Real-Time Building Performance Monitoring using Semantic Digital Twins

Alex Donkers[1[0000-0002-8809-3277]] and Dujuan Yang[1[0000-0003-3124-6604]], Bauke de Vries[1[0000-0002-7885-8221]] and Nico Baken[1]

[1] Eindhoven University of Technology, Groene Loper 6, 5612AZ Eindhoven, The Netherlands
a.j.a.donkers@tue.nl

Abstract. Higher building performance saves operational costs, helps sustainability goals, and increases the comfort, satisfaction, productivity, and health of occupants. However, models simulating the occupants' perceived performance of indoor environments require highly heterogeneous input data. This paper aims to show how semantic web technologies can help to overcome problems deriving from this heterogeneity issue. Literature is studied to categorize the necessary input information for modeling occupants' perceived building performance. Two perspectives were consulted, namely the Indoor Environmental Quality approach and the Healing Environments approach. Based on the results, a core IEQ data model, integrating building topology, static properties, and dynamic properties, is proposed. We introduced a method to integrate this information by using the Building Performance Ontology (BOP). This method was tested by manually transforming the Open Smart Home (OSH) data to BOP vocabulary. Time-series data from various sensors were stored in InfluxDB and connected to the linked building data. A custom-built python tool was created to compute the thermal comfort of the OSH using the PMV/PPD method. The results indicate that a common data structure for static and dynamic properties helps to integrate the heterogeneity input data. Furthermore, we showed that adding occupants' data or system information could improve thermal comfort through multiple reactive approaches.

Keywords: Linked Data, Semantic Web, Building Performance Ontology, Thermal Comfort, Building Performance

1 Introduction

Monitoring building performance is essential to improve quality of life. Apart from static performance indicators, such as office layout, colors, and materials [1, 2], dynamic performance indicators such as the indoor environmental quality (IEQ) heavily influence the occupant's satisfaction with a building.

Kim and Dear found that workplace satisfaction is largely influenced by noise distraction [3], temperature, air quality, and visual comfort [1]. The indoor climate also influences productivity. Lee et al. [4] found a correlation between IEQ complaints and student learning performance. Office workers' productivity is amongst others affected by thermal comfort, indoor air quality, noise, acoustics, and lighting [2]. Experiments by Geng et al. [5] show that the optimal productivity is reached at a neutral or slightly cool temperature. Next to productivity issues, multiple researchers identified health-related problems due to bad indoor conditions. Fabian et al. [6] found that improving the IEQ significantly reduces asthma events. Patino and Siegel [7] concluded that poor IEQ in social housing negatively affects health conditions. Fisk et al. [8] found how low thermal comfort and air quality could increase the short-absence of knowledge workers. Eventually, poor buildings could lead to symptoms of the Sick Building Syndrome (SBS) [8].

Creating a better indoor environment should therefore be a key strategy in real estate. However, multiple challenges exist. Currently, building managers in commercial buildings have no disposal to the full set of tools that is necessary to monitor, control, and optimize the indoor environment for its occupants [9]. According to Adeleke and Moodley [10], monitoring IEQ is often cumbersome, capital intensive, and dependent on manual processing.

The booming development of the IoT domain is promising. Multiple literature reviews [11, 12] evaluated the opportunities of the integration of IoT and BIM. Boje et al. [12] explain how such semantic enrichment of building data could result in dynamic cyber-physical models, or Digital Twins. Those models help to improve building performance [13], facility management [14], monitoring [12], energy management [15], and many more. However, the data to create those Digital Twins often originates from heterogeneous sources and is stored in heterogeneous data formats [12].

This paper aims to show how semantic web technologies could be applied to integrate heterogenous data for monitoring building performance cases. Section 2 describes the state-of-the-art building performance monitoring and the IEQ parameters accompanied with this. It ends with a summary of semantic web ontologies related to this domain, and how they could be used to integrate the different types of data. Section 3 describes the method of this study, including a short description of the BOP ontology and the data used in this study. Chapter 4 discusses the results. The paper ends with a conclusion and discussion.

