Linked Data Ontology for Urban Scale Building Energy Simulation

James Allan, Léonie Fierz, Andrew Bollinger, Kristina Orehounig
Empa, Überland Str. 129, 8600 Dübendorf, Switzerland

Abstract

This paper details the Urban Energy Simulation (UES) ontology, which is designed to facilitate the handling and organisation of heterogeneous data used in urban building energy modelling projects. The UES ontology has been integrated into an existing urban energy modelling platform and contains a standardised vocabulary that aims to overcome challenges of data availability, accuracy and traceability that are commonly encountered in urban scale building energy modelling. This paper reviews the existing data models, formats and modelling tools before detailing the UES ontology and giving examples of its use.

Introduction

Urban scale building energy models (UBEM) simulate the energy performance of every building contained within a geographic area such as a district, city, or entire country. These models are valuable for urban planning, energy system design and the evaluation of energy initiatives. Over the past 10 years, there has been considerable research into UBEMs. Despite these advances, challenges remain regarding data collection, data modelling and data accuracy. This paper details the Urban Energy Simulation (UES) Ontology which has been integrated into the CESAR-P UBEM platform[1]. CESAR-P is an open-source python implementation of the CESAR tool detailed in (Wang et al., 2018). The primary purpose of CESAR-P is the large scale simulation of individual buildings. It uses archetypical assumptions for some of the input data (but not for geometry). The archetypes contain statistical information about buildings from a range of different data sources. The UES ontology defines the classes, properties and individuals that are used in the formation and application of the archetypes. Ontologies are key components of semantic knowledge graphs which allows automated and standardised reasoning of the data.

Urban Energy Tools

A comprehensive review of tools for UBEM has been carried out by Hong et al. (2020). UBEM platforms are often developed to interface established simulation engines such as EnergyPlus (CESAR (Wang et al., 2018), Umi (Reinhart et al., 2013)); whereas some tools use their own calculation engines (TEASER (Remmen et al., 2018), CitySim (Robinson et al., 2009), SimStadt (Nouvel et al., 2015)). Some are designed to be standalone (CitySim), whereas others are plugins for existing software (Umi, UrbanOpt(Polly et al., 2016)).

Data Resources and Archetypes

The simulation of detailed, bottom-up engineering models requires information on each building, and the data used to parameterize the models is often sourced from multiple datasets and sources. Quite often data is missing, inaccurate or requires processing before it can be integrated into a model (Braun et al., 2018).

Building archetypes are representative buildings for a specific category and they are typically created from statistical data. One of the largest collaborative projects into archetypes was the Tabula project which defined a range of building archetypes for individual EU countries (Loga et al., 2016).

The energy performance of an entire country's building stock can be predicted using only archetypes. Streicher et al. (2019) grouped the entire building stock of Switzerland into 54 archetypes (age/building type/urban typology) and then evaluated the residential space heating demand for the country. Clustering has also been used to define representative buildings and districts for multi-objective optimisation of retrofit measures (Murray et al., 2020).

CESAR-P uses archetypes (age/building type/building use) to populate the simulation parameters for each building. The information contained within the archetypes can be categorised as:

- **Building Construction Characteristics** - Based on the year of construction and includes information on the materials, construction types, infiltration rates and glazing ratios.
- **Internal Conditions** - Based on building usage and includes information on user behaviour, operational set-points and ventilation rates.

Because archetypes contain assumptions, it is essential that the data sources are traceable; however, this they are often not clearly documented, making it difficult to establish where information originated.

[1] https://github.com/hues-platform/cesar-p-core

Data Models and Data Formats

UBEMs often require data from multiple sources. A UBEM project will typically have;

1. **Spatial data points** - representing the building location and/or geometry and defined using a coordinate reference system.

2. **Factual data** - contains data fields with factual information such as age, energy system, usage and address.

3. **Statistical data** - data from sources such as surveys, is clustered and aggregated for building categories and used to create archetypes.

4. **Measured data** - monitored data on the energy performance or the variables that influence it, such as occupancy or temperature. This could either be in the form of a time-series or aggregated values.

