. Even though these converters retain a broad range of building object information and convert them into IFC, BEO, and BOT-based entity classes, some objects' information remains undefined (e.g., building element proxy class) and/or lost (e.g., object geometry).

Building object classification through semantic enrichment

By semantic enrichment, implicit and missing information in a data model is inferred and supplemented into the data model for model enrichment, which makes it easy to use by any receiving application (Bloch and Sacks, 2018). The supplemented information (e.g., topology, spatial, geometry, and relationships between the model's objects) is deduced and appended to the data model by a computer program that utilizes artificial intelligence (AI), mainly rule-based inferencing and machine learning (ML) techniques (Sacks et al., 2017). Koo et al. examined the semantic integrity among mapped building elements from six architectural BIM models and IFC classes by classification of building elements based on their geometry and relational behaviors (Koo et al., 2019). Wu et al. integrated the invariant features of the building objects (i.e., object geometry, location, and metadata) into ML for the BIM object classification in five categories (beam, column, footing, slab, and wall) (Wu et al., 2022). Xue et al. conducted a literature survey on the semantic enrichment of the BIM model over ten years. They showed that there are 22 enriched BIM cases in the aspect of geometric semantics, non-geometric semantics, and both over ten years. Additionally, regarding semantic enrichment of the physical entities and their subtypes, there are over 20 object types. These object types are categorized under (i) indoor facility (e.g., furniture and room space); (ii) building interior entities, and (iv) exterior entities (Xue et al., 2021). As a result, these objects belong to mainly the architectural domain and followingly the structural domain. Thereby, this shows that there is a lack of semantic enrichment of BIM models in the aspect of the building object classification in the mechanical, electrical, and plumbing (MEP) domain.

To sum up, the identified problem is that the data quality of building objects in BIM models is not reliable and that data exchange often leads to incomplete data, incorrect object labels, and misclassified objects. Based on the identified problem, this study focuses on classifying building objects in the MEP domain by applying knowledge-graph-driven semantic web technology and rule-based inferencing for semantic enrichment. The rule sets are founded on interdomain (architectural and MEP domains) object relationships based on topology and objects’ exact geometry.

Research Method and Tools

Step 1: Dataset preparation

A dataset of 32 residential BIM models with architectural and MEP building objects was obtained and used for generating the knowledge graphs. Figure 1 shows the 32 residential BIM models.

Export the BIM model to IFC. The 32 BIM models for the apartments were separately exported to architectural and MEP IFC data models in the IFC4 design transfer view using Revit.

Convert IFC data models to LBD graphs. IFCtoLBD converter was used to transform the IFC data models into LBD graphs, which allows flattened relationships in the graph. In addition, the IFC GUID for each entity was automatically converted to a Global Identifier (GlobalID),

