COMPARISON OF BRICK AND PROJECT HAYSTACK TO SUPPORT SMART BUILDING APPLICATIONS

Highlights

- Comparison of Brick and Project Haystack ontology for use with Smart Building applications
- Qualitative document review of ontologies
- Quantitative expressiveness and completeness assessment of ontologies
Abstract

Enabling buildings with Smart Building applications will help to achieve the ongoing efficient commissioning of buildings, ultimately attaining peak performance in energy use and improved occupant health and comfort, at minimum cost. For these technologies to be scalable data ontology must be adopted to semantically represent data generated by building mechanical systems, acting as conduit for connection to Smart Building applications. The viability of Brick and Project Haystack ontologies, as found by industry and academia, prompted a quantitative comparison of completeness and expressiveness using a case study with an industry ontology as the baseline. Additionally, a qualitative comparison was completed using key ontology qualities outlined in literature. A recommendation of Brick is made based on results. Brick achieved higher assessment values in completeness and expressiveness achieving 59% and 100% respectively, as compared to Haystacks 43% and 96%. Additionally, Brick exhibited five of six desirable qualities, where Haystack exhibited only three. The recommendation of the appropriate ontology forms the basis for longer-term Smart Building application development,
which will support innovative approaches to sustainability in building operations across scale, as well as next-generation building controls and automation strategies.

Keywords: Brick; Haystack; Smart Building; Ontology
1 Introduction

Smart Building applications are receiving an increasing amount of attention within the Architecture Engineering and Construction (AEC) industry. These applications use data generated by building data sources, allowing for the scalable oversight required for the ongoing commissioning of a building. Purpose driven Smart Building applications such as fault detection and energy optimization of controls, or information access driven tools such as parametric designs and Facilities Management Building Information Models (FM-BIMs) fall within the Smart Building application domain. Smart Building applications are of value to a host of building stakeholders including FM, building owners, operators, and tenants. These applications allow for testing and planning of maintenance projects, observation of building conditions, retrieval of specific sensor data, optimize controls strategies, and improved occupant comfort.

Information required for Smart Building applications comes from a variety of heterogeneous data sources, including: Building Management System (BMS), Building Information Model (BIM), security, weather, maintenance records, etc. Data sources cannot easily be cross referenced. The disparate nature of building data is the major hurdle to the research and development of Smart Building applications and is therefore of interest to the academic community. Normalization of data is possible though the creation of semantic data, metadata which gives meaning to, and is kept separate from, raw data sources. Semantic data allows for cross referencing and the creation of an interconnected web of datasets called Linked Data. Linked Data sets can be systematically accessed by Smart Building applications through a query processor (ex: SPARQL, SQL). Semantic data of a specific domain is defined using a data ontology.

The term ‘ontology’ can refer to two components of knowledge base: TBox and ABox. Firstly, it
can refer to a formalization of semantic data, where data concepts are used to define the structure of semantic domain knowledge; this is the definition of a TBox ontology. Conversely, it can also be used to reference an instantiated version of a TBox ontology; this is an ABox ontology. For example, “ontology X” can be used to define a specific ontology for an office building. The former (ontology X) is general and thus a TBox ontology; the latter (office building ontology) is instantiated and therefore an ABox ontology. While many TBox ontologies have been proposed to define building HVAC system data in Linked Data structures, two have gained traction in academia and industry: Project Haystack (henceforth referred to as “Haystack”) and Brick.

There is a paucity of research in the comparison of Brick and Project Haystack. This is a pertinent area of research in industry and academia as it will allow the development of Smart Building applications, which requires an ontology to give context to building data sources, to move forward. Modularization of building data sources through ontology will allow applications to be supplied by a variety of vendors, as well as updated to meet the needs of system autonomy, maintenance tracking, human system interaction, reporting, etc. The recommendation of an appropriate ontology will allow Smart Building application research and development to move forward with more efficiency. This research investigates and recommends an ontology to serves as a conduit, feeding Smart Building applications with building data. The investigation evaluates two ontologies (Brick and Haystack) for their suitability to semantically represent BMS data through quantitative completeness and expressiveness measures as well as a qualitative review.

2 Literature Review

Applying the Linked Data approach to Smart Building applications has created the need for the comparison of Brick and Haystack. These ontologies have become prevalent in academia and
industry, respectively. This literature review begins with a discussion of ontology use with the Linked Data approach and then moves to a detailed discussion of Brick and Haystack.

Integrating and accessing building data sources is challenging because each one is organized in a bespoke manner despite shared concepts existing, resulting in a heterogeneous data set. The most common method used for integrating building data sources is referred to as Linked Data [1, 2, 3].

A significant amount of research has been conducted to define a standardized semantic model, Industry Foundation Class (IFC), for static building information such as BIM that contribute to the linked data mode [4]. However, for data sources which include dynamic data the IFC model is inadequate because it does not describe the behavior of entities [4]. In the Linked Data approach, raw timeseries building data sources are stored separately from semantic data. This allows static and dynamic building data sources to be cross referenced through standardized semantic data representation. Different semantic data serialization formats exist within the building domain [5, 6]. Some examples of semantic web serialization formats include Turtle (.ttl), N-Triples (.nt), JSON-LD (.jsonld) among others, including ontology specific custom formats.

Linked Data approaches effectively create a data lake that is accessible through a common data management system [7] such as a query processor [8, 9]. This query processor will receive a request from an application, query semantic data to retrieve pointers/unique identifiers to data points within data sources such as a security system or BMS, and then query these stores for time-specific data values. The data management system relies on the previously described standard serialization of semantic data to retrieved data from relevant data sources for applications. If standard serialization is not used, query processors would need to use
equivalency logic to convert semantic definitions between data sources semantic representations. Custom query languages can act as a data management system and are required when using a custom serialization, however all building data sources would need to be serialized to a single custom format to ensure that a single query language could be used to access data. Bajaj [10] reviewed the ontologies in the building domain based on their ability to respond to expected application queries, and support Smart Building applications. and found that ontologies that reuse existing ontologies, have been assessed with an ontology validator, are modular and accessible, are properly annotated, and well documented, are the most appropriate to support Smart Building applications. Brick and Haystack meet these criteria and are regarded as leading ontologies to serve Smart Building applications in industry and academia.