The CityGML format was developed to represent and exchange 3D City Models. The building feature can be represented using 5 defined Levels-of-Detail (Gröger and Plümer, 2012). The semantic labelling of features in CityGML enables spatio-semantic coherence checking of the data (Stadler and Kolbe, 2007). Despite this, there are still issues with both the factual and geometric data contained within raw files. Braun et al. (2018) describes some of the challenges experienced when preparing UBEM using a CityGML dataset; this included missing data, incorrect data and geometric inconsistencies. CityGML is extensible through the use of Application Domain Extensions (ADE). A recent review revealed 44 different ADEs that have been applied to CityGML (Biljecki et al., 2018). The most established of the ADEs is the EnergyADE which provides a model for storing information related to building energy performance (Agugiaro et al., 2018). The development of CityGML Energy ADE has addressed the requirements of BEDES (Spears et al., 2019) and INSPIRE (European Commission, 2007), which are efforts to harmonise the terms used in energy assessment and spatial modelling respectively (Nouvel et al., 2015).

Even with well-developed specifications, it remains a challenge to map raw data to data models. An evaluation of available public data sets in San Francisco found that there was a lack of common keys to enable easy mapping; despite using CityGML, it was necessary to use generic attributes to keep a record of all of the collected information (Chen et al., 2019). Similar conclusions were drawn by Rosser et al. (2019), who demonstrated the mapping of datasets to EnergyADE using two example case studies of locations in the UK. They also showed the impact on energy demand of using geometric simplifications of roof geometries - something necessary if the methodology is to scale with large datasets.

Relational Databases

The challenge of managing all of the data sources for UBEM is tackled in CityBES by generating a Master Building Dataset Chen et al. (2017). CityBES interfaces with the Commerical Building Energy Saver (CBES) (Hong et al., 2015) to generate the building demands. The purpose of CityBES is to extract the relevant information from raw datasets for representation in a 3D City Model.

An alternative solution to storing geometric data is 3DCityDB; an Open Source geodatabase solution, based on relational databases, that manages, analyses and visualises 3DCity models. The development of 3DCityDB is currently focused on handling the ADE extensions of CityGML (Yao et al., 2018). Nageler et al. (2017) used a relational PostgresSQL database to organise the multiple data sources encountered during UBEM. They defined the workflow around two databases: a project database, containing input data, assigned data and results; and a typology database containing reusable data such as building types, constructions and load profiles. Schiefelbein et al. (2015) developed a City Information Model, managed using an relational database using PostgreSQL and PostGIS, to extract the parameters required for simulation.

Linked Data and Semantic Graph Databases

Unlike relational databases, semantic graph databases do not require a fixed schema to store data. This means that there are no restrictions on the data that can be stored within them. This makes them ideal for processing the non-heterogenous datasets encountered in UBEM, but necessitates the need for an ontology with standardised terminology. The construction of semantic graph databases is based on the principles of linked data. Linked data incorporates a number of semantic technologies to provide structure and context to data. Although the idea of linked data was originally conceived for the internet, the technologies have been implemented to share information between data silos within enterprises (Allemang, 2010).

There have been several applications of semantic graph databases to process building data. O'Donnell et al. (2013) reports on an implementation approach based on linked data to overcome interoperability issues, and complex event processing to handle real-time scenarios. Corry et al. (2014) further develops the work and demonstrates how semantic web technologies can be used to facilitate the exchange of cross-domain data. At urban and national scale, Bischof et al. (2015) describes the use of the Siemens Open City Data Platform, which uses an automated approach to collect and enrich open data as a means of gathering city performance indicators. Kotoulas et al. (2014) describes the SPUD framework, a semantic environment for carrying out operations on urban