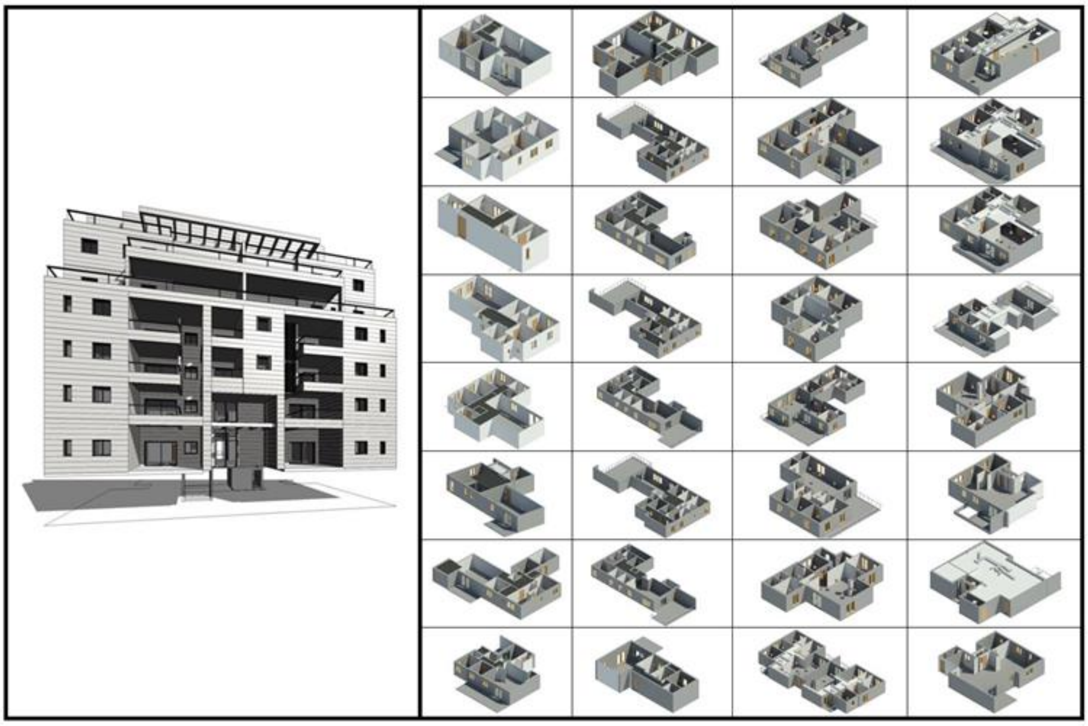

Figure 1: BIM Model for Dataset in Step 1 (left); 32 Different Apartment Models (right)

which is a full Universal Unique Identifier (UUID), through the IFCtoLBD converter.

Generate exact geometry. The disadvantage of the LBD graph is the loss of the geometry relationships. Linked Data-based Common Data Environment (CDE) was suggested combining (i) the core graph layer dataset storing semantics and objects' relationships in the BIM model and (ii) the extension layer dataset storing BIM-related resources in any kind of data format (Ouyang et al., 2022). Following this approach, each building object in an IFC file is extracted in its solid geometry, called exact geometry using IfcOpenShell (IfcOpenShell, 2022), and Trimesh library in the Python environment (Trimesh, 2022). The exact geometry files were saved with the corresponding building object’s globally unique ID in PLY format, containing 3D object data in a collection of polygons (McHenry and Bajcsy, 2008), and stored in an external dataset. Association of the exact geometry file of each building object and the relevant instance in the graph was achieved via *BOT:has3Dmodel* and *BOT:hasSimple3DModel* relationships using RDFLib (RDFLib Team, 2021) As a consequence, the exact geometry of its relevant instance was appended to the LBD graphs.

Set topological relationships. Sacks et al. (2022) generated a topological relationship algorithm, Cloud-based Building Information Modelling (CBIM) algorithm, executing on the graph of each BIM model and appended the topological status (in total 27 positions) to the corresponding object nodes in the graph. In this study, the CBIM algorithm was executed over the architectural and MEP LBD graphs for the same BIM model. Finally, an enriched unique knowledge graph for each model was generated by combining the architectural and MEP sub-graphs with the CBIM topology graph.

Step 2: Rule sets generation

Examine building object classes. The physical objects in the dataset, from the BIM models to graphs, were examined to figure out: (i) the misclassified (mislabeled and/or unlabeled) building objects; and (ii) physically connected interdomain object pairs. The primary object classes in the architectural domain (ceiling, door, floor, wall) were preserved through the BIM models, IFC files, and LBD graphs. On the other hand, in the MEP domain, 1,405 objects - 47.6% of the total MEP objects in the dataset - were exported as building element proxies. These include electrical equipment (468 switches), electrical fixtures (880 sockets), communication devices (47 speakers), and mechanical equipment (10 variable air volume (VAV) units). Further, the direct relations between these MEP objects and architectural objects were investigated. The object pairs found were: (i) wall and electrical equipment; (ii) wall and electrical fixture; (iii) wall and communication device; (iv) ceiling and mechanical equipment. These object pairs were used for the formation of object classification rule sets.

Generate rule sets. Here, the adopted approach is rule-based inferencing using object pairs having unique conditional sets, developed originally in the SeeBridge project (Sacks et al., 2016; SeeBridge, 2017a, 2017b).

The object classification rule sets consist of topological relationships among interdomain object pairs and the comparison of exact geometry conditions among them. Table 1 shows the selected rules for object classification.

Four rule sets were generated for each MEP object. In the rule sets, the topological conditions were executed over each knowledge graph using a SPARQL query. The exact geometry conditions were evaluated by Trimesh. As an example, Figure 2 displays the topological query and the implementation algorithm of the rule set.

Results and Discussion

The number of interdomain direct relations between the MEP objects and architectural objects between the object pairs, after applying the CBIM algorithm in Step 2, is shown in Figure 3. The topological relationships compose of nine positions in three coordinates; however, Figure 3 shows the observed relationships in the examined 32 BIM models. The observed topological relations were evaluated manually by checking through 32 knowledge graphs. These observed topological relations were used as a basis for the formation of object classification rule sets. Indeed, the topological rule selection (Table 1) including the topological query (Figure 2) came from the statistics of the interdomain direct relations in Figure 3.