2.1 Project Haystack

Project Haystack [11] is a non-profit corporation, formed in 2014, and acts as the steward to the open-source Haystack Ontology. An industry board of directors and associate members maintain and develop the ontology. The board is comprised of individuals from smart edge hardware and software vendors including: ConserveIt, Intel, J2 Innovations (by Siemens), Legrand, Siemens, and SkyFoundry. Siemens is the major industry BMS provider involved in Project Haystack, though Honeywell is also indirectly involved through an associate member (Accutemp).

Haystack uses some terms exclusively in either their TBox or ABox components. The Haystack TBox ontology definition is a semantic data representation where dictionaries of name value pairs are defined; for example, to describe individual HVAC concepts in a building, where a value is the definition of the concept, and the name is the unique string representing the concept.
The same names are used in Abox but are referred to as Tags. Name value pairs are called Defs [12], and are stored in portable groups called libraries; one or more libraries is used to define an ABox ontology of a building [13]. Multiple Defs can be used to describe a concept and are referred to as Conjunets [12]. Defs in the Haystack TBox ontology can exhibit parent child relationships, effectively defining a hierarchy of concepts, referred to as associations [14]. Within Abox relationships are defined using one of two methods: Ref, a type of Def that effectively functions as a pointer; or Child Protos, a Conjunct defined within a TBox Def. ABox Haystack relationship are derived from Haystack relationship types containedBy, contains, receives, or supplies. Haystack is serialized in Zinc or Trio; RDF serializations are not yet supported [15]. Querying Haystack is done using a custom query language refers to as Filters [16]. Figure S1 shows a sample of Haystack describing an AHU bypass damper command point.

Earlier versions of Haystack consisted of a standardized vocabulary to define semantic concepts (i.e. a meta model). Haystack 4 has elevated its semantic representation to an ontology with hierarchy and relationships. Haystack is grounded in object-oriented design, attempting to digitally represent HVAC concepts semantically, as opposed to explicitly describing semantics. Haystack 4 documentation has stated that semantic web technologies would be supported, however this has not happened for the version assessed in their research. A critique of Haystack has been its excessive flexibility, leading to ABox ontologies that are not accessible to applications due to unexpected definitions of semantic data. The Haystack Tagging Ontology (HTO) proposed by Charpenay et al [17] is an application of Haystack which supports semantic web technologies, and structures the use of tags while extending the vocabular included in the ontology. HTO uses Semantic Web technologies (RDF, OWL, SPARQL) to address this gap in
2.2 Brick

Brick was initially described and used within the academic community, initially published in 2016 [18], further publications have since added detail to the ontology description [19]. Brick is being collaborated on by researchers at Carnegie Mellon, Berkeley, University of California San Diego, University of California Los Angeles, University of Virginia, and the University of southern Denmark. Additionally, Brick is supported in industry by Johnson Controls and some regulatory bodies such as the US Department of Energy and the European Commission [20]. Haystack has more industry partners than Brick, however Brick offers more ABox ontology samples and more robust development documentation.

Unlike Haystack, Brick uses consistent language to define ABox and TBox ontology concepts. Brick was developed using a dataset developed by extracting data from six buildings using a variety of BMS vendors, and has been demonstrated to semantically represent 98% of concepts [17]. Brick is grounded in descriptive logic and was designed to semantically describe building HVAC systems. Brick exhibits a hierarchical design, where Classes and Subclasses define varying level of detail [17]. There are four primary Classes (Equipment, Location, Measurable, and Point). Additionally, there is a relationship Class that defines each of the nine bidirectional ontology relationships in subclasses. Brick uses a prescribed approach to defining semantic data where complete HVAC concept in an ordered string are represented in Classes and Subclasses. Figure S2 shows a sample of Brick representing an AHUs outdoor air damper command.
2.3 Ontology Comparison Methods

Ontology schemas are difficult to evaluate because they are declarative and only describe the domain that must be digitally represented rather than describing an instance of that domain. Evaluation through test cases often giving quantitative results and is the preferred method to evaluate ontologies [21, 19, 17, 22]. Additionally domain-specific document comparison has been identified as a valuable means of ontology comparison [23]. Brick was validated using a case study method by Balaji et al. [19]. The ontology was compared to SAREF, Haystack and IFC, each being implemented for six buildings running eight Smart Building applications. Each ontology was measured in each building for completeness, expressiveness, and usability, by assessing each ontologies recall of data points required by each of the applications. In this comparison Brick achieved higher completeness and expressiveness scores. Haystack has been validated using a case study by Bhattacharya et al. [24] comparing it against IFC and SSN using three buildings. Instead of using a set of using Smart Building applications the Haystack validation used a summarized list of key relationships. The quantitative assessment done in the paper assessed completeness, and expressiveness. Additionally, flexibility was discussed qualitatively. The paper found that Haystack offered the best completeness of the three assessed ontologies with 63% coverage of baseline data, as well as the best expressiveness with 77% coverage.

2.4 Summary of Literature Review

The use of the Linked Data approach for semantic data representation offers significant benefits to Smart Building applications [1, 2, 3]. This approach is preferred because it allows for the
integration of multiple data sources, and facilitates the fast and effective retrieval of building data for Smart Building applications [9, 6]. Many ontologies have been developed in the hopes of rendering building data sources more accessible to Smart Building applications. Two ontologies have however captured the attention of industry and academia – Brick and Haystack. These are both “open-source” ontologies with ample publicly available documentation.

Despite the significant research to date on the topic of data ontology to support Smart Building applications, there remains a paucity of literature identifying the most appropriate ontology for Smart Building applications. Specifically, when considering the most widely available, and discussed Brick and Haystack ontologies. Previous versions of Brick and Haystack have been compared [19], and it was found the Brick was superior, however both ontologies have been updated significantly since this comparison. Project Haystack has grown from a standardized schema to an ontology, and a new comparison for the purpose of Smart Building is required. This research aims to fill this gap by presenting a qualitative and quantitative (completeness and expressiveness) comparison of the Brick and Haystack ontologies.