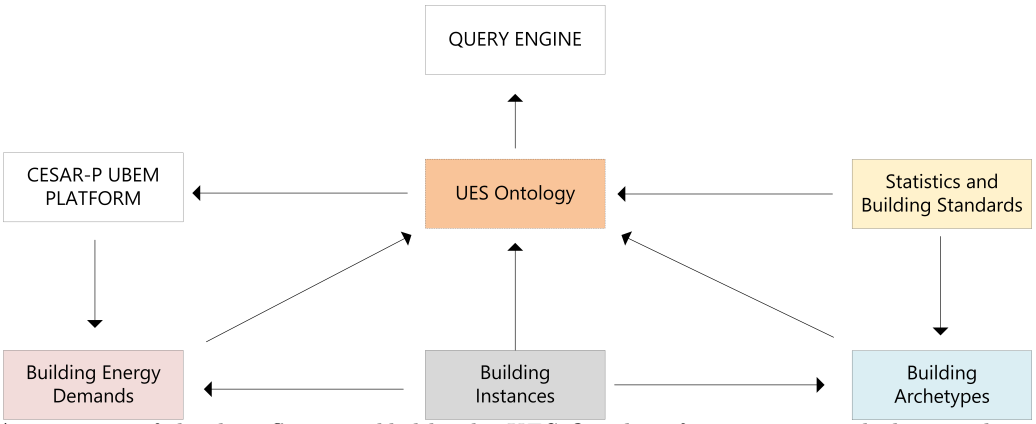


Figure 1: A summary of the data flows enabled by the UES Ontology for structuring, linking and querying data. The ontology is the central component to the data architecture making it possible to query both the simulated energy demands and the assumptions that were made by the application of building archetypes.

information. The SPUD platform enabled continual integration of static and streaming city data from sources such as social media. Consoli et al. (2017) detailed a comprehensive data model for generating insight into smart cities using semantic technologies to integrate data resources from heterogeneous sources; this included geo-referenced data, public transport, urban-fault reporting, road maintenance and waste. Hoare et al. (2019) developed the Dynamic District Information Server (DDIS) to flexibly store undefined data structures that enables querying across different spatial scales ranging from neighbourhoods to regions.

Semantic Technologies

Linked data incorporates three main semantic technologies:

1. **RDF** - Stores data in the form of relationships between two unique objects defined by Uniform Resource Identifiers (URI).

2. **OWL** - A language used to represent a set of generalised or domain specific vocabularies known as ontologies, that are used to determine or infer relationships between objects.

3. **SPARQL** - The query language used to retrieve and process data stored in RDF.

Costin and Eastman (2019) provides an overview of available frameworks, ontologies and platforms for the exchange of information in a smart and sustainable energy system. They conclude that the most significant challenge is the lack of standardisation and consistency between the approaches which is preventing interdisciplinary interoperability. Holten Rasmussen et al. (2018) reviewed both the generalised and domain specific ontologies used in the architecture, engineering and construction and proposed the Building Topology Ontology (BOT) as a simplified vocabulary to describe the topological concepts of a building[2]. Schneider (2017) demonstrated how the BOT ontology could be aligned with five domain specific ontologies.

Of the ontologies reviewed, the published SEMANCO ontology[3] is the most comprehensive for exchanging and storing urban energy data. Corrado et al. (2015) explains that a set of standard tables[4] were created using a terminology based on various international standards used in energy assessment and certification. These standard tables were then used to construct the SEMANCO ontology[5]. The purpose of the SEMANCO ontology is to facilitate access to disperse data sources in the urban energy domain. It is envisaged that the standard tables provide a foundation for the creation of urban models and can handle aggregation of data across multiple urban scales.

One of the key aspects of ontology design is the reuse of existing classes and properties. The SEMANCO ontology provides a means of structuring and storing urban energy data; however it is not clear how this information can be used to generate simulation models and then query the subsequent results.

Ontology Requirements

To the best of the authors knowledge, there are currently no published ontologies that facilitate the simulation of urban energy models and querying of their results. The UES ontology addresses this gap by providing a standard vocabulary for creating and applying building archetypes in UBEM projects. The UES Ontology will be developed to contain a vocabulary of terms related to UBEM that can be used to create an RDF knowledge graph. The UES ontology will implement classes and properties that facilitate the simulation and querying of UBEM data. Classes and

[2]https://w3c-lbd-cg.github.io/bot/
[3]http://www.semanco-tools.eu/urban-enery-ontology
[4]http://www.semanco-tools.eu/standard-table
[5]http://semanco-tools.eu/ontology-releases/eu/semanco/ontology/SEMANCO/SEMANCO.owl

properties from existing established ontologies such as BOT will be used wherever possible. It is also important to recognise the emergence of standardised data exchange formats, such as the CityGML schema, that are increasingly used as direct inputs to UBEM platforms. The UES ontology should be able to extract and import data readily from such formats based on their schemas. Based on these considerations, the following list of requirements were specified for the ontology:

- Traceability of data sources and assumptions.
- Creation of dynamic archetypes to represent the data.
- Standardized querying of results and inputs.
- Accommodate existing ontologies and data models.