The object labels obtained using the four rule sets and the object labels from the original BIM models were compared manually. The performance of the generated rule sets was evaluated based on false negative and positive as well as accuracy values (Table 2). These values were calculated according to the object numbers in the BIM models and the detected object numbers by rule sets. The MEP objects were classified with at least 90 % accuracy.

In the detection of mechanical equipment (VAV), one object was undefined in the dataset models, which lead to a false negative. The number of objects detected by the rule set was one less than the real number in the BIM models. The reason for the false negative is that the rule set structure was unable to detect all the VAV units in the dataset. Therefore, the rule set's structure must be improved by adding more object geometry features (e.g., volume, area, etc.) and more exact geometry comparison conditions (e.g., cardinality, orthogonality, and so on).

The communication devices (speakers) were classified with the highest accuracy rate. Even though the accuracy satisfies the dataset, the existence of different shapes of the object in the model could degrade the performance of the rule set. More object shapes should be investigated with a more advanced and sophisticated rule set.

Table 1: Selected rules for object classification

		Mech. Equipment (VAV) & Ceiling	Comm. Device (Speaker) & Wall	Electr. Equipment (Switch) & Wall	Electr. Fixture (Socket) & Wall
Topology	Position in X-direction	Contain, Left, Right,	Contain, Left, Right, RightOverlap, LeftOverlap	Contain, Left, Right, RightOverlap, LeftOverlap	Contain, Left, Right, RightOverlap, LeftOverlap
	Position in Y-direction	Contain, Back	Contain, ContainedIn, Back, Front, FrontOverlap	Contain, ContainedIn, Back, Front, FrontOverlap, BackOverlap	Contain, ContainedIn, Back, Front, FrontOverlap, BackOverlap
	Position in Z- direction	ContainIn, Below	Contain	Contain	Contain
Geometry	Object1 Length (X-dim)	0.5< X-dim <1	0.1< X-dim <0.5	0< X-dim <0.1	0< X-dim <0.1
	Object1 Width (Y-dim)	0.5< Y-dim <1	0.1< Y-dim <0.5	0< Y-dim < 0.1	0< Y-dim < 0.1
	Object1 Height (Z-dim)	0.1< Z-dim <0.5	0.1< Z-dim <0.5	0< Z-dim < 0.1	0< Z-dim < 0.1
	Is object1 bounding box length greater than object2?	NO	NO	NO	NO
	Is object1 bounding box width greater than object2?	NO	NO	NO	NO
	Is object1 bounding box height greater than object2?	YES	NO	NO	NO
	Distance between object1 Z-center and Object2	-	-	$0 <= \varepsilon_1 <= 0.65$	$0.5 <= \varepsilon_1$
	Elevation of Object1 bottom	-	-	$0.6 <= \varepsilon_2 <= 1.5$	$0 <= \varepsilon_2 <= 1$

```
Topological_query = """
SELECT ?s ?o1 ?o2
WHERE
{
  ?s CBIM:hasObject ?o1 .
  ?s CBIM:hasSubject ?o2 .
  OPTIONAL
  {{?s CBIM:topology "Contain, Contain, Contain" . }
   {?s CBIM:topology "Contain, ContainedIn, Contain" .}
   {?s CBIM:topology "Contain, Back, Contain" . }
   {?s CBIM:topology "Contain, Front, Contain" .}
   {?s CBIM:topology "Right, Contain, Contain" .}
   {?s CBIM:topology "Left, Contain, Contain" .}
   {?s CBIM:topology "RightOverlap, Contain, Contain" .}
   {?s CBIM:topology "LeftOverlap, Contain, Contain" .}
   {?s CBIM:topology "Contain, FrontOverlap, Contain" .}
   {?s CBIM:topology "Contain, BackOverlap, Contain" .}
   {?s CBIM:topology "Right, Back, Contain" .}
   {?s CBIM:topology "Left, Back, Contain" .}
   {?s CBIM:topology "FrontOverlap, Front, Contain" .}
   {?s CBIM:topology "FrontOverlap, Back, Contain" .}
   {?s CBIM:topology "RightOverlap, Front, Contain" .}
   {?s CBIM:topology "RightOverlap, Back, Contain" .}
   {?s CBIM:topology "Left, Front, Contain" .}
   {?s CBIM:topology "Left, FrontOverlap, Contain" .}
   {?s CBIM:topology "Right, Front, Contain" .}
   {?s CBIM:topology "Right, FrontOverlap, Contain" .}}
}"""
```

```
for each result of the Topological_query:
  if Object1_type == "Buildingelement" & Object2_type == "Wall":
    if 0 <Object1_Xdim<0.1 & 0<Object1_Ydim<0.1 & 0<Object1_Zdim < 0.1:
      if Object1_BB_Xdim <= Object2_BB_Xdim == True:
        if Object1_BB_Ydim <= Object2_BB_Ydim == True:
          if Object1_BB_Zdim <= Object2_BB_Zdim == True:
            if 0 <= ε1 <= 0.65 & 0.6 <= ε2 <=1.5:
              List SWITCH.append(Object1)
              for i in SWITCH:
                if i not in result:
                  result.append(i)
                end if
              end for
            if 0.5 <= ε1 & 0 <= ε2 <=1
              List SOCKET.append(Object1)
              for i in SOCKET:
                if i not in result:
                  result.append(i)
                end if
              end for
  end if
end for
```