3 Methodology

Both quantitative and qualitative assessment methods are used in this research, with the goal of is assessing the ability of each target ontology, Brick and Haystack, to accurately represent the real-world domain of Smart Building. This process is referred to as ontology validation [22]. The quantitative assessment was completed using a case study and evaluates both completeness and expressiveness, which are measures demonstrated to be valuable in literature [19, 25, 9]. Additionally, this research qualitatively assesses target ontologies through document review.
The quantitative measures (completeness and expressiveness) used in this research are a combination of those from prior publications, defined herein as completeness and expressiveness. The measure of an ontologies completeness is the relative number of semantic concepts represented [19, 21], and expressiveness is the number of key smart building application required relationships expressed. To measure completeness and expressiveness a representative industry ontology was used as the baseline. This case study approach differs from previous research because it uses an ontology as a baseline, rather than one or more individual buildings. This approach offers the largest representation of building systems and data points and is therefore preferred to provide the most comprehensive comparative evaluation of Brick and Haystack.

The study used the most current versions of both target ontologies: the beta Haystack Version 3.9.7 (referred to as Version 4 in marketing material) and its documentation as published on October 24th, 2019 [26], and Brick Version 1.1.0 and its documentation as published on February 21st, 2020 [27]. To manage potential change of schema, ontologies are compared qualitatively through a documentation review and assessment against a set of key qualities identified in previous research. Additionally, completeness and expressiveness assessment results are interpreted relative to the baseline, with a focus on identifying gaps in either target ontology.

3.1 Baseline Industry Ontology

KGS Clockworks is a for-profit organization providing customers a Smart Building application that provides equipment diagnostics, recommendations for energy savings, and occupant comfort condition ratings. Underpinning the KGS Smart Building application is a proprietary ontology. The offerings of KGS align with the goals of some Smart Building applications and therefore
their ontology is an appropriate baseline for this case study.

The baseline ontology is defined in a hierarchical structure, as seen in Figure 10. *Equipment Class* represents HVAC systems and common sub-equipment, while *Equipment Type* represents equipment subtypes. Equipment Types can be related to each other using an *Allowed Equipment Association*. Semantics of BAS data points are represented in *Point Types* which can be implicitly or explicitly related to equipment concepts. Point Type is a subclass of *Point Class*, which describe measures within a system. Each Point Class is associated with an *Engineering Unit* which defines the measurement of Point Classes. Finally, the *Measurement/Control Type* give DI/DO AI/AO context to Point Types, and *Service* indicates the medium the Point Types is acting on.

![Figure 1: KGS Baseline Ontology Schema](image)

In the KGS ontology includes has 1422 Point Types to capture the purpose of a data point in
building systems. To manage the scope of *Point Types* included in the quantitative assessment, a subset of points associated with HVAC critical systems \{AHU, Chiller, Boiler, Terminal Units, and Loops\} were selected for mapping and within each system Point Types containing redundant concepts were removed, resulting in the *representative set* of 440 Point Types used for the comparative evaluation. Representative Point Types contain at least one unique *word* within the HVAC system that they are used where a word is a substring of the Point Type. For example, the point name *RoomAirDpTemp* was broken into the words: *Room*, *Air*, *Dp*, and *Temp*. This approach ensured that Point Types and their related equipment could be tested for representation in target ontologies. Some exceptions were made in selecting the representative set as not to include obscure Point Types used by KGS to represent “one of” system despite having unique words.

The breakdown of selected and not selected representative Point Types by system is shown by subsystem in Figure 5 (Table S1 provides additional details on the selected points).
3.2 **Completeness Measurement**

Completeness was measured by assessing the percent of representative Point Types that could be mapped from the baseline ontology to each target. Engineering Units were not considered in this the completeness assessment as they were not easily identified for Point Types in the baseline ontology, additionally Brick does not yet support the semantic representation of units. Each representative Point Type was considered and classified when assessing the completeness of a target ontology. If *all semantic data* from the baseline ontology Point Types could be mapped to the target the Point Type would be classified as one that *Maps*. If Equipment Class and Point Class mapped, but one semantic gap existed in either measurement/Control Type, Service, or Equipment Type the Point Types was classified as *Partially Maps*. Finally, if there is more than one gap in Point Class, Service, or Equipment Type, or if the Equipment Class did not map, the Point Type was classified as *Does Not Map*. Examples of classifications of Point Types can be seen in Figure 6.

The use of word mapping semantic data from a baseline data set to a target ontology to assess completeness has been previously demonstrated within the literature [21, 19]. While the approach requires little manual effort, semantic data beyond that explicitly stated in a word will not be evaluated. Direct string matching of words was also not used in this research because baseline ontology Point Type word might not have exact string matches in the target ontology, despite having semantic mappings. For example, *HEX* in the baseline ontology maps to *Heat_Exchanger* in the Brick ontology. This research manually maps all connotations.
represented by words in each Point Type to ensure appropriate classification.

To better understand trends in completeness, *Partially Maps* and *Does Not Map* classified Point Types were assessed for gaps. Each piece of missing semantic information (a gap) in a Point Type was coded as a measure, equipment, medium, or concept, and the missing piece of semantic data was indicated. Point Type could thus exhibit multiple gaps, and each would be considered in the completeness trend analysis. Gaps were interpreted relative to their *Does Not Map* and *Partially Maps* classification and were classified as either significant (affecting 2% of more of Point Types in the representative set) or insignificant.

### 3.3 Expressiveness Measurement

Expressiveness was measured by quantifying a set of key relationships. Each of these key relationships was found in the baseline ontology for the set of previously identified systems (AHU, Chiller, Boiler, Terminal Units, and Loops) on both the air and water sides. The total
number of relationships assessed was 27.

**Key relationships** required by Smart Building applications have been identified in previous publications [24, 19, 9, 25]. These include the six relationships \{Sensor ↔ Location, Location ↔ Location, Equipment ↔ Location, Sensor ↔ Equipment, Equipment ↔ Equipment, Location ↔ Persons\} posited by Bhattacharya et al. [21] and one additional relationship \{Equipment ↔ Name\} based on Balaji et al. [19]’s expanded relationship set used for ontology validation. These key relationships were also used in research for query processors serving Smart Building applications [25] [9]. The baseline ontology defines semantic relationships within Point Types and Allowed Equipment Associations. Key relationships were cross-referenced with the baseline ontology to guide the selection of the set of representative baseline ontology **expressed key relationships** (Table S2). Using a similar logic to completeness, trends in expressiveness were assessed by classifying expressed key relationships as **Maps** or **Does not Map**.

### 3.4 Qualitative Comparison

A qualitative assessment of each target ontology was performed to evaluate within the Linked Data context. To undertake this evaluation ontology documentation was reviewed, assessing the flexibility, portability, readability, extensibility, interoperability, and queryability of each ontology, using a set of qualifying questions. The outputs of this assessment were the lists of positive key qualities each target ontology supported.