Methodology

The specific needs of the CESAR-P application were considered by identifying the parameters, their origin and determining the meta-data useful for querying. Once identified, the relevant data inputs along with the metadata, were stored in spreadsheets and converted into RDF using OpenRefine and the Grefine RDF Extension[6]. The resulting data was then imported into an Ontotext GraphDB and queried using SPARQL. The UES ontology was developed in parallel to this process, using Protégé, and contains a vocabulary of standardised classes, properties and datatypes that can be used to represent the data. The documentation of the ontology was compiled using WIDOCO (Garijo, 2017) and the first version of the UES ontology is published on GitHub[7]. Key aspects of the ontology development is discussed below in relation to the parameters and available data resources. A summary of the data flows enabled by the UES Ontology are shown in Figure 1.

Sources of Data

In CESAR-P the following attributes are required for each building:

- Construction and retrofit year.
- Building type.
- Footprint vertices and height.
- Heating and hot water fuel type.
- Number of occupants.

This information comes from multiple sources, which means there are multiple datasets connected to a single instance of a building. To make it easier to organise this information, an abstract building class has been implemented in the ontology. This means that a building instance can be separated from its data. This enables evaluation of how well each dataset represent the building. Buildings that exist in multiple datasets can be linked through the common abstract building together using the buildingInstance property. This process is illustrated in Figure 2.

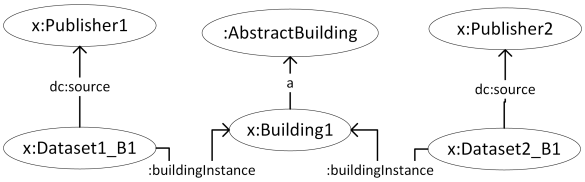


Figure 2: Abstract building class to manage multiple data resources. The prefix x: refers to URI instances within the building data.

Geometric Data

CESAR-P creates zones for simulation in EnergyPlus. Each zone needs to be defined geometrically as a water tight volume. The zone is enclosed by multiple surfaces which are defined by a set of XYZ coordinates. Three dimensional city data is becoming increasingly available in CityGML format. In CityGML, the building volumes are described by a set of surfaces, each defined by their vertices. A coordinate reference system is also specified so that the buildings can be projected correctly onto maps. Due to differences in construction and heat transfer coefficients for different envelope elements, it is important to determine whether the surface is an external wall, internal wall, ground floor or roof. CESAR-P creates different zones for different building usage and for each storey in the building. To account for this, the existing BOT ontology (Rasmussen et al., 2019) is incorporated within the UES ontology to define the relationship between the zones of the building. An illustration of how geometries are handled in the UES ontology is shown in Figure 3.

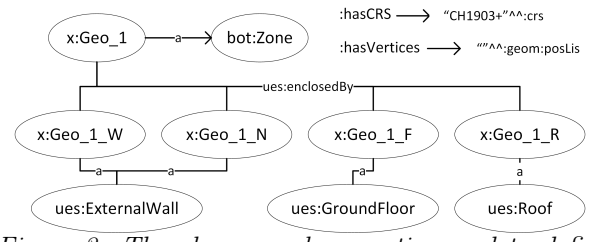


Figure 3: The classes and properties used to define the geometry of the building. The data properties displayed in the top-right can be linked to any of the building surfaces and zones. The prefix x: refers to URI instances within the building data.

Archetypes

Like other UBEM tools, CESAR-P relies on archetypes to generate a full set of simulation parameters for each building. Archetypes are constructed from statistical data and can be generally classed as:

- Building Construction archetypes, containing the physical properties of the building.
- Internal Conditions archetypes, containing

[6]https://github.com/stkenny/grefine-rdf-extension
[7]https://ja98.github.io/ues/release/0.0.1/index-en.html

schedules and parameters associated with the operation of the building.

The parameters contained within the archetype are used to populate the parameters of buildings with matching categories. When designing the ontology to handle archetypes, there were several key requirements that needed to be incorporated:

- Category ranges i.e. an archetype might be relevant for a range of years between 1900-1918.
- Parameter ranges due to variability i.e. parameters such as infiltration may vary between a specified minimum and maximum value.
- Multiple building elements within the archetype category i.e. buildings in the 1900-1918 category may contain multiple representative roof constructions.
- Stochastic nature of building design and operation. i.e. the user must be able to specify a distribution to indicate how the parameter varies over the specified range.

