

# Development of a National Scale Digital Twin for Domestic Building Stock

Cathal Hoare<sup>1,\*†</sup>, Tareq B. M. AlQazzaz<sup>1,†</sup>, Usman Ali<sup>1,†</sup>, Shushan Hu<sup>2,†</sup> and James O'Donnell<sup>1,†</sup>

<sup>1</sup>*School of Mechanical and Materials Engineering and UCD Energy Institute, University College Dublin, Belfield, Dublin 4, Dublin, Ireland*

<sup>2</sup>*Hubei University, Wuhan, Hubei, China*

## Abstract

The operation of buildings accounted for 40% of global energy consumption and 27% of greenhouse gas emissions (GHG) in 2022. Access to integrated information sources about a building stock is key to supporting policy and decision makers as they pursue green house gas reductions. However, over time, information has evolved into functional silos which accordingly limits the ability of experts in functional areas to exchange data and implement broader decision support systems. This paper describes the creation of a national scale digital twin for a national domestic building stock and is achieved through the use of semantic technologies to create a homogeneous knowledge graph from multiple heterogeneous data sources. The utility of the digital twin is demonstrated by the development of a virtual surveyor. This tool is used to predict building features such as window u-values for buildings that have not been surveyed as part of the national EPC scheme. In turn, these values are used to enrich the digital twin.

## Keywords

Digital Twin, National-Scale Building Stock, Semantic Web, Computer Vision

## 1. Introduction

The operation of buildings accounted for 40% of global energy consumption and 27% of greenhouse gas emissions (GHG)[1] in 2022. According to the International Energy Agency, further statistics indicate that 8% of GHG emissions and 19% indirect GHG emissions related to buildings are due to the production of electricity and heat. The EU member states have established a legislative framework to boost sustainable strategic planning and improve the energy performance of buildings. The framework includes the Energy Performance of Buildings Directive (EPBD) 2010/31/EU and the Energy Efficiency Directive 2012/27/EU. The members of this directive promote policies directed towards implementing measures to achieve a highly energy-efficient and decarbonized building stock by 2050 [2].

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\*Corresponding author.

†These authors contributed equally.

✉ cathal.hoare@ucd.ie (C. Hoare); tareq.alqazzaz@ucdconnect.ie (T. B. M. AlQazzaz); usman.ali@ucd.ie (U. Ali); shushan.hu@hubu.edu.cn (S. Hu); james.odonnell@ucd.ie (J. O'Donnell)

ORCID 0000-0002-0877-7063 (C. Hoare); 0000-0002-0877-7063 (U. Ali); 0000-0001-9043-2875 (S. Hu); 0000-0001-7116-9338 (J. O'Donnell)



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Long-term renovation strategies are required to achieve higher level of sustainability and decarbonize the building stock. The information that must be managed to support these strategies is, however, complex and heterogeneous, both in content and organization [3]. Information sources are dynamic, evolving, and multifaceted; information can be distributed across multiple sources providing related, yet heterogeneous collections of data that inform utility companies, planners and other stakeholders [4]. National and district level views of the same entities are managed by separate formats and systems, requiring expensive data reorganization in order to extract relevant information for planners and policy makers [5, 6, 7]. Taken together these data sources, as an integrated whole, would provide rich insights to a variety of stakeholders; however, their current utility is diminished by their disjointed and heterogeneous nature. This work develops a national-scale digital twin to overcome these difficulties and increase the utility of the data sets by integrating these diverse sources into a single connected homogeneous data source[8].

This paper describes the use of the Dynamic District Information Management Server (DDIM) [9] to integrate multiple government, national agency and commercial data sources. In so doing, a country scale digital twin is created to provide a rich view of national domestic building stock. The work utilizes the DDIM to create a common context for these data sources and provides a platform to support data access. The creation of this context and overarching data structure will be described. The utility of the approach will be further illustrated by a use case that uses the digital twin's data and computer vision to enrich its own data.

After providing a background to key concepts used in this work, the paper will continue by describing the data sources and how a common context was created for these. The enrichment use case will then be described before concluding with potential future directions for the work.