2 Building performance and the semantic web

Multiple literature studies indicated the potential of integrating the IoT domain with building information. One of the major assets of IoT development is the possibility to sense the indoor environment using sensors. Building performance indicators related to sensor data are often part of the indoor environmental quality (IEQ)-umbrella. Al Horr et al. [16] extensively studied how building performance indicators related to IEQ influence occupants' well-being, and categorized these into indoor air quality (IAQ), sick building syndrome (SBS), thermal comfort, acoustic comfort, and visual comfort.

Central in the IEQ approach is the use of physical quantities - often measured by sensors – to compute people's comfort [17]. The performance is often expressed using a calculated or measured value and could be compared against guidelines or other buildings [17, 18]. These values could be calculated using various methods depending on the building and its available systems, often varying in spatial and temporal procedures

[19]. Current semantic web ontologies in the AEC domain often lack the expressivity to address this spatiotemporal resolution.

The deterministic nature of IEQ methods results in unambiguous methods to improve the building performance; a building manager simply needs to improve the variables used in their calculation methods. Variation in layout, function, and systems does require a tailored approach for each building, however, multiple ontologies in the AEC domain have proven to add the semantic expressivity related to these variations [20–22]. Common strategies to improve the IEQ during the operational phase of a building are reducing polluting sources and improving natural ventilation (to improve air quality) [16], changing temperature or air velocity (to improve thermal comfort) [16, 18, 23], reduce noises and improve communication privacy (to improve acoustic comfort) [16] and increase (day-)light and reduce glare (to improve visual comfort) [16].

Frontczak et al. [24] argue that the influence of IEQ parameters differs per individual, and also varies for different countries (with different outdoor climates). Paradoxically, occupants prefer to have individual control over the IEQ, even if this leads to lower task performance [25].

Willems et al. [17] argue that the IEQ paradigm approaches environmental perception as a passive, deterministic process, monitored by sensors. They researched the healing environments (HE) approach as a counterpart of IEQ, focusing more on the dynamic interaction between mind, body, and space. In HE, perception of the environment is intertwined with the actions, emotions, and cognitive system of individuals [17], as well as their emotions. Different affective phenomena (such as preferences, attitudes, mood, affect dispositions, and interpersonal stances) influence the emotions and thus the experience of space [26]. This experience is always triggered by multiple sensations simultaneously and approaches to model this experience should therefore be multi-sensory [17]. Richer information about people's preferences would be needed to model such epistemic acts.

A gap between designed, measured, and perceived building performance could be identified [27]. High scores on various environmental assessment methods (LEED [28], BREEAM [29]) were found to not significantly improve perceived comfort levels. Combining IEQ and HE methods is expected to reduce this gap [17]. A combination of those methods could only be achieved by integrating a wide range of heterogeneous data. Based on the reviewed methods related to IEQ and HE, a core linked data model for IEQ should integrate both building topology (e.g. by using BOT [20]), static properties (e.g. by using BOP [30] or PROPS [31]) and dynamic properties (using for example SOSA [21], OPM [22] or BOP [30]).

Boje et al. [12] emphasize the opportunities of data integration to better adapt building performance to occupant needs while simultaneously optimizing resources. There has not been scientific consensus on the optimal data integration method for building information models with time-series data yet. Tang et al. [11] mention five integration methods. Three of these methods don't use semantic web technologies and either store BIM data in relational databases or directly query from IFC models. Since these methods don't solve the heterogeneity issues of a building's lifecycle data, two semantic web approaches have been proposed by Tang et al. [11].

In the first SWT approach, both the BIM data and the sensor data are converted to RDF. Using unique identifiers (for example, GUIDs), the data in both RDF files could be integrated. A python script, a web application, or any other custom-built tool could query information from both datasets. Multiple SWT developments hint at using this approach. Almost any sensor-related ontology describes classes for storing time-series data (e.g. `sosa:Result`, `seas:Evaluation`, `saref:Measurement`), including a literal and a unit. A general argumentation to do so is that RDF is well able to describe the context of a time-series measurement, adding the necessary semantic richness. Moreira et al. [32] however argue that such representations are not suitable for exchanging real-time sensor data, as the payload per message would be too high. Therefore, they introduced the `s4ehaw:TimeSeriesMeasurements` class which links to an array of `xsd:float` values using an `s4ehaw:hasValues` datatype property.