Figure 2: (a) Topological query; (b) Rule sets implementation algorithm

Interdomain Topological Relationships	Ceiling											
	X				Y					Z		
	L	C	RO	R	F	FO	C	CI	B	C	CI	B
Mechanical Equipment (VAV)	8	2	0	0	0	0	8	0	2	0	1	9
Interdomain Topological Relationships	Wall											
	X				Y					Z		
	L	C	RO	R	F	FO	C	CI	B	C	CI	B
Electrical Equipment (Switcher)	140	215	45	64	93	29	152	0	190	451	0	13
Electrical Fixture (Socket)	231	405	111	126	141	53	345	0	334	826	0	49
Communication Device (Speaker)	13	26	2	6	13	2	17	1	14	47	0	0

**Positions in X-direction: (L) Left, (LC) Left Contact, (LO) Left Overlap, (C) Contain, (CI) Contained In, (EO) Exact Overlap, (R0) Right Overlap, (RC) Right Contact, (R) Right*

**Positions in Y-direction: (F) Front, (FC) Front Contact, (FO) Front Overlap, (C) Contain, (CI) Contained In, (EO) Exact Overlap, (BO) Back Overlap, (BC) Back Contact, (B) Back*

**Positions in Z- direction: (A) Above, (AC) Above Contact, (AO) Above Overlap, (C) Contain, (CI) Contained In, (EO) Exact Overlap, (BO) Below Overlap, (BC) Below Contact, (B) Below*

Figure 3: The number of observed interdomain topological relationships in 32 BIM models

When looking at the electrical equipment (switch) and device (socket), in both object classes, two errors were observed: (i) false positives, which infers that the number of objects detected by rule sets is higher than the real number in the BIM models, and (ii) false negatives.

Ideally, the sum of false negatives and positives should be zero. However, here, the sum is greater than zero due to the disjoint object classes (VAV, speaker, switch, and socket). Said another way, if one object is not distinguished through the rule set, it will not be categorized through the other rule sets. This condition was observed in the VAV object class. Alternatively, an object might be classified under more than one class - this condition was seen in the switch and socket objects' classes.

The false positive came from the non-discrete geometrical features of the switch and socket. Figure 4 displays an example of the non-discrete geometry features of the switcher and socket in the dataset. In cases where these two objects are located at different heights and positions, the rule sets distinguish them. Otherwise, if they are located at the same height and even positioned close to each other, this situation creates an overlap in the rule sets, leading to a false positive. Figure 4 shows the overlapping area where the objects' location height is between 500 and 1200 mm. The socket object, at the height of 1200 mm, was detected as a switch object via the rule set.

The highest overlapping rate in the socket cluster was 61%, where 20 switches were labeled as sockets by the rule set. On the other hand, the highest overlapping rate in the switch cluster was 42%, where five sockets were labeled as switches (Table 3).

Based on that, in the dataset models, there were very few sockets at the height of the switches, which resulted in false positives in the switch cluster. On the other hand, the switch cluster had a broader range of possible positions, and thus any switch would be detected easily as a socket through the rule set. Consequently, the switch class had a narrower range of false positives than the socket class.

To summarize, non-discrete geometry and topology properties for objects result in false positives and negatives in classification via rule-based inference. The only way to address this situation is to look at the appearance of objects, which is the human way of understanding physical objects. Therefore, integrating the proposed method with image recognition using a convolutional neural network (CNN) algorithm (ML technique) would potentially be reliable.

