Using Ontologies for Knowledge-based Monitoring of Building Energy Systems

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ABSTRACT

Many developments and research have led in last decade to enhanced building automation systems embedding data analytics algorithms and performing energy-optimized building systems control. The presented approach aims at providing a complementary analysis layer compared to such systems by the means of semantic modeling and knowledge reuse. For that purpose, it relies on a semantic description of a building energy system from which energy conservation measures can be derived. Starting from an ontological description of the building energy system, an expert system is proposed that provides a monitoring plan and operation advices to building users and managers. This system consumes for a part real-time building data gathered during its operation. For another part, it relies on information about the built-in technical systems which is usually available in initial design models. The resulting software application might be used in the future as an add-on to existing building management systems and for easing their configuration.

INTRODUCTION

Modern building management systems (BMS) play a major role in today’s race for the reduction of energy use and greenhouse gas emission. They are able to handle a huge amount of data that are analyzed for supervising, controlling and benchmarking buildings (Mehmood et al. 2019). BMS data are mainly gained through sensors and meters that provide information in real time about e.g. the operational state of technical equipment, indoor environmental conditions or energy consumption. Even though their deployment can lead to reduction of resource usage, their installation and configuration is still a tedious process. In most cases providers rely on drawings of the building and schematics for planning their databases and automation services. Many ad-hoc visits and settings on-site ensure then the most reliable installation and configuration of their systems. Moreover, once installed, building owners and facility managers generally lack sufficient expert knowledge to evaluate the proper functioning of building automation and control systems (BACS). Thus faulty states or inefficiency of the whole building energy system often remain unnoticed.

Most of time building users and facility managers need guidance to ensure correct control settings and change their habits towards more energy efficiency. Furthermore, BACS lack more systemic monitoring taking into account external disturbance factors, like users themselves who may cause energy wasting. Indeed, building users represent a major factor of energy inefficiency and waste due to energy unaware behavior (leaving lights on and windows open, room overheating or undercooling, etc). The proposed recommendation system shall enhance interactions between the building and its users. In particular, it aims at increasing the awareness and engagement of
building users and facility managers with regards to their energy consumption and building operation costs.

To achieve this goal, the presented system analyses building data in order to identify suitable energy conservation measures (ECMs). These ECMs consist of avoiding faults and energy wastes by the means of corrective actions that can be applied by building users or facility managers to save energy. In view of that, the system translates ECMs into tailored recommendations that can be provided to end-users through a graphical user interface for achieving a so-called indirect control. The recommendation system is built as an expert system whose core algorithms follow a rule-based as well as model-based approach for addressing the goals and constraints that are encountered. First, the expert system depends on the availability of building operation and monitoring data (e.g. energy meters, indoor temperatures, weather data, etc.). Thus, a monitoring system relying on sensors and meters must be available and data must be accessible. Moreover, the system has to be applied in real time during building operation in order to provide it as an energy assistant in daily building usage. Consequently, it must require limited computational time and be executed continuously in a proper runtime environment. Furthermore, the major constraint is the ability to be applied to any kind of building regardless of their type, size, usage, users as well as existing heating, ventilation and air-conditioning system (HVAC). For that purpose the tool must be able to interpret by itself information about the building and its built-in energy system (type of heating system, cooling system, building rooms and zones, building topology, etc.). In that manner, it can be easily applied to any building without having to reprogram the tool because of the specificities and uniqueness of each. Tackling these constraints allow us to propose an autonomous and highly scalable energy expert system as add-on to existing BMS.

LINKED DATA IMPLEMENTATION

Ontologies. For providing the expert system with the ability to interpret an existing building and configure by itself underlying monitoring functions, we rely on the use of Semantic Web technologies (W3C 2021). Introducing ontologies into that system enables a model-based monitoring of building energy systems in contrast to purely data-driven approaches (Mehmood et al. 2019). One common critic to classical rule-based systems is that rules and the semantics of the analysed problem are usually hard-coded into the used programming language. In our case, the building topological structure, metadata about its energy system and monitoring data are maintained in separated data structures. That way, the targeted monitoring algorithms, that use these data and metadata as input, are kept generic. By analogy, this approach is already established in the simulation field where a distinction is made between the model, that embeds the problem semantics together with physics laws, and the solver that undertakes the algorithmic part at runtime. This distinction between model and algorithm is also the backbone of ontology-based logical reasoning (Rattanasawad et al. 2018). Logical reasoners are programs that process the description logics inside an ontology without necessarily understanding the semantics of the specific domain of interest. As a result, a model-based approach allows for interchanging models respectively buildings in a flexible manner.