The second SWT approach does store building data using RDF but keeps the time-series data in its original format (storing it in either a relational or time-series database). Hu et al. [33] used this approach to integrate sensor data and BIM data using the sensor ID. They described the context of the measurement using SSN but stored the measurements in a relational database. Similar approaches were applied by Van Gool et al. [34] and Petrova et al [35]. Esnaola-Gonzalez and Diez [36] argue that time-series databases are most suitable to store IoT data, as this result in the best querying performance.

The integration of static properties with topological BIM data using RDF seems common research practice. Some ontologies advocate a one-file approach (e.g. ifcOWL), while others follow the decentral nature of the semantic web, combining multiple domain ontologies [9, 33, 34]. Different levels of detail could be found in the various approaches describing static properties. The shortest route links a feature of interest directly to a literal, using the object property to describe the measured property (e.g. in simpleBIM [37] or PROPS [22]). Multiple ontologies (BIMDO [38], BPO [39]) introduced an intermediate 'property' class to support easier querying. The OPM ontology of Rasmussen et al. [22] introduces a second intermediate class (`opm:PropertyState`) allowing the description of temporary properties, also implemented by OMG [40].

A unified approach to integrating the different heterogeneous data categories is currently lacking. The complexity of building performance models is therefore not yet covered by semantic web technologies. Data integration might lead to reducing the gap between designed, measured, and perceived building performance.

3 Method

The concept of linked data for building performance will be demonstrated in a case study monitoring the thermal comfort of the Open Smart Home (OSH), an existing apartment in Nuremberg, Germany. The original dataset [41] was edited in Revit to add multiple sensors. An RDF Turtle file [42] (following the BOT [20] ontology for topology and the BOP [30] and QUDT [43] ontologies for properties) has been manually created and stored in Ontotext GraphDB. To ease the process, this conversion is inspired by a conversion using the LBD-to-RDF converter [31]. The added properties include thermal resistance, geometry, and orientation. The file semantically describes the context of the sensors, such as the properties they measure and the databases their data is stored in. Following the second SWT approach (chapter 2), the sensor data of the OSH – which originally came as .csv files – was converted to the InfluxDB line protocol format and imported to the InfluxDB database mentioned in the RDF Turtle file of the OSH.

A custom-built python tool was developed to query the different datasets from their databases. The tool first queries information from GraphDB using the SPARQLWrapper[1] library. The results are used to query sensor data from InfluxDB using the influxdb[2] library. The predicted mean vote and percentage of people dissatisfied (PMV/PPD) methods [18] were used to calculate thermal comfort. Using the pythermalcomfort [44] library, the PMV/PPD could be calculated by using the dry-bulb temperature, mean radiant temperature (T_{mr}), the air velocity, relative humidity, metabolic rate of the occupant, and clothing insulation of the occupant. The dry-bulb temperature and relative humidity were acquired from sensors and the air velocity is set to 0.1 m/s by default. The T_{mr} could be calculated using the equation 1:

$$Tmr = \frac{\sum_{i=0}^{n}(T_{s,i} * A_{s,i})}{\sum_{i=0}^{n}(A_{s,i})} \tag{1}$$

where: T_{mr} = mean radiant temperature [°C]
$T_{s,i}$ = indoor surface temperature [°C]
$A_{s,i}$ = surface area [m^2]

The indoor surface temperature was computed by using the dry-bulb temperature and relative humidity (returned from the sensors), area, tilt and solar azimuth of walls, windows, doors, floors, and ceilings (queried from the OSH graph), meteorological data (accessed via local weather stations) and the insulating properties of all the boundary faces of the room (queried from the OSH graph). Weather data has been acquired via CustomWeather [45]. Different from [34], this paper uses `bot:Interface` to create interfaces between walls and spaces to determine the surface area, to overcome the geometric issue of walls covering multiple spaces in IFC.

Personal influences, such as metabolic rate and clothing insulation, remain variables in the tool to allow personalization of the thermal comfort assessment. By default, they were set to 1.0 met and 0.7 clo respectively.

The results of the PMV/PPD calculations were compared against the ASHRAE-55 standard [18] based on work by Loomans et al. [46]. Next to this, personal influences on the IEQ will be tested by advising the occupant to wear extra clothes and by activating the radiator. A visual overview of the workflow is given in figure 1.