The **qualities** mentioned above have been regarded as positive and relevant in the academic
literature [21, 19, 8, 28]. Flexibility answers the question ‘can the ontology capture uncertainty in semantic data and does it use non-restrictive methods to define concept semantically?’ [21]. Portability answers the questions ‘can the same set of applications be applied across buildings (with applicable HVAC systems) using the specified ontology?’ and ‘is semantic data represented consistently in a machine-readable format.’ [19]. Readability answers the question ‘can domain experts and applications developers unambiguously decipher real world meaning from semantic data as presented in the ontology?’ [19]. Extensibility answers the question ‘can the ontology be customized to add new semantic concepts?’ [21, 19]. Interoperability answers the questions ‘can the ontology integrate with, and convert to, other ontologies with little to no human effort?’ and ‘Is the ontology serialized in an industry accepted format?’ [8]. Finally, Queryability answers the questions ‘can an instantiated ontology be machine traversed and necessary information retrieved?’ and ‘Is there low variability in semantic relationships?’ [28, 24]. The response of yes is the desired outcome to quality questions, indicating that the quality is expressed in the ontology.

4 Results

The following results present the comparison of completeness, expressiveness, and qualitative assessments of Brick and Haystack. Completeness and expressiveness assessments used the KGS ontology as a baseline; as noted previously, this ontology was developed for Smart Building applications that performed fault detection, energy optimization, and human comfort tracking functionality, and is therefore well suited to provide relative results. Completeness was measured by quantifying the number of baseline ontology Point Types classified as Maps in the target ontology while expressiveness was measured by quantifying the number of baseline ontology
expressed key relationships classified as *Maps* when mapping comparable relationships from the baseline to the target ontology. Finally, a defined set of desirable qualities were assessed for representation in either target ontology by evaluating relevant documentation and classifying qualities as *supported* or *unsupported*.

### 4.1 Completeness

Brick was found to be more complete than Haystack with a higher percent of representative Point Types classified as Maps: 59% vs. 43%. When Point Types classified as Map or Partially Maps Brick again achieves higher completeness with 77% of Point Types covered, while only and 69% of Point Types were so classified for Haystack. Brick was able to represent a greater number of representative Point Types from the baseline ontology than Haystack. This was true across all subsystem considering Point Types classified as Maps, excluding the Boiler system which achieved the same value; this is illustrated in Figure 12.
The numerical results for the completeness of Haystack and Brick by system type can be seen in Table 4. Brick offered a more complete ontology where a greater number of semantic concepts were represented. There were fewer Significant gaps in Brick and ultimately it would require fewer custom semantics to be defined to accurately represent a building.

| System       | Haystack | Brick |
|--------------|----------|-------|
|              | % Point Types with Maps Classification | % Point Types with Maps or Partially Maps Classification | % Point Types with Maps Classification | % Point Types with Maps or Partially Maps Classification |
| AHU          | 32%      | 67%   | 56%      | 82% |
| Chiller      | 54%      | 70%   | 55%      | 60% |
| Boiler       | 74%      | 87%   | 74%      | 77% |
| Loop         | 27%      | 55%   | 42%      | 77% |
| Terminal Units | 54%    | 77%   | 75%      | 84% |
| Total        | 43%      | 69%   | 59%      | 77% |

A primary finding of completeness measurement was the identification of semantic gaps in either target ontology. This study found the Haystack ontology had more (60) unique gaps and overall occurrences (303) than Brick (50 gaps and 208 occurrences). These gaps are shown in Table 2.
(Haystack) and Table 3 (Brick). Significant Gaps (those affecting 2% or more of Point Types in
the baseline ontology) are discussed below. Haystack had 8 Significant gaps, where Brick has 6.
There are many Insignificant Gaps (those affecting less than 2%) which, in aggregate, have a
large impact on completeness; each impact only a few Point Types but are nonetheless necessary
in the baseline ontology. It should be noted that these Insignificant Gaps could be more
significant if the representative Point Type set was expanded to include all Point Types in the
baseline ontology.
### Table 2: Semantic Gaps of Haystack Ontology Affecting Completeness Assessment Score

| Gap Type      | Significant | Classification | Gap (# Point Types)                                                                 |
|---------------|-------------|----------------|-----------------------------------------------------------------------------------|
| Missing       | Yes         | Does Not Map   | Alarm (13)                                                                         |
|               | Yes         | Partially Maps | Primary/Secondary (24)                                                             |
|               | No          | Does Not Map   | Conditioning Mode (1), Pre Heat (1), Set Back Status (1), Setup Mode (1), Relief (1), Holiday (1), Superheating (1), Natural Ventilation (1), Occu
|               | No          | Partially Maps | Heat Source (1), Medium (3), Low (5), High (6), Reset (8)                           |
| Missing       | Yes         | Does Not Map   | Heat Recovery (15)                                                                  |
|               | Yes         | Partially Maps | Generic Compressor (18), Enthalpy Wheel (20)                                       |
|               | No          | Does Not Map   | Hot Water Loop (2), Humidifier (3), Economizer (7), Thermal Energy Storage (3), Generator (4), Generator (4), Filter (5), Dual Temp Loop (7) |
|               | No          | Partially Maps | Dual Temp Coil (3)                                                                 |
| Missing       | Yes         | Does Not Map   | Enthalpy (9)                                                                        |
|               | Yes         | Partially Maps | Position (54)                                                                       |
|               | No          | Does Not Map   | Vibration Amplitude (1), Volume (1), Suction                                        |
| Missing | Partially Maps | Does Not Map | N/A |
|---------|----------------|--------------|-----|
| No      | Partially Maps | N/A          |     |
| Yes     | Does Not Map   | N/A          |     |
| Yes     | Partially Maps | Equipment Discharge Air (10) |     |
| No      | Does Not Map   | CO (2), Lubrication Oil (3), Return Water (3), Supply Water (4) |     |
| No      | Partially Maps | Clean Steam (2), Equipment Inlet Air (6) |     |
Table 3: Semantic Gaps of Brick Ontology Affecting Completeness Assessment Score

