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# From Semantic Models to Cognitive Buildings

**Joern Ploennigs**
IBM Research - Dublin
Damastown Industrial Estate, Dublin, Ireland
Joern.Ploennigs@ie.ibm.com

**Anika Schumann**
IBM Research - Zurich
Sauemerstr. 4, Rueschlikon, Switzerland
ikh@zurich.ibm.com

**Abstract**

Today's operation of buildings is either based on simple dashboards that are not scalable to thousands of sensor data or on rules that provide very limited fault information only. In either case considerable manual effort is required for diagnosing building operation problems related to energy usage or occupant comfort. We present a Cognitive Building demo that uses (i) semantic reasoning to model physical relationships of sensors and systems, (ii) machine learning to predict and detect anomalies in energy flow, occupancy and user comfort, and (iii) speech-enabled Augmented Reality interfaces for immersive interaction with thousands of devices. Our demo analyzes data from more than 3,300 sensors and shows how we can automatically diagnose building operation problems.

## Introduction

Almost 32% of the total energy consumption in industrialized countries is used for electricity, heating, ventilation, and air-conditioning (HVAC) in buildings. Between 15% and 30% of that energy could be saved if faults in the HVAC system and its operation could be detected in a timely manner (Zhou, Wang, and Ma 2009). Existing diagnosis approaches are either data driven or model driven (Katipamula and Brambley 2005). However, data driven statistical methods do not provide detailed fault information and approaches that require a model of the building behaviour suffer from a lack of adaptability across buildings, which differ in their HVAC equipment installed, the building size, layout and material.

The adaptability problem can be tackled using semantic mapping and the need for it was identified by several reviews such as (Livingood et al. 2011). Semantic techniques have already been applied to the diagnosis of buildings (Han, Jeong, and Lee 2011; Dibowski, Holub, and Rojicek 2016), but they require manual modelling of the devices and do not scale well with the size of systems.

We show how the model of a given building can be generated almost automatically based on (i) the building's sensor data, (ii) a generic semantic model characterizing the relationships among sensors and (iii) a generic physical model characterizing the physical dependencies between data points. In fact, the only step of our approach that is not fully automatic is the semantic mapping. Once it is captured what the different data points of the building represent, all models are build automatically and hence they can also be updated automatically e. g. when the performance of HVAC equipment changes. Thus our work enables *Cognitive Buildings*, i. e. buildings that automatically optimize their operation in view of changes in their environment.

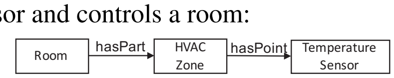
Based on data from the IBM campus Dublin with 3,300 sensors we demonstrate that our work can be used for diagnosing building operation problems and show how speech-enabled augmented reality assists technicians in taking the right actions when repairing the faulty HVAC equipment we identified.



## Approach

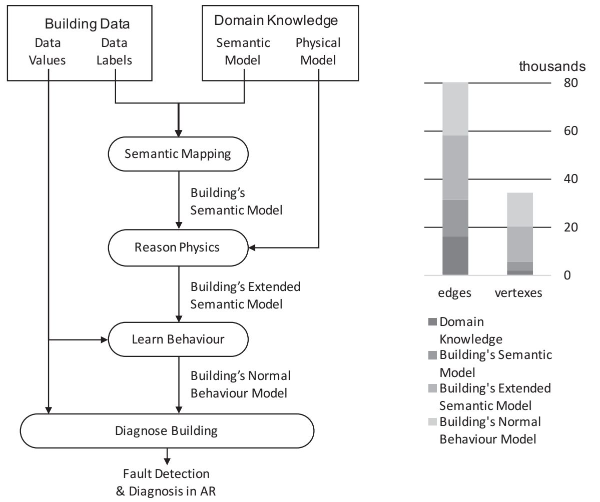
We start by introducing the three inputs needed for our approach:

- Building Data: For commercial buildings, the data is managed and stored in a Building Management System (BMS) which is commonly available.
- Semantic Model: We use Brick 1.0, the newly developed metadata schema for buildings which consists of a class hierarchy of entities describing the various building subsystems and their entities (Balaji et al. 2016). For example, this graph depicts that a HVAC zone has a temperature sensor and controls a room:




- Physical Model: We extract the dependencies between entities using the model described in (Wetter 2006). Here we capture, for example, that the temperature in a room rises if its heater is on.

The overview of our approach is shown in Figure 1a. It starts by computing the semantic model of the particular building. A difficulty here is that each BMS has a unique labelling scheme that often is not even consistent in itself. This results from the fact that despite some standardization efforts (ISO16484-3 2005) technicians label data in an adhoc manner when the BMS control strategy is updated for new equipment additions. Hence, performing the semantic mapping cannot be done completely automatically, but us-




a) Overview of the approach

b) Numbers of elements after each step

Figure 1: Approach and example Figures

ing our previous work (Schumann and Lécué 2015) we can reduce the requirements for manual input.

The remaining steps of our approach are all done automatically. The extended semantic model captures also the physical dependencies between entities that are obtained as we described in (Ploennigs, Schumann, and Lécué 2014). For the computation of the normal behaviour we use different machine-learning and statistical approaches, depending on the semantic types. For temperature comfort in rooms, we use Artificial Neural Networks (ANN) as they capture well the non-linear properties of the room behaviour. For energy, we use Generalized Additive Models (GAMs) as these are not only suited for modeling the behaviour but also for determining the factors that govern it. Furthermore the residuals of the GAMs have the property that they are serially correlated. We can therefore use Autoregressive Moving Average (ARMA) models for characterizing the normal behavior of sensor readings more precisely by determining the upper and lower bounds within which sensor readings can still be classified as normal (Ploennigs et al. 2013).

If abnormal sensor readings are detected we use the approach in (Ploennigs, Schumann, and Lécué 2014) to perform the diagnosis. It makes use of the physical dependencies between sensors readings for determining the root cause. Once the root cause is detected we use augmented reality to assist a technician in taking the right actions for resolving the problem.

## Demonstration

Our approach is demonstrated for a campus consisting of 6 buildings with 3,300 sensors. They are mapped to 220 semantic concepts from the Brick ontology. We automatically derive 14,830 physical relationships between the sensors. The resulting graph sizes are shown in Figure 1b. The total computation time for deriving all graphs takes 30 minutes (Ploennigs, Schumann, and Lécué 2014). On these we train models for anomaly detection and diagnosis for energy and thermal comfort. The user can seamlessly access the results in the field through Augmented Reality on their smart phones or AR glasses by looking on the system.

## Conclusions

The flexibility and scalability properties of semantic graphs make them an ideal vehicle for tackling building operation problems. They can be used for capturing device semantics as well as physical relationships among sensors. This representation allows for configuring and feeding user interfaces such as augmented reality. In combination with statistical and machine-learning approaches they enable the diagnosis of building operation problems related to energy usage and occupant comfort.

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