A generic archetype class has been implemented in UES, which allows for flexibility in the assignment of categories and parameters. In the UES ontology, a generic archetype can either have the property hasParameter or hasCategory. This allows a user to perform queries to quickly establish which data is available in the archetype and how it can be linked to building instances. Typically archetype categories are building use or age of construction. The process of archetype property assignment is shown in Figure 4.

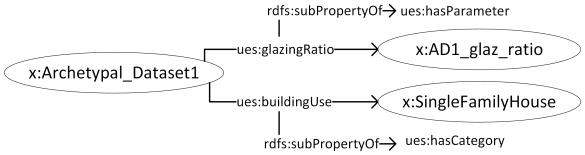


Figure 4: The sub properties used to define the archetype.

Building Construction Properties

Building construction archetypes provide typical construction properties for buildings in a given category. There are several key aspects to address using the archetype. Simulation programs treat each surface element separately. In CESAR-P there are multiple construction possibilities for each building surface. For example, buildings from between 1900-1918 have a variety of different roofing designs. To take this into account, the ontology introduces a probability of occurrence for each building surface defined in an archetype. It is also possible that the value of a parameter lies between a specified range for a given category. The handling of different elements within the same archetype and parameter ranges are illustrated in Figure 5.

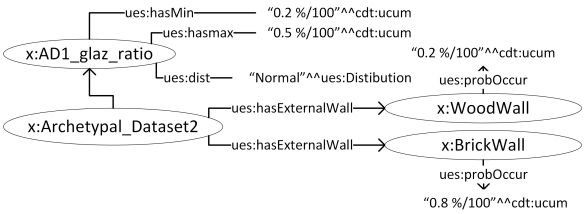


Figure 5: Handling of the parameter properties of archetype classes.

Each building surface is also comprised of layers of different materials. CESAR-P requires each material to be specified to create the input files for an EnergyPlus simulation. To achieve this, the layers of each surface can be assigned a thickness and a material. An RDF materials library was created and can be linked to each layer. The Custom Datatypes ontology (Lefrançois and Zimmermann, 2018), was used to handle units of measure.

Internal Conditions

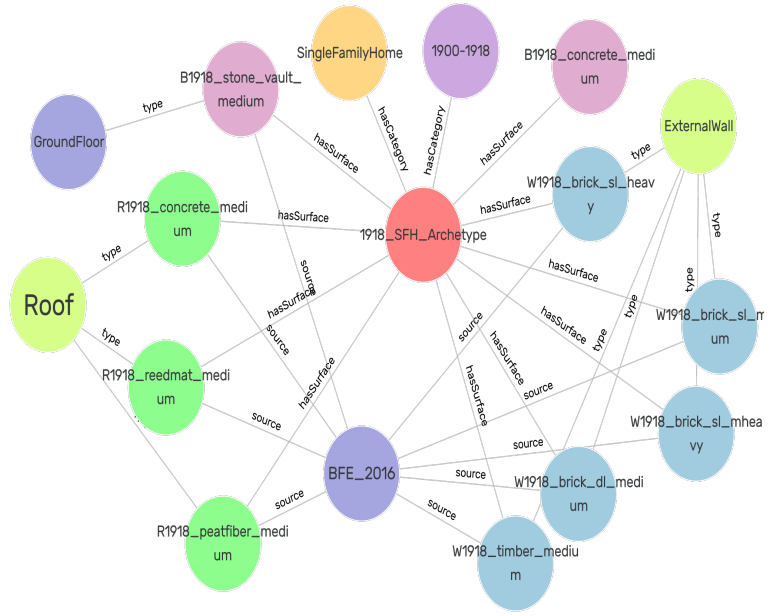
CESAR-P generates a set of time series and parameters as inputs for EnergyPlus. These time series are calculated from input data based on the Swiss Building stock and therefore may not be representative of buildings outside of Switzerland. The complexity of assumptions made during the assignment of internal conditions is difficult to trace, as this is something integral to CESAR-P. To avoid limiting the scope of the ontology, the scheduling inputs have also been considered for EnergyPlus. This will allow flexibility of the user to assign their own schedules. To accomplish this, a set of datatypes for handling time series is incorporated within the UES ontology.