| Gap Type       | Significant | Classification | Gap (# Point Types)                                                                 |
|----------------|-------------|----------------|-----------------------------------------------------------------------------------|
| Missing Concept| Yes         | Does Not Map   | N/A                                                                               |
|                | Yes         | Partially Maps | Setpoint Limit (21), Primary/Secondary (22)                                         |
|                | No          | Does Not Map   | Fan Only (1), Superheating (1), Cooling Enable (Outdoor Air ) (1), Setback Status (1), Setup Mode (1), Holiday (1), Part Run (2), All Run (2), Tracking Mode (2), Subcooling (2), Tracking Status (3), Stage Command (3), Free Cooling (4), Heat Source (5) |
|                | No          | Partially Maps | Occupancy Mode (1), Return Air Reset (4)                                            |
| Missing Equipment| Yes        | Does Not Map   | Heat Recovery (15)                                                                 |
|                | Yes         | Partially Maps | Enthalpy Wheel (20)                                                                |
|                | No          | Does Not Map   | Mixing Valve (1), Relief Damper (1), Thermal Energy Storage (3), Generator (4), Pre Heat/Cool Coil (5), Radiant Terminal Unit (6) |
|                | No          | Partially Maps | Dual Temp loop (1), Face Damper (1), Cold Deck (3), Hot Deck (3),                 |
| Missing Measure | Bypass Valve (7) |
|-----------------|------------------|
| Yes             | Does Not Map     | N/A |
| Yes             | Partially Maps   | N/A |
| No              | Does Not Map     | Fire Rate (1), Oxygen Fraction (1), Ph(1), Suction Pressure (1), Vibration Amplitude (1) Illuminance (1), Cooling Rate (1), Heating Rate (2), Humidity Ratio (2), Boiling Temp (2), Efficiency (2), Differential Pressure (3) |
| No              | Partially Maps   | Volume (2) |
| Yes             | Does Not Map     | Refrigerant (21) |
| Yes             | Partially Maps   | Equipment Inlet Air (9) |
| No              | Does Not Map     | Clean Steam (2), CO (2), Process Water (6) |
| No              | Partially Maps   | Equipment Discharge Air (1) |

Figure 12 offers a visual representation of these individual and shared gaps classified as Does Not Map. Haystack exhibited eight such Significant gaps, six being unique and included the lack of alarms and generic compressors, additionally it could not represent the measurement of enthalpy, position, and sub equipment discharge air. Three of Haystack’s Significant gaps overlapped with those in Brick and included the lack of description for enthalpy wheel and heat recovery equipment, as well as the ability to differentiate between primary and secondary equipment. Brick exhibited six
Significant gaps, three as previously stated and three of which were unique and included the lack of a refrigerant substance, sub-equipment inlet air, and limits. On a system level, loops were the most poorly represented, with the lowest completeness scores. Smart Building applications will benefit from the higher completeness offered by Brick as a wider breadth of HVAC concepts can be described and therefore accessible by applications. Buildings using a more complete ontology could be compatible with a wider variety of Smart Building applications, specifically those relying on clear and descriptive semantic data. While gaps in ontology schema can be filled as to not affect application effectiveness, their completion is preferred to avoid additional work in defining semantic concepts when developing a Smart Building application.

![Figure 5: Overlaps and Discrepancies in Brick and Haystack Ontology Significant Gaps classified as “Does Not Map”](image)

### 4.2 Expressiveness

As noted in the methodology, expressiveness was measured by quantifying the number of key
relationships required by Smart Building applications as found in the baseline ontology that map to the target ontology. The Brick ontology was found to be marginally more expressive than Haystack. Brick relationships are well suited for describing representative baseline ontology expressed key relationships, 100% of the 27 relationships assessed were classified as Maps. Haystack relationships were able to describe almost all representative baseline ontology expressed key relationships: 96% were classified as Maps, all but one sub-equipment relationship. The Brick ontology explicitly defines relationship function and their constraints whereas the relationship function in Haystack is implicit. The explicit and implicit approach to relationships of Brick and Haystack align with eithers overall ontology schema where Brick is prescribed, and Haystack more flexible.

A common relationship used for Sensor ⇔ Equipment relationship mapping was equipRef, this relationship is used to reference an equipment, which contains the sensor appropriate tag being used. Only ten other Ref relationships are defined in the Haystack ontology, of which ahuRef, hotWaterPlantRef, and chilledWaterPlantRef were used in mapping. In addition to Ref relationships,Defs can have Child Protos defined and are contained by a Def. Child Protos were used to map the Equipment ⇔ Equipment air side relationship. Haystack relationships were able to bridge the gap between the air and water side of HVAC systems; however, this required the use of both Ref and Child Proto relationships which in practice would necessitate complex queries.

The set of Brick relationships is clearly defined in a Class with defined constraints (Table S3). Brick has nine bidirectional relationships, each with a defined inverse relationship. The explicit
support of direct inverse relationships made expressiveness assessment simpler as only one use/direction of the relationship needed to be found to confirm the support of the bidirectional key relationship. For example, it was found that the Brick relationship $hasPoint$ can be used to represent the Boiler Equipment $\rightarrow$ Sensor relationship, therefore it is known that the inverse relationship $isPointOf$ can be used to represent the Boiler Sensor $\rightarrow$ Equipment relationship. The most used Brick relationships in the expressiveness assessment were $hasPoint/isPointOf$, $hasPart/isPartOf$, and $feeds/IsFeedBy$. These relationships were used because their constraints aligned with end points in key relationships such as Equipment and Sensor. Other Brick relationships such as measures and regulates are better suited to relate more granular semantic concepts such as measurables.

A single Brick relationship could not describe some Equipment $\leftrightarrow$ Equipment relationships, specifically those between loops and other HVAC systems. These relationships could be represented in Brick using the feeds/isFedBy relationship; however, the feeds relationship is permitted only for a sequential process where a media is passed between the two end points. Because a loop is a cycle and the media within the loop changes as it interacts with different equipment, multiple relationships are needed to be used to represent their key relationships. For example, the Chiller $\leftrightarrow$ Loop could be represented with Chiller $feeds\rightarrow$ Loop and Loop $feeds\rightarrow$ Chiller. Where the first relationship is passing chilled water from the chiller to the loop, and the second is passing return warm water from the loop to the chiller.