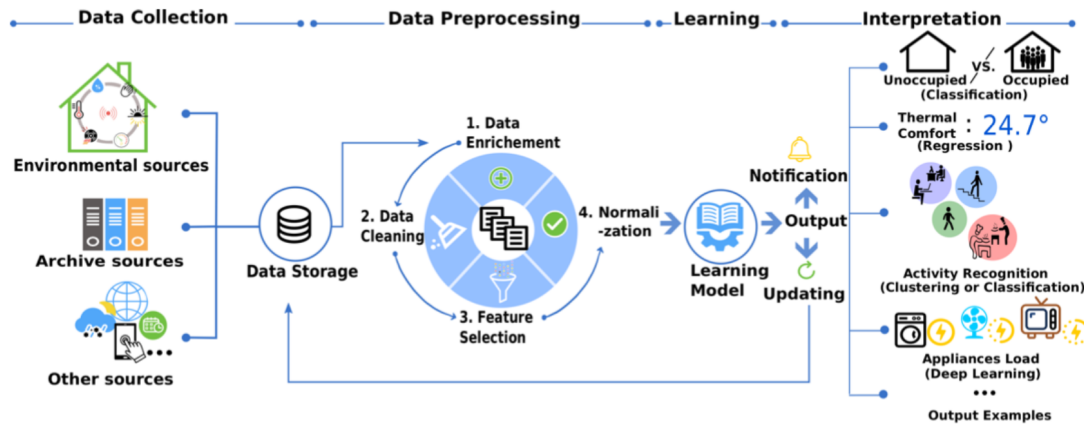
## **2. Background**

This work uses semantic technologies to create mapping relationships between a collection of data sources. These mappings seek to define a context that is common to all data sources. Having defined this core or common context, other data sources are integrated with this data structure to create an integrated homogeneous data source.

### **2.1. The Semantic Web and Energy Modelling**

Digital twins (e.g. [11, 12, 13]) provide data and analysis that can inform decision support systems. Typically, the architecture of decision support systems broadly follow that shown in Figure 1 [10]. Four general tasks, including data collection (including integration and enrichment), data processing, learning and interpretation combine human intelligence and machine learning techniques to inform decisions with many dynamic variables.

This work uses semantic technologies[14] to create the digital twin. While data are encoded as RDF, meaning is imbued by providing ontologies that define the concepts and relationships of a domain, and so provide meaning to the encoded data [15]. These meanings provide a common vocabulary between different data providers, ensuring that data can be exchanged and integrated in a structured way. These ontologies are represented using Web Ontology Language (OWL). This approach has been used extensively in both industry and research to facilitate data



**Figure 1:** The general organisation of simulation and other machine learning systems [10]

integration and exchange. The use of ontologies to facilitate data exchange and integration was explored by [16], while the ability to reuse, and so broaden the adoption of these ontologies was explored by [17]. Linked data has been used to support complex reasoning. For example, Baumgärtel et al [18] used semantic approaches to reason about the application of building performance regulations to design and operation; in doing so, they improved the efficiency and effectiveness of a complex form of analysis.

## 2.2. The Role of Context

Context provides a framework to allow entities to be related to one another. The concept of using a common context has been used by several works to provide a mechanism to integrate and share AEC information. ISO 21597's approach provides a framework that expresses a common context by creating a document container that represents some context [19]; documents and other data related to that context can be grouped together in this container. The embedded documents are not modified and the notion of relatedness between them is communicated through their common association with the container. This approach is, in itself, a combination of the Multi-model [20] and Linked Building Data (LBD) approaches [21]. The former created a common context for distributed information collections that form a federated database. A series of ID-based links are formed between collections, creating an interlinked collection of data that can then be subject to query. These federated queries - queries that can be distributed amongst several linked data sources - are submitted to a single authority, which responds by querying the distributed members of the database and returning an aggregation of those results. The approach is beneficial because data can be maintained in its original format, though some compatible API must be provided to make each source queryable [22, 23]. LBD also admits the concept of a common context; in this approach, relationships between represented entities are captured through relationships that are defined as part of some ontology defined using the Web Ontology Language (OWL). Objects within the resulting model are uniquely identified using a URI and related objects can be retrieved by querying across relationships using the SPARQL

language which supports federated queries; as a result, data can be distributed across multiple servers.