[1] https://pypi.org/project/SPARQLWrapper/
[2] https://github.com/influxdata/influxdb-python

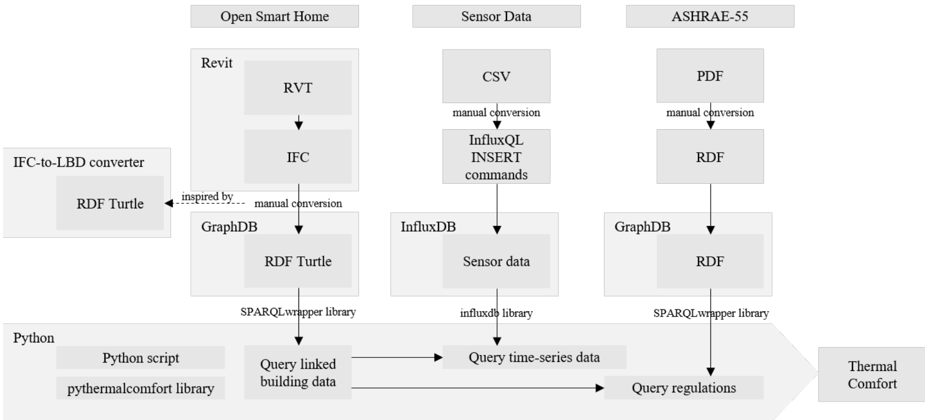

Fig. 1 Heterogeneous data conversion workflow to calculate the thermal comfort

The Open Smart Home has been converted to RDF using multiple domain ontologies. The topology of the building is described following the BOT [20] ontology. To integrate all the static and dynamic properties with the topology, the BOP [30] ontology has been used (figure 2). The ontology allows static property results to be stored directly in the RDF file. The ontology does store the necessary context of the time-series data in RDF but stores the actual measurements in a time-series database. To represent different types of properties, QUDT's quantitykind and unit ontologies [43] were used.

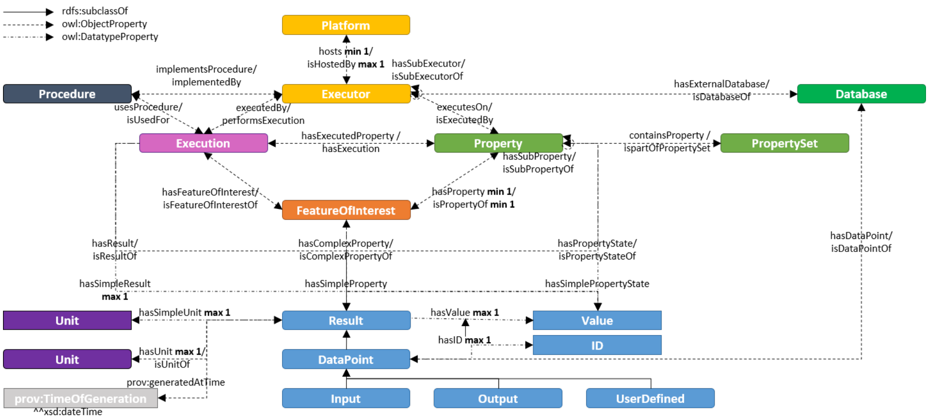

Fig. 2 The Building Performance Ontology (BOP)

Figure 3 shows the resulting linked data structure of the OSH. The colors represent the `rdf:type`'s of each instance, adopted from the BOP ontology. Both static and dynamic properties are described similarly and could be queried using similar SPARQL queries. BOT has been used as a core ontology to describe the room and its building elements. In practice, those elements often overlap with the `bop:FeatureOfInterest`. Since `bot:Element` and `bop:FeatureOfInterest` are not necessarily the same things, the ontologies are used next to each other instead of aligning them using alignment modules. Interfaces are used to represent the boundaries between a space and a building element, such as walls, windows, and doors. Static and dynamic properties are both described as instances of `bop:Property`. The state of each property is described using `bop:Result` and is linked to the property using the `bop:hasPropertyState` object property. Dynamic properties hold information about the time-series database their measured states are stored in. Only one unit-instance is used to describe the units of the entire time series.