Simulation Results

The purpose of UBEM is to simulate the energy performance of the building stock. CESAR-P uses EnergyPlus simulations to generate energy demand profiles (heating, cooling and electricity) for each building. These consist of annual time series with hourly time steps. It is not efficient to store time series data in an RDF database; therefore, only the aggregated annual results are stored. Several data classes have been proposed to enable efficient storage of the demand data, including AnnualEnergyDemand and PeakDemand, both of which are subclasses of electricity, heating and cooling.

Comparison with Measured Data

Monitored data is becoming increasingly available for use in UBEM; however it is often not available for all buildings. This data is useful for validation and calibration of data driven models. The UES ontology defines a set of classes and properties for storing measured data.



Construct Query

```
PREFIX ues: <https://ja98.github.io/ues/release/0.0.1/index-en.html#>
PREFIX dc: <http://purl.org/dc/elements/1.1/>
Construct where {
     <http://uesl_data/sources/archetypes/1918_SFH_Archetype>
        ues:hasSurface ?surface;
        ues:hasCategory ?cat.
    ?surface dc:source ?source;
             a ?type
} VALUES ?type {ues:ExternalWall ues:Roof ues:GroundFloor}
```

Select Query

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX ues: <https://ja98.github.io/ues/release/0.0.1/index-en.html#>
select ?archetype ?archetype_use ?bldg where {
    ?archetype rdf:type ues:Archetype;
     ues:buildingUse ?archetype_use.
    ?bldg ues:buildingInstance ?bldgIns;
        ues:buildingUse ?archetype_use.
        }
```

	archetype	archetype_use	bldg
1	data:archetypes/1918_SFH_Archetype	ues:SingleFamilyHome	data:datasets/GWR_2017/GWR_2017_1001

Figure 6: Two types of query that can be applied to a GraphDB: The Construct Query returns a subset of the data, containing the unique classes and can be visualised as a graph. The Select Query returns the variables of the query in tabular form.

Example Usage

The methodology section detailed the consideration of specific data structures covered by the ontology. This section details results of example SPARQL queries applied to an example database compiled using the UES ontology. These are not exhaustive, but provide usage examples to users and developers of applications who adopt the ontology.

Matching Archetype Data

The process of matching archetypes to data is a key feature of the linked data approach. There are two main types of query to manipulate and extract data from a semantic graph database: Construct and Select Queries. The Construct Query is used to generate a visual representation of the data in the form of nodes and edges. Each node within the graph is a unique data instance with an URI, and the edges are the relationships that connect them. Using SPARQL it is possible to query the contents of the database using either specific instances or properties. The UES ontology can be used as a map to build the queries and navigate the database. The Construct query shown in Figure 6 gives an example of this process. Here a query has been created to determine the surfaces, categories and sources of a specific archetype. The specific archetype queried is displayed by the red node, labelled 1918_SFH_Archetype. The categories represented by this archetype are ues:SingleFamilyHome and a construction period ranging from 1900 to 1918. The archetype is linked to multiple instances of the class ues:ExternalWall (blue), ues:GroundFloor(pink) and ues:Roof (blue). The source used to derive these constructions is identified as the the BFE_2016 dataset. The Construct Query is useful for visualising the data but to be able to extract data the Select Query is required. The select query in Figure 6 shows an example of matching the instance of a building with an archetype. This returns the tabular data identifying the URI of the archetype the archetype use and the building.

Conclusion

This paper outlines the development and application of the UES ontology, which has been integrated into the CESAR-P UBEM tool. In the current release, the ontology is used to manage the formation and application of archetypes used to parameterize the simulation models. The ontology provides a means for new project users to quickly establish how a UBEM was created, by tracing the data sources and assumptions that were made. This paper provides some example queries demonstrating how archetypes can be linked with building data to populate inputs for a simulation. The UES ontology incorporates established terms for the representation of geometries and energy characteristics. This will enable the data to be easily converted into other data models and for-

mats. Further work will demonstrate the application of the ontology in UBEM projects. The ontology will also be extended to be compliant with common data exchange formats used in the UBEM field e.g. CityGML.

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