### **3. Methodology**

The paper continues by describing the implementation of the digital twin using the Dynamic District Information Server (DDIM) server [9]. The text further describes the initial data sources used and the DDIM server that marshalled these data. The structure used to support data integration is examined, before a description of the mechanism for data access is provided.

#### **3.1. Data Sources**

GeoDirectory GeoAddress [24] and GeoBuilding Intel [25], SEAI's BER research tool [26] and commercial data form the core data that is managed by the digital twin. GeoDirectory's GeoAddress and GeoBuilding Intel databases are created by the Irish Postal Service, An Post, and Ordnance Survey Ireland, the Irish State's National Mapping Agency. GeoDirectory contains an extensive database on Irish domestic stock, including geographical contexts (addresses, Irish postal codes (Eircodes) and longitude/latitude), mappings to organisational geographical contexts (small areas, urban areas, counties, etc) and building information, including details of building fabric, building epoch, and other data relevant to energy modelling; this later data is extensive, though not comprehensive across the entire stock.

Each building is related to a small area and other administrative areas. Equivalence tables are created between building address, longitude/latitude and Eircode. These building data are also enriched by adding Building Energy Rating (BER) certificate data (Ireland's Energy Performance Certificates (EPC) scheme). This data provides a detailed picture of the building fabric, heating systems and other data significant to energy modelling. BER certificates are required by home owners when selling, renting or applying for energy oriented renovation grants. As such, certificates exist for just under one half of Irish domestic building stock. Both Geodirectory data and BER sources are provided in comma separated file (CSV) format. For the purposes of the use case described later, one other category of data is collected. This data is building imagery. This was collected from a variety of commercial sources including images used in realtor oriented websites and street level imagery. While the raw images are maintained in their original format in a file hierarchy, CSV formatted meta data about the images was also collected and submitted to the DDIM for management. Like the BER data, these meta data were associated with individual buildings through longitude/latitude, address or Eircode.

#### **3.2. Using the DDIM to Create a Common Context**

The Dynamic District Information Model (DDIM) [9], is used to mine and manage relationships between the data sources mentioned above. For this project, the DDIM uses the relationships that exist between geographical areas and locations to provide a common context between data sources. This context is captured through an RDF graph where relationships conform to a context ontology (see Section 3.3). This allows queries at one level of geographical granularity,

for example, details of individual buildings, to be associated with data stored at a different granularity; this approach allows data to remain in context, reducing data duplication. Furthermore, data sources remain general and are not specific to any one purpose; they can be reused for other interrogation tasks.

The server implementation consists of three key functional areas:

- A 'Core Spine' or RDF schema that can be used to place other information in the space and time covered by the project. This spine allows information to be associated with entities in either the urban or building information spaces, and creates a bridge to allow seamless querying across these spaces;
- A series of interfaces to allow client software to query (through RESTful or SPARQL based interfaces);
- A DCAT compliant data catalogue;

The server is implemented using the Django Framework [27] with RESTful [28] extensions. This framework also provides user management and security. GraphDB [29] is installed within the same domain. SPARQL queries are submitted through the Django server to this and its functionality is responsible for the execution of any federated queries to the distributed sources.