The sensors in this example measure the properties of the room while being hosted at a wall. By separating the property (connected to `:Bedroom`) and the sensor (connected to `:Wall_01`), the graph adds information about the viewpoint of the sensor, adding the necessary spatial resolution of the sensor data for complex IEQ computations.

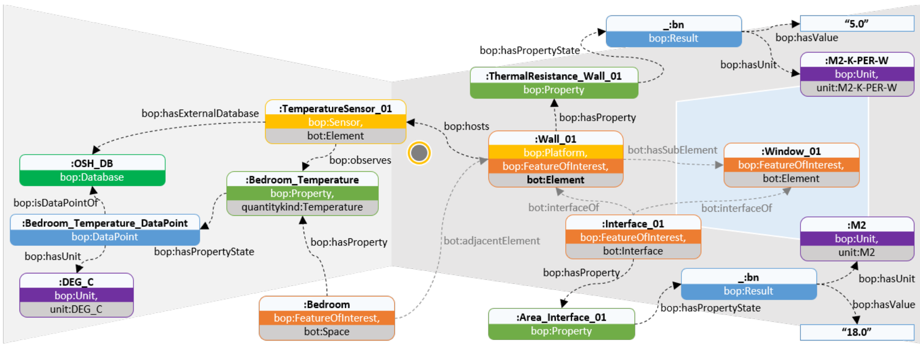

Fig. 3 Representation of static and dynamic properties of the Open Smart Home

4 Results

Loomans et al. [46] presented multiple assessment methods for assessing the thermal comfort of a building. Their most detailed method for buildings in operation assesses the PPD, PMV, and the stability of the environment. While the PPD and PMV could be calculated at any given time, the stability metric measures the percentage of the operating/occupation time in which the PPD and PMV criteria are met. The criteria are given in table 1.

Table 1 Assessment criteria of indoor thermal comfort

Assessment	PPD [%]	PMV [-]	Stability [%]
Excellent	< 6	-0.2 < PMV < 0.2	≥ 95%
Good	< 6	-0.2 < PMV < 0.2	≥ 80%
Adequate	< 10	-0.5 < PMV < 0.5	≤ 80%
Acceptable	< 15	-0.7 < PMV < 0.7	≤ 80%
Poor	≥ 15	PMV < -0.7 or PMV > 0.7	≤ 80%

Using the custom-built python script and the assessment criteria in table 1, the PPD and PMV were assessed over a full day (June 1st, 2017). Figure 4 shows how the initial situation scores poorly. As the figure indicates, there is a direct relationship between the indoor temperature measured by `:TemperatureSensor_01` and the PPD; once the temperature drops, the PPD rises.

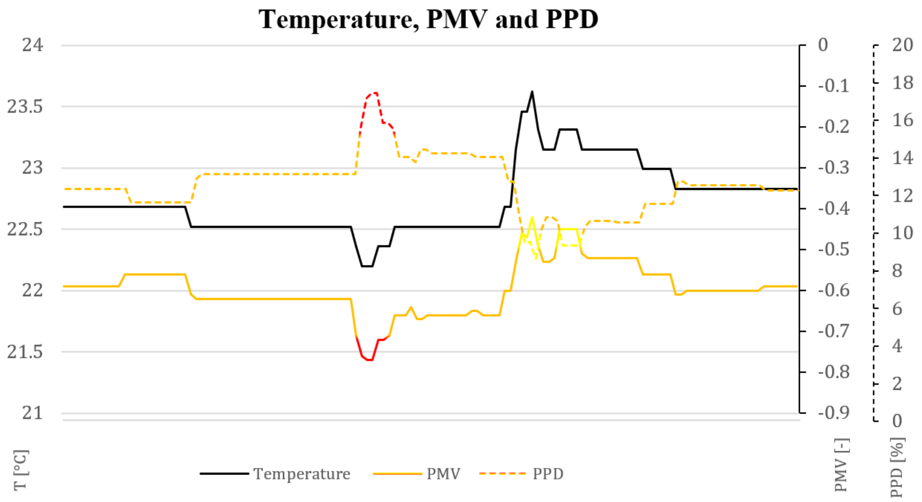

Fig. 4 Temperature and the assessed PMV/PPD

Two strategies to improve thermal comfort were tested. Since the temperature affects the thermal comfort directly, the first approach tries to automatically trigger the radiator to increase the temperature. The radiator in this room is connected to the same temperature property as the sensor by using the `bop:actsOn` object property. The script has been adapted to set the room temperature to 23.5 °C once the PPD or PMV assessment drops to 'poor'. Figure 5 shows how this could increase the PMV and decrease the PPD. After increasing the room temperature, the PPD and PMV levels stayed within 'adequate' boundaries for 100% of the time.