### 4.3 Qualitative Analysis

Brick exhibited more desirable qualities than the Haystack ontology after documentation review. The qualitative analysis assessed the target ontologies for six desirable qualities by responding to
answering qualifying questions given statements made in supporting documentation, results can be seen in Table 10, and are discussed in more detail below. Brick exhibited five of the six, where Haystack only exhibited three. The Brick schema is based in descriptive logic whereas Haystack is in object-oriented design. These fundamentally different ontology schema approaches trickle down to different Linked Data approaches and affect the qualities the ontologies can exhibit.

Table 4: Qualitative Results

| Quality       | Qualifying Questions                                                                 | Brick | Haystack |
|---------------|--------------------------------------------------------------------------------------|-------|----------|
| Flexibility   | Can the ontology capture uncertainty in semantic data and does it use non-restrictive methods to define concept semantically? |       | ✓        |
| Portability   | Is semantic data represented consistently in a machine-readable format that is building agnostic? | ✓     |          |
| Readability   | Can domain experts and applications developers unambiguously decipher real world meaning from semantic data as presented in the ontology? | ✓     |          |
| Extensibility | Can the ontology be customized to add new semantic concepts?                         | ✓     | ✓        |
| Interoperability | Can the ontology integrate with, and convert to, other ontologies using an industry accepted format with little to no human effort? | ✓     |          |
| Queryability  | Can the instantiated ontology be machine traversed and necessary information retrieved? Is there low variability in semantic relationships? | ✓     | ✓ *      |

*Haystack is only queryable through a custom Filter functionality, this does not meet the full “queryability” quality definition

Flexibility

Haystack offers flexibility through the Tag based schema using Defs, which focuses on representing smaller units of semantic information than Brick. Tags allow Haystack to represent
uncertainty by allowing a limited number of Tags to be used when representing minimal semantic information. The freedom of using small units of semantic information to represent concepts offers a non-restricted way of defining semantic data, whereas Brick ensures concepts are prescribed with their more descriptive Classes composed of a set of unit Tags. The flexibility exhibited by Haystack will allow the ontology to represent a wide variety of buildings typologies with HVAC systems that might fall outside of the norm. Flexibility will also allow for the semantic description of a subset of specific concepts within a building if the whole ontology is not desirable and beneficial to a Smart Building application. Flexibility could decrease the portability of Smart Building applications across buildings.

Portability
The Brick schema’s prescribed representation of whole HVAC concepts ensures consistency across ontology instantiations facilitating Smart Building application portability. The same Smart Building application can be used in multiple buildings that employ Brick because similar HVAC system components across building are guaranteed to use the same Classes or subclasses of those. Alternatively, Haystack’s Tag based schema does not ensure consistency because it is flexible. Both ontologies are machine readable because they are serialized in a standardized format.

Readability
Brick was designed using descriptive logic and is therefore a readable ontology with explicitly defined semantic concepts and relationships. Semantic concepts are represented with a hierarchy of Classes: Equipment, Point, Measurable, Relationships, and Location, setting a clear
expectation of ontology use for end users. Alternatively, Haystack’s use of Tags can be used to represent semantic concepts in a variety of ways. The potential for inconsistency in semantic representation yields an ontology that is difficult to read and relate to real world meaning with confidence. An ontology that is not readable will mean that end user could have difficulty querying the ontology to access time series building HVAC system data not directly available in the BAS.

Extensibility

Both ontologies are extensible. The Brick can be extended by updating the schema definition file. Concepts are added to Brick by naming the concept, placing it within the existing class hierarchy, and defining tags associated with the concept, within in a Python script used to build the schema definition (.ttl) file. Haystack can be extended by defining new Defs directly in a library (.trio) file following the custom schema syntax.

Interoperability

Brick is interoperable with other ontologies serialized in an RDF format – the basis of ontology interoperability in the Linked Data approach described by W3C [29]. ontologies supporting the RDF format can be integrated with Brick by cross-referencing common concepts, giving Smart Building applications robust access to data. Additionally, Brick defines tags related to each Class which can be used to directly convert an instantiated Brick ontology to Haystack. Haystack is currently in the process of building functionality to serialize to the RDF format; however, it is not yet supported, and integration with other ontologies would need to be done manually.
Queryability

Brick uses a small set of nine bidirectional relationships, and SPARQL this facilitates the consistent retrieval of semantic data given the limited number of relationships and the high capacity for complexity in queries. Haystack documentation describes a query method ("Filters") that allows for the retrieval of semantic data using basic logic. The Haystack approach is less sophisticated than the semantic web query technology found in SPARQL supported by Brick, potentially affecting data recall. Without accurate data recall, Smart Building applications would not be able to access timeseries building data via the ontology.

5 Conclusions

Brick is better suited to represent and relate semantic HVAC data for buildings because it is more complete (77% of points fully or partially map), expressive (100% of relationships can be mapped), and is superior from a qualitative assessment. Brick is grounded in descriptive logic and use a communicative manner that is clear and concise to represent semantics facilitating the implementation and use of Smart Building applications in a Linked Data architecture. While Haystack achieves comparable scores in completeness (69%) and expressiveness (96%), it was only able to achieve three of the six key qualities, while Brick achieved five.

The Brick schema was structured in a prescribed manner that allows for the qualities of readability and portability to be supported, which was not supported by Haystack. These qualities facilitate Smart Building application development because concepts are represented unambiguously and consistently. Portability and readability together allow Smart Building applications to be modular, where they can be implemented across multiple buildings. Brick also
used W3C semantic web technologies, including RDF and SPARQL, which facilitate the support of other key qualities – interoperability and queryability – resulting in a functional Linked Data approach. Brick’s Linked Data approach allows for heterogeneous semantic data normalization of building data sources including HVAC data. The interoperability and queryability of Brick provide Smart Building applications the most robust and holistic representation of building data. Haystack uses Filters, a custom querying method to retrieve semantic data, this is as opposed to SPARQL used by Brick. SPARQL allows for portable queries to be written in Smart Building applications that can then be used in buildings with an ABox Brick ontology. The support of SPARQL will also allow Smart Building applications to have more easily interpreted yet complex queries because it is an established language. The qualities allow ontologies to facilitate Smart Building applications which reduced energy consumption and improved building HVAC system performance.

