SCCER FEEB&D Sharing and Algorithms & Data

DATAFOR URBAN MODELLING

There are many data models and formats to store and exchange information about city objects, including for instance 3D geometric models and CityGML. **Semantic web technologies** have been used to break down data silos and overcome barriers to data accessibility and sharing. We are developing the **Urban Energy Simulation (UES) ontology** and a graph database platform for the organization of digital resources for urban energy simulation (Figure 1). Using the UES ontology to parametrize and explore results, users can create a knowledge base that can be queried to gain a deeper understanding of the data. This approach also aims to enable full data provenance. A conceptual example of how archetypes are modelled using the UES ontology is shown in Figure 2.

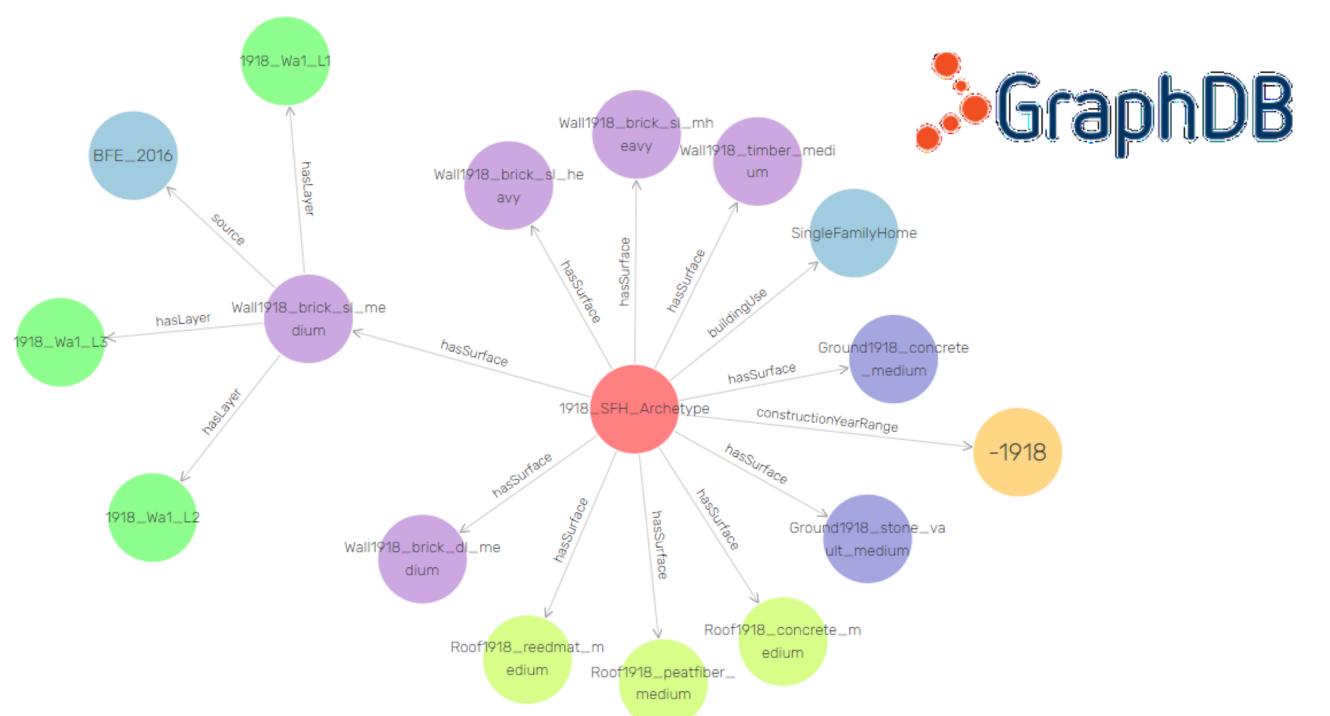


Figure 1. Archetypal data stored as RDF triples in the GraphDB following the properties of the UES ontology.

KEY RESULTS

- Data for urban modelling: We have developed an ontology for the organization of input data used for urban scale building simulation, and deployed a centralized GraphDB server, making results more transparent and shareable.
- Calibrated energy models: In terms of heating and cooling, not much difference is observed when the calibrated temporal resolution is higher than 30-minutes, see Figure 3a. Electricity is notably sensitive to the measurement intervals, whilst DHW has the highest sensitivity to the temporal resolutions, see Figure 3b.