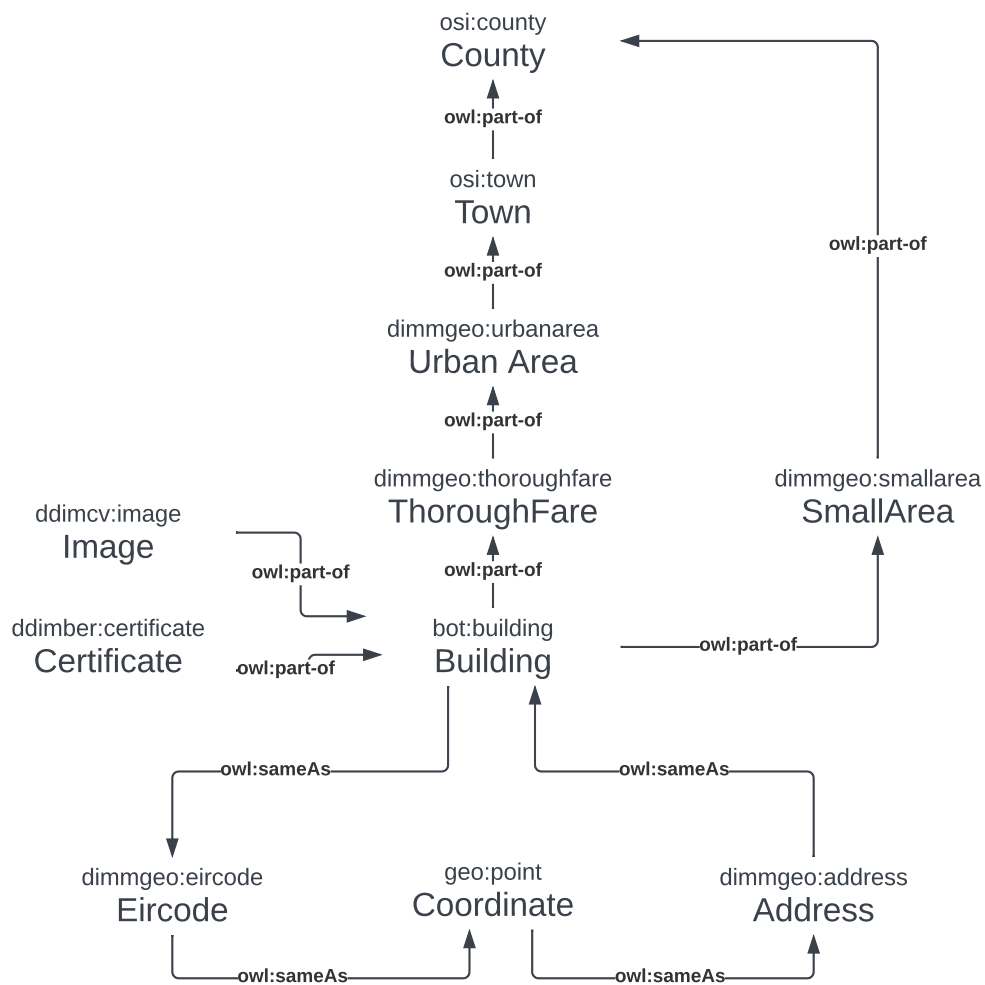
As well as describing an entity's context, the 'core spine' also informs relationships mined from uploaded data. For example, in this project, buildings are contained by small areas. These relationships are defined as rules at project setup and as information sources are uploaded to the server, triples are generated by applying these rules. Federated queries are also supported. In this case, triples are generated, again from the rules, but the named entities include the Uniform Resource Identifier (URI) of remote entities; the model permits the data sources' owners to maintain complete ownership and access control over their information on their own servers; this allows them to contribute information while mitigating against any reluctance due to commercial or regulatory concerns.

### 3.3. Data Integration

Data integration was achieved using semantic web technologies. Figure 2 shows the resulting data structure. The core context places the Building at the core of two different contexts, both by defining entity hierarchies to a county level (counties represent high level administrative areas and their aggregation represents the national level). These hierarchies are grouped by county and local administrative entities through to individual buildings. A second organisation uses small area - areas containing 65-90 households to create a second hierarchy. These entities and relationships are defined either by the OSI ontology or by using a project ontology (until the entities are also defined as part of OSI). Buildings can be uniquely<sup>1</sup> identified by Eircode or address, and depending on the building type (bungalow, detached, semi-detached) by their geographic co-ordinates. Buildings can be associated with two other entities, imagery of the building (via realtor data or street level imagery) and with their BER certificate data; one or other or both of these entities may not be present, and indeed, the range of properties for each building may also vary depending on their availability in the original data sources.