Although expressiveness assessment was practically inconclusive in recommending and ontology which better represents relationships it led to the consideration of the quality of relationships in target ontologies. Haystack used two bidirectional relationships to create Refs and Child Protos that relate various concepts but otherwise added no semantic information. Alternatively, Brick used a set of nine descriptive bidirectional relationships, each describing a type relationship used in a specific scenario. While Haystack relationships achieved a high score in expressiveness, they were not descriptive and as such the nature of the relationship could only be inferred. Smart Building applications will benefit from the small but descriptive set of relationships used in Brick because they offer more semantic information not provided in Haystack relationships.
Although the baseline ontology offered a wide variety of building systems to be considered in completeness and expressiveness testing it is assumed that the designers of the ontology have covered systems accurately and completely. If the baseline ontology is not representative of all building semantic data, then completeness and expressiveness assessments will not be accurate. Additionally, the qualitative assessment relies on a small body of available beta documentation, publications, and sample implementations of ontology schemas. Furthermore, the fluid state of beta versions implies changes in ontology schema by contributors over the course of study. Alternatively, using archived ontology versions would not lead to the most representative results as future implementations will not use such versions.

This research provides direction for the selection of an ontology to support the development of Smart Building applications. It should be recognized however that these ontologies are in a fluid and evolving state, requiring constant reevaluation as the requirements for Smart Building applications and ontology schemas change. After reaching a consensus on the selection of an ontology to support Smart Building applications, the largest hurdle to mass adoption will be the implementation of ontologies in brownfield buildings. The open question of “how ontologies can be implemented for brownfield buildings with minimal manual effort while offering high quality data normalization?” persists in current discourse. This research has however provided a firm footing for the conversation in asserting the aptitude of Brick in facilitating Smart Building applications.

Acknowledgments
This research was financially supported by the Natural Science and Engineering Research Council [CREATE 510284-2018], the Mitacs Accelerate program [IT15509], and Schneider Electric. The authors would specifically like to acknowledge the guidance and leadership of Oskar Nilsson and Jonas Bülow at Schneider Electric whose contributions were invaluable to this paper.

6 References

[1] Y. Li, R. García-Castro, N. Mihindukulasooriya, J. O'Donnell and S. Vega-Sánchez, "Enhancing energy management at district and building levels via an EM-KPI ontology," *Automation in Construction*, vol. 99, pp. 152-167, 2019.

[2] S. Hu, E. Corry, M. Horrigan, C. Hoare, M. Dos Reis and J. O'Donnell, "Building performance evaluation using OpenMath and Linked Data," *Energy and Buildings*, vol. 174, pp. 484-494, 2018.

[3] C. E. Kaed, B. Leida and T. Gray, "Building management insights driven by a multi-system semantic representation approach," in *2016 IEEE 3rd World Forum on Internet of Things (WF-IoT)*, 2016.

[4] M. Venugopal, C. M. Eastman, R. Sacks and J. Teizer, "Semantics of model views for information exchanges using the industry foundation class schema," *Advanced Engineering Informatics*, no. 26, pp. 411-428, 2012.

[5] E. Corry, P. Pauwels, S. Hu, M. Keane and J. O'Donnell, "A performance assessment ontology for the environmental and energy management of buildings," *Automation in Construction*, pp. 249-259, 2015.
[6] J. Gao and M. Bergés, "A large-scale evaluation of automated metadata inference approaches on sensors from air handling units," *Advanced Engineering Informatics*, vol. 27, pp. 14-30, 2018.

[7] P. Pauwels, E. Corry and J. O'Donnell, "Representing SimModel in the Web Ontology Language," in *International Conference on Computing in Civil and Building Engineering*, Orlando, 2014.

[8] D. Couloumb, C. E. Kaed, A. Garg, C. Healey, J. Healey and S. Sheehan, "Energy efficiency driven by a storage model and analytics on a multi-system semantic integration," in *Big Data*, Boston, 2017.

[9] G. Fierro and D. E. Culler, "Design and Analysis of a Query Processor for Brick," *ACM Transactions on Sensor Networks*, vol. 1, no. 1, 2018.

[10] G. Bajaj, R. Agarwal, P. Singh, N. Georgantas and V. Issarny, "A study of existing Ontologies in the IoT-domain," *arXiv preprint*, 2017.

[11] "About Project Haystack," [Online]. Available: https://project-haystack.org/about. [Accessed January 2020].

[12] "Defs," 24 October 2019. [Online]. Available: https://project-haystack.dev/doc/docHaystack/Defs. [Accessed Jan 2020].

[13] "Namespaces," 24 October 2019. [Online]. Available: https://project-haystack.dev/doc/docHaystack/Namespaces. [Accessed January 2020].

[14] "Relationships," 24 October 2019. [Online]. Available: https://project-haystack.dev/doc/docHaystack/Relationships. [Accessed January 2020].

[15] "File Formats," 24 October 2019. [Online]. Available: https://project-haystack.dev/doc/docHaystack/index. [Accessed January 2020].

[16] "Filters," 24 October 2019. [Online]. Available: https://project-haystack.dev/doc/docHaystack/Filters. [Accessed January 2020].
[17] V. Charpenay, S. Käbisch, D. Anicic and H. Kosch, "An Ontology Design Pattern for IoT Device Tagging System," in *International Conference on the Internet of Things (IoT)*, Seoul, 2015.

[18] B. Balaji, A. Bhattacharya, G. Fierro, J. Gao, J. Gluc, D. Hong, A. Johansen, J. Koh, J. Ploennigs, Y. Agarwal, M. Berges, D. Culler, R. Gupta, M. B. Kjærgaard, M. Srivastava and K. Whitehouse, "Brick: Towards a Unified Metadata Schema For Buildings," in *Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, Palo Alto, 2016.

[19] B. Balaji, A. Bhattacharya, G. Fierro, J. Gao, J. Gluck, D. Hong, A. Johansen, J. Koh, J. Ploennigs, Y. Agarwal, M. Bergés, D. Culler, R. K. Gupta, M. B. Kjærgaard, M. Srivastava and K. Whitehouse, "Brick : Metadata schema for portable smart building applications," *Applied Energy*, vol. 226, pp. 1273-1292, 2018.

[20] "Community," 2019. [Online]. Available: https://brickschema.org/community. [Accessed January 2020].

[21] A. Bhattacharya, J. Ploennigs and D. Culler, "Short Paper: Analyzing metadata schemas for buildings: The good, the bad, and the ugly," in *ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys)*, Seoul, 2015.