Instead of controlling systems, the linked building data could also be used to give personal advice to the occupant, for example using a mobile device or an in-home dashboard. Both metabolism and clothing insulation are personal factors influencing thermal comfort; clothing insulation is the easiest variable to change. By advising the occupant to wear an extra long-sleeve shirt, his/her clothing insulation would increase by approximately 0.3 [23, 44]. Figure 5 shows how such advice, triggered by an increasing PPD (at 04:18), could improve the perceived thermal comfort directly. After putting on an extra shirt, the PMV and PPD stayed between the 'excellent' boundaries for 99,1% of the time, resulting in an 'excellent' thermal comfort assessment.

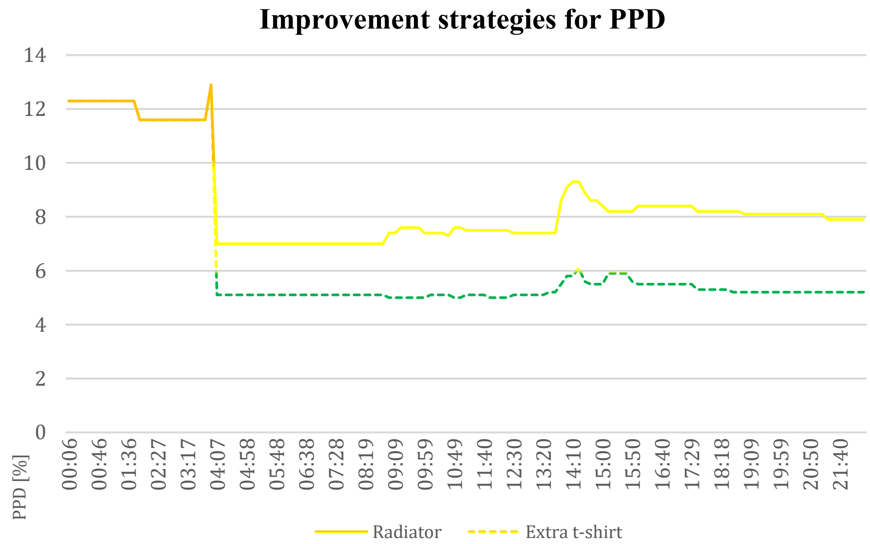

Fig. 5 Improving the PPD at 04:18, radiator and extra t-shirt scenarios

5 Conclusion and discussion

Monitoring building performance is a crucial step towards improving the quality of life inside buildings. The complex building performance indicators which simulate indoor environmental quality require the integration of a wide range of information. Current practice showed that this information is often siloed and heterogeneous. This paper aimed to show how semantic web technology could be used to integrate the myriad of information to automate the process of monitoring building performance.

By representing the Open Smart Home as linked data – using the BOT and BOP ontologies – a custom-built python tool was able to query the topology, static properties, and dynamic properties from a graph database and automatically query the corresponding sensor data from a time-series database. By doing so, the thermal comfort of a space could be computed in real-time. While this paper focused on IEQ, the workflow presented in figure 1, in which linked building data is used to navigate to the correct time-series data, could be generalized and used for various use-cases such as energy management, facility management or smart building control.

Using linked data, the python tool can provide the user with different opportunities to improve the building performance. Both a reactive method (triggering the radiator) and a recommendation (advising the occupant to put on an extra t-shirt) were applied, resulting in a drop of dissatisfaction with the thermal comfort.

Improving the building performance is an interesting research direction that deserves further attention in the near future. To improve the current methods, future research should aim at individualization of the monitoring and control of buildings. Research should also aim at predictive methods to shift from reactive to proactive improvement methods.

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