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<sup>1</sup>Strictly speaking, some rural addresses are not unique until the home owner name or Eircode is included



**Figure 2:** Graph structure for National Scale Digital Twin for Domestic Building Stock.

### 3.4. Data Access

The DDIM server provides a data registry where entries are described using W3C's DCAT ontology to aid knowledge discovery. This creates a catalogue of data sources, versions of data published and other metadata such as the publishing agent. A catalogue record includes an endpoint for data sources published (a network address where SPARQL queries can be submitted to query the source) and the source's schema or data model. Together, these models allow a stakeholder to examine source models, formulate federated queries across these and submit the query through the DDIM server.

## 4. Use Case: A Computer Vision Agent for Data Enrichment

Having described the implementation of the digital twin, with a focus on Irish datasets, this paper will now describe a use case to illustrate the utility of the approach. The digital twin supports energy modelling and so must serve a minimum set of parameters for each building. The existing data ingested to populate the twin with these parameters provide limited coverage of the national domestic building stock. A virtual surveyor is trained using the twin's data. In turn, the surveyor is used to classify other data contained by the twin and in so doing, derives values for some of the missing parameters.

While the focus of this work so far has been on Irish data, the need for similar solutions in other jurisdictions is apparent. The United Kingdom, Ireland, Belgium, Denmark and Portugal have coverage of greater than .1 registered EPC certificates per capita, the highest figures in the EU [30]. When average household occupancy is considered, this indicates significant gaps in coverage even in countries with high EPC registrations. The need to carry out accurate enrichment of these data sets is urgent. This process is enabled by the availability of national-scale digital twins of the type described in Section 3.

### 4.1. Minimum Set of Energy Modelling Attributes

Several studies have identified the non-geometric and geometric parameters associated with the existing building stock to perform a parametric simulation for energy modelling. For instance, the building physics parameter values (window, wall, roof, and floor u-values) and their ranges can be extracted from EPC data such as that contained in the digital twin. Studies by Egan et al. [31] and Ali et al [32] have identified other relevant non-geometric parameters that influence the energy performance of the Irish building stock.

When the available data sources are examined, it is found that 2,377,498 domestic properties are listed (including derelict sites). In total, details of 1,055,975 BER certificates are available for research purposes (coverage of 44% of all properties); where available, BER data contains all of the parameters listed in Table 4.1. Building attributes that can inform parameter values are also present in the Building Intel database. In this case, coverage varies depending on the attribute sought. The Virtual Surveyor Agent was proposed to improve these coverage figures.

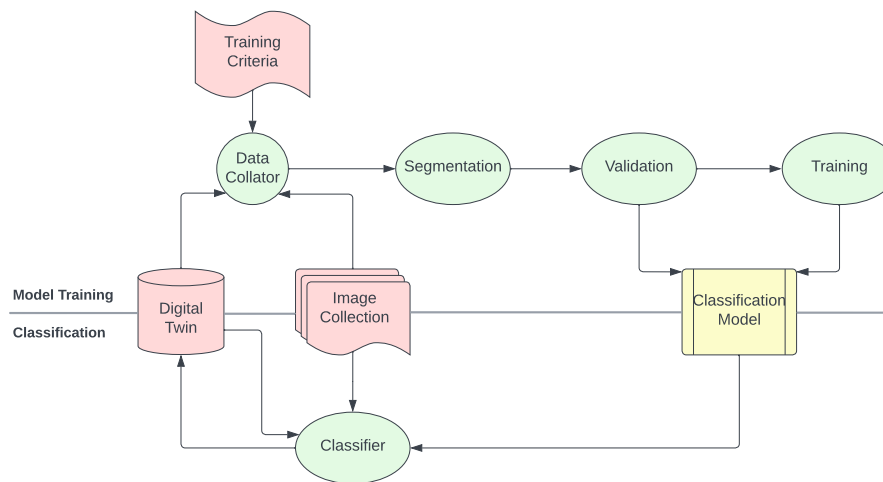
### 4.2. Approach to Data Enrichment

The Digital Twin was used to conduct self-enrichment by informing a virtual surveyor agent. The agent, trained using data stored in the digital twin, will classify building elements contained in high quality realtor imagery of buildings in order to determine some of the values listed in Table 4.1. Once the surveyor has been trained, it could be used to classify street level imagery that has high coverage of building stock with the agreement of commercial data providers. Initially, the approach has been used to determine window u-values for a small area.