[22] D. Vrandečić, "Ontology evaluation," in *Handbook on Ontologies*, S. Staab and R. Studer, Eds., Berlin, Heidelberg, Springer Berlin Heidelberg, 2009, pp. 293-313.

[23] J. Brank, M. Grobelnik and D. Mladenic, "A survey of ontology evaluation techniques," in *Proceedings of the conference on data mining and data warehouses (SiKDD 2005)*, 2005.

[24] A. A. Bhattacharya, D. Hong, D. Culler, J. Ortiz, K. Whitehouse and E. Wu, "Automated Metadata Construction To Support Portable Building Applications," in *International Conference on Systems for Energy-Efficient Buildings*, Seoul, 2015.

[25] C. E. Kaed and M. Boujonnier, "FOrT E: A Federated Ontology and Timeseries query Engine," in *iThings*, Exeter, 2017.
[26] "Downloads," 24 October 2019. [Online]. Available: https://project-haystack.dev/download. [Accessed December 2019].

[27] "Brick/Brick.ttl," 21 February 2020. [Online]. Available: https://github.com/BrickSchema/Brick/blob/master/Brick.ttl. [Accessed February 2020].

[28] G. Fierro, M. Pritoni, M. AbdelBaky, P. Raftery, T. Peffer, G. Thomson and D. E. Culler, "Mortar: An Open Testbed for Portable Building Analytics," in *ACM International Conference on Information and Knowledge Management (BuildSys)*, Shenzen, 2018.

[29] W3C, "SEMANTIC WEB," 2015. [Online]. Available: https://www.w3.org/standards/semanticweb/. [Accessed March 2020].

[30] J. Gao, J. Ploennigs and M. Bergés, "A Data-driven Meta-data Inference Framework for Building Automation Systems," in *ACM International Conference on Information and Knowledge Management (BuildSys)*, Seoul, 2015.

[31] B. Balaji, C. Verma, B. Narayanaswayy and Y. Agarwal, "Zodiac: Organizing Large Deployment of Sensors to Create Reusable Applications for Buildings," in *ACM International Conference on Information and Knowledge Management (BuildSys)*, Seoul, 2015.

[32] D. Hong, H. Wang and K. Whitehouse, "Clustering-based Active Learning on Sensor Type Classification in Buildings," in *ACM International Conference on Information and Knowledge Management (CIKM)*, Melbourne, 2015.

[33] D. Hong, H. Wang, J. Ortiz and K. Whitehouse, "The Building Adapter: Towards Quickly Applying Building Analytics at Scale," in *ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys)*, Seoul, 2015.

[34] J. Koh, B. Balaji, D. Sengupta, J. McAuley, R. Gupta and a. Y. Agarwal, "Scrabble: Transferrable Semi-Automated Semantic Metadata Normalization Using Intermediate Representation.," in *ACM International Conference on Information and Knowledge Management (BuildSys)*, Shenzhen, 2018.
[35] A. Ratner, P. Varma, B. Hancock and C. Ré, "Weak Supervision: A New Programming Paradigm for Machine Learning," The Stanford AI Lab Blog, Stanford, 2019.

[36] Z. Shi, G. R. Newsham, L. Chen and H. Gunay, "Evaluation of Clustering and Time Series Features for Point Type Inference in Smart Building Retrofit," in ACM International Conference on Systems, New York, 2019.

[37] F. Leonardi, H. Reeve, T. Wagner, Z. Xiong and J. Park, "Assisted Point Mapping to Enable Cost-effective Deployment of Intelligent Building Applications," in International High Performance Buildings Conference, West Lafayette, 2016.

[38] J. Koh, D. Hong, R. Gupta, K. Whitehouse, H. Wang and Y. Agarwal, "Plaster: an integration, benchmark, and development framework for metadata normalization method," in ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys), Shenzhen, 2018.

[39] P. Pishdad-Bozorgia, X. Gao, C. Eastman and A. P. Selfa, "Planning and developing facility management-enabled building information model (FM-enabled BIM)," Automation and Construction, vol. 87, pp. 22-38, 2018.

[40] M. G. Damm, "Method and system to manage complex systems knowledge". United States of America Patent 8,595,258, 2013.

[41] B. East and M. Carrasquillo-Mangual, "The COBie Guide," National Institute of Building Sciences, Washington, 2013.

[42] P. Pauwels, S. Zhang and Y.-C. Lee, "Semantic web technologies in AEC industry: A literature overview," Automation in Construction, vol. 73, pp. 145-165, 2017.

[43] A. Mahdavi and M. Taheri, "An ontology for building monitoring," Journal of Building Performance Simulation, vol. 10, no. 5-6, pp. 499-508, 2017.
[44] O. H. Uribe, M. Adil, M. C. Garcia-Alegre and D. Guinea, "A context-awareness architecture for managing thermal energy in an nZEB building," in *2015 IEEE First International Smart Cities Conference (ISC2)*, 2015.

[45] D. Schachinger and W. Kastner, "Ontology-based generation of optimization problems for building energy management," in *2017 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 2017.

[46] B. Bortoluzzi, I. Efremov, C. Medina, D. Sobieraj and J. J. McArthur, "Automating the creation of building information models for existing buildings," *Automation in Construction*, vol. 105, p. 102838, 2019.

[47] S. Borgo, E. M. Sanfilippo, A. Sojic and W. Terkaj, "Towards an ontological grounding of IFC.," 2014.

[48] B. Frank, "VRF support status & v4 release timeline," 13 December 2019. [Online]. Available: https://project-haystack.org/forum/topic/771. [Accessed February 2020].

[49] B. Butzin, F. Golatowski and D. Timmermann, "A Survey on Information Modeling and Ontologies in Building Automation," in *43rd Annual Conference of the IEEE Industrial Electronics Society*, Beijing , 2017.

[50] J. J. Bender, "Will Haystack 4 substitute Brick and Haystack 3?," Google Groups, 1 12 2019. [Online]. Available: https://groups.google.com/forum/#!topic/brickschema/Hpm8QDruJ4I. [Accessed 2020].

[51] pwnall, "google/LevelDB," Google, 13 April 2020. [Online]. Available: https://github.com/google/leveldb. [Accessed April 2020].

[52] M. Andersen, "BTrDB: Berkeley Tree Database," [Online]. Available: http://btrdb.io/. [Accessed April 2020].

[53] "Home," 2019. [Online]. Available: https://brickschema.org/#home. [Accessed April 2020].