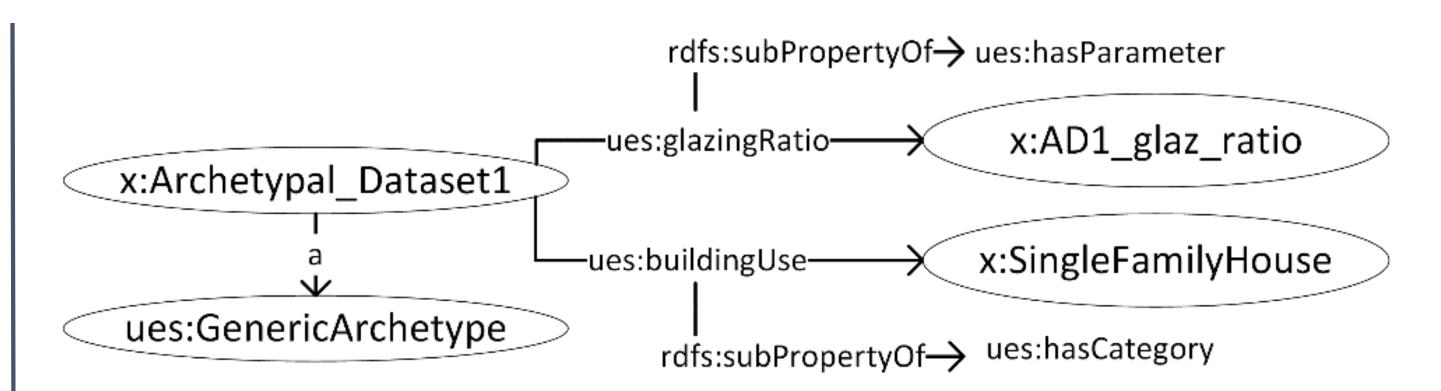


Figure 2. Structuring of archetypal data using the UES ontology.

CALIBRATED ENERGY MODELS

A calibrated building energy model not only creates a reliable baseline to assess modifications to an existing building, but also enriches the prior assumptions about the energy model. Given the importance of a measurement's temporal resolution, a systematic study on utilizing measured data for calibration purposes is necessary. This research contrasts the benefits and drawback of calibrating a building energy model with coarse and fine temporal resolutions, and highlights the effects of information loss on prior inference.

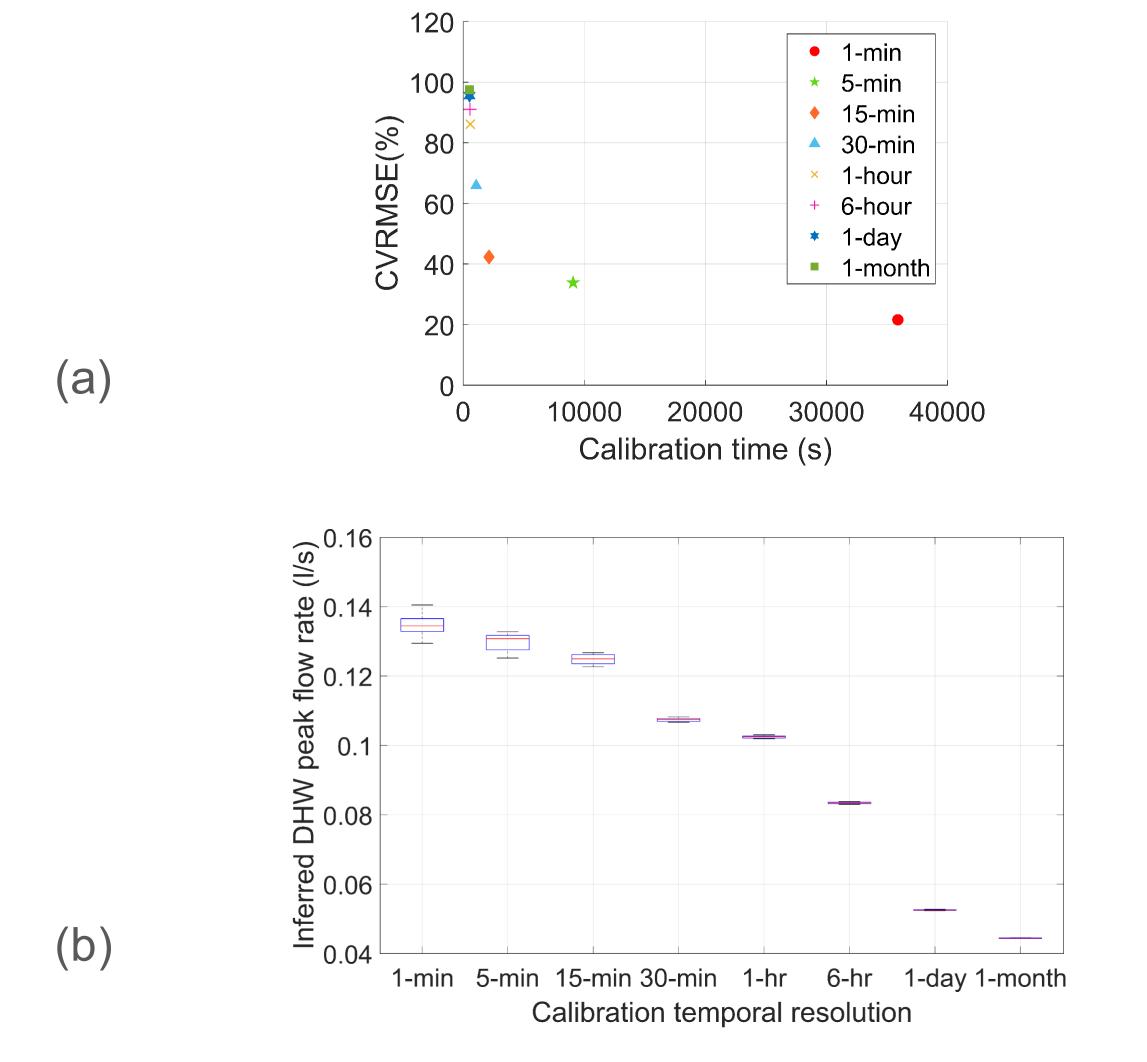


Figure 3. (a) Coefficient of variation of the root mean square error vs. calibration time (b) The inferred DHW peak flow rate vs temporal resolution of the calibration data.



Research supported by: Innosuisse | EU Horizon 2020 | Marie Skłodowska-Curie