A high-level architecture of the virtual surveyor is shown in Figure 3. This is divided into two elements, training and operational classification. Data training criteria are used to identify imagery to use for training and validation of the classifiers. These criteria include identifying buildings with known u-values, building epoch, and building type. Having applied these criteria

Number	Parameters	Unit
P1	Wall U-value	$W/m^2K$
P2	Window U-value	$W/m^2K$
P3	Floor U-value	$W/m^2K$
P4	Roof U-value	$W/m^2K$
P5	Door U-value	$W/m^2K$
P6	Orientation	North Axis {deg}
P7	Lighting density	$W/m^2$
P8	Occupancy	Person(s)
P9	Equipment density	$W/m^2$
P10	Heating setpoint	$^{\circ}C$
P11	Heating setback	$^{\circ}C$
P12	HVAC efficiency	%
P13	Renewables	boolean
P14	DHW	$l/m^2/day$
P15	ACH	Air changes per hour
P16	Window-to-wall ratio	%
P17	Heating factor	numeric
P18	Electricity factor	numeric

**Table 1**  
Parameters needed for parametric simulation of archetypes [32].



**Figure 3:** Virtual Surveyor architecture for training and classification of building imagery to determine simulation parameters.

to filter appropriate imagery, the images are segmented into training and validation sets. A Python implementation using TensorFlow is used to create a classifier. After the classifier's accuracy is validated it is made operational and used to classify street level imagery for buildings in the digital twin. Once windows for a building are classified, their  $\mu$ -value is written back to the digital twin to update building's data.



### **4.3. Preliminary Results**

The virtual surveyor has been trained to classify window u-values. While results are promising, it remains a work in progress. Currently the classifier achieves an accuracy of 76% when classifying images of windows with no other building fabric. Initial work has show that this figure improves to 81% when some of the building facade is included as it offers more context to the classifier; the amount of facade to include remains an open question. It has been found that the approach works well when classifying second floor windows and higher for buildings in urban and suburban areas. This is because a clear view of ground floor windows can be obstructed by traffic, garden plants, etc. One off builds are also less likely to provide a clear view of the windows, or have problems identifying windows due the the heterogeneous design, building orientation or location of building on property. It is expected that these difficulties will extend to other ground level features such as door u-values. However, it is anticipated that enrichment for up to 70% of building stock that currently have no EPC data will be possible.

## **5. Conclusions and Future Work**

Energy oriented renovation policies are an important pillar for green house gas reduction. Energy modelling at regional and national scales can provide decision support to policy makers and other stakeholders. While large data sets exist to inform decision support, the data's heterogeneous structure is costly to integrate and utilize. Creation of a knowledge graph through the use of semantic technologies and the development of a common context.

The work described here creates a national scale digital twin Irish domestic building stock. The graph is created, managed and queried through the DDIM server. This uses rules to define relationships that can be used to mine triples from the data set. These are, in turn, managed by a GraphDB instance that is part of the DDIM. The utility of the digital twin is demonstrated by the development of a virtual surveyor. This tool is used to predict building features such as window u-values. It is trained by data queried from the digital twin, and in classifying window types is capable of accurately enriching the its data.

The development of both the digital twin - through the addition of new data and data sources will continue in parallel with the development of classifiers to expand the virtual surveyor. In addition to windows and other external features, other forms of imagery such as aerial views will be integrated to determine values for other parameters used in energy modelling. Together these advances will continue to improve the accuracy and coverage of data available to guide Ireland's move towards energy efficient building stock.

## **6. Acknowledgments**

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