The object classification task through ML techniques has been examined by researchers. Researchers have developed open-source datasets for object classification based on IFC entity classes through semantic enrichment of BIM models (e.g. IFCNET (Emunds et al., 2021) and BIMGEOM (Collins, 2021)).

In light of these previous studies, future work will integrate the proposed method with image recognition at the design stage of the BIM models. The integration of the proposed method with image recognition can be achieved via a dual examination of object labels through the multi-view convolutional neural network (MVCNN) algorithm (ML technique) over open-source datasets and rule base inferencing over knowledge graphs. By doing that, we suppose that the overlapping areas for the objects will be eliminated.

Conclusions

This study aims to classify MEP domain objects based on interdomain topological relationships among the MEP and architectural objects and exact geometry conditions that define the nature of the physical objects. With this aim, the suggested approach utilizes (i) semantic web technologies for a knowledge graph covering architectural and MEP domain subgraphs bonding with the topological relations and (ii) semantic enrichment with a rule-based inferencing technique that executes rules over the knowledge graphs to detect the unclassified/misclassified MEP objects among the object pairs.

Table 2: The performance of the generated rule sets over 32 knowledge graphs in the dataset

MEP Object Class	Object Number in BIM Models	Detected Object Number	False Negative	False Positive	Accuracy (%)
Mech. Equipment (VAV)	10	9	1	0	90
Comm. Device (Speaker)	47	47	0	0	100
Electr. Equipment (Switch)	464	479	19	34	96.77
Electr. Fixture (Socket)	874	961	29	116	90.05

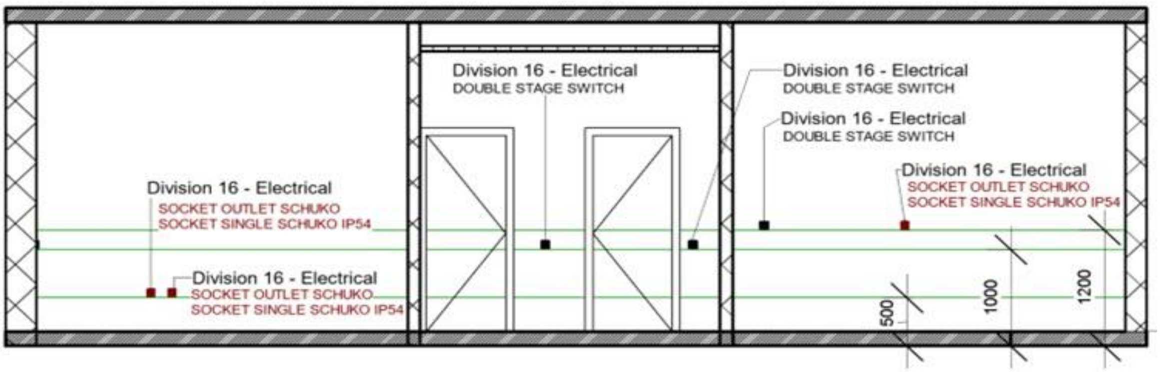

Figure 4: Representation of the non-discrete geometry of the switcher and socket in the dataset

Table 3: The highest overlapping rate in switch and socket clusters

Apart Number	Switch Object Number in BIM Models	Detected Switch Object Number	Overlapping Rate	Socket Object Number in BIM Models	Detected Socket Object Number	Overlapping Rate
12	24	25	0.04	33	53	0.61
18	12	17	0.42	31	26	-0.16

In this context, 32 BIM models were converted to knowledge graphs and enriched with object topological relations. Based on these data models, four rule sets containing object pairs topology and exact geometry conditions were generated for the object classification (mechanical equipment (VAV), communication device (speaker), and electrical equipment (switch) and fixture (socket)) via rule-based inferencing. The results showed that the rule sets had at least 90% accuracy.

Although the results satisfy the examined models, the main limation is the lack of unique geometry and topology properties for the objects, resulting in false positives and negatives that reduced the accuracy of the rule sets. Following that, future work will test the integration of the proposed method with image recognition.

Consequently, the main conclusion of this study is that building object classification can be improved using knowledge graph-based semantic enrichment. The main beneficiaries are expected to be design teams, who work in a multi and inter-disciplinary field in the AEC sector. During the design process, the design team utilizes different vendor-specific BIM software, and the extracted information from this software leads often to incomplete and incorrect object labeling and misclassified objects. Therefore, the building physical objects with their interdomain relations and attributes need to be classified explicitly by preserving data integrity and quality. The semantic enrichment over the knowledge graph seems to be an encouraging way of providing high-resilience object classification and relationships.

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