To implement this approach, a core information model is introduced inside the expert system that is composed of a set of ontologies which per definition conceptualize specific technical domains. Two main information domains are covered, the building HVAC and BACS domains. The first provides a representation of a building and its built-in energy system while the second focuses on representing the monitoring system of the building. Different data modeling standards
exist that can catch these domains. First, the Industry Foundation Classes (IFC) introduced and maintained by (BuildingSMART International 2020) cover many AEC disciplines including also to some extent the HVAC domain. In the Semantic Web field, several ontologies have emerged for abstracting these domains on a metadata level. The automation domain has been formally described into the SSN/SOSA model (W3C 2017) introducing among others the superordinate concepts of \texttt{ssn:System}, \texttt{sosa:Observation}, \texttt{sosa:Actuation}, \texttt{sosa:Sample} and \texttt{sosa:FeatureOfInterest}. For representing HVAC systems, the Brick ontology (Fierro et al. 2020) has emerged since a few years which has comprehensively covered the ventilation domain and which is in permanent further extension. Further useful ontologies are the Building Topology Ontology (BOT) which is a lightweight ontology for describing the spatial structure of buildings (Rasmussen et al. 2019), and the QUDT ontologies which have been initiated by the Constellation Program at NASA (FAIRsharing.org 2021). QUDT enables enriching measurements data from sensors with meaningful annotations by providing comprehensive vocabularies for units systems, physical dimensions and quantities from among others physics or chemistry. Other efforts and specifications have been developed so far, but we first focus on the previously listed schemas which best cover our requirements and are actively maintained by international standardization institutions. All rely on Semantic Web data standards like RDF (Resource Description Framework) and OWL (Web Ontology Language) (W3C, 2021).

As each ontology covers a specific domain with its limitations, we developed inside the core model further ontologies which enable a full description of a building in its operation phase and at metadata level. The resulting overall ontology is illustrated in Figure 1. Additional ontologies consist of the Energy System Information Model (ESIM), Metric, Sense and Risk models. Their purpose is on the one hand to aggregate the different described domains into one full exploitable model. On the other hand, they fill semantic gaps in the existing standards with additional concepts and knowledge that is necessary for configuring and executing the targeted energy monitoring and recommendation system that is fully described in next chapter. Similarly to Brick, ESIM describes the built-in energy system except that it covers a wider range of HVAC types like solar, geothermal

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{ontology_system.png}
\caption{Ontology system}
\end{figure}
or heat pump systems. Moreover, it enlarges the building scope to the district and energy grid level. The Metric model consists of a set of quantity kinds and KPIs (Key Performance Indicator) that complement QUDT with specific metrics for HVAC engineering (e.g. mm:HeatingEnergyConsumption, mm:HeatingCoilValvePosition, mm:SupplyAirTemperature, mm:IndoorAirTemperature, etc.) in contrast to the rather too fundamental quantities from QUDT (e.g. quantitykind:Irradiance, quantitykind:Temperature…). The Risk model provides a catalog of possible faults and operation errors that can lead to energy wastes, together with corrective energy conservation measures (ECMs). Finally the Sense Ontology represents the central knowledge model that aggregates the several concepts and in which logical axioms and rules are encoded for formalizing expert knowledge.

**Knowledge Base.** Despite the broad scope of disciplines they represent, the external ontologies depicted in Figure 1 lack reasoning logics and especially expert knowledge that can be applied for specific use cases. For our purpose of automatic setup of a monitoring and recommendation system, this knowledge has been integrated into the Sense ontology. The Sense ontology is named by analogy to the word “sensing” and is meant to interpret a system by the means of logical axioms and internal rules based on predicate logic. This ontology is used to emulate the cognitive reasoning of a HVAC or BACS expert who would setup a monitoring system on the basis of information about the building energy system. When processed by a reasoner, the Sense model is able to identify the locations within a building, its topology and built-in systems. Key inferred facts are for example the presence and types of heating / cooling systems, energy distribution components, shading system, the presence or not of a heat recovery system, the types of terminals (e.g. radiators or air outlets) and which of those are actuable by users.

For describing this knowledge, there exist a certain number of ontology modeling constructs and rule languages which are applied. A comparative overview of some rule languages and logical reasoners is provided by (Rattanasawad et al. 2018). Table 1 gives some examples of so-called class axioms which are used to classify individuals respectively objects inside the ontology system. The first example allows to identify HVAC zones inside a building which should then be considered by the expert system for analyzing the usage of heating energy. More specifically, it selects heating zones by checking if they host some distribution component like e.g. radiators from a heating system. The second example is a simple class axiom that select all entities that should be analysed for some fault detection if they are threatened by some energy risk.

<table>
<thead>
<tr>
<th>Table 1. Class axiom examples</th>
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<tbody>
<tr>
<td><strong>OWL class axiom in Manchester Syntax</strong></td>
</tr>
<tr>
<td>Class: esim:HeatingZone</td>
</tr>
<tr>
<td>Annotations: rdf:comment &quot;A space or group of spaces with heating requirements&quot;</td>
</tr>
<tr>
<td>esim:SpatialStructureElement and [sosa:hosts some (esim:EnergyDistribution and [esim:composes some esim:HeatingSystem])</td>
</tr>
<tr>
<td>ConditionedZone</td>
</tr>
<tr>
<td>Class: risk:EntityAtRisk</td>
</tr>
<tr>
<td>Annotations: rdf:comment &quot;Thing that is subject to a possible threat or fault&quot;</td>
</tr>
<tr>
<td>risk:hasRisk some risk:Risk</td>
</tr>
<tr>
<td>sosa:FeatureOfInterest</td>
</tr>
</tbody>
</table>
Table 2 gives some examples of rules defined in the Semantic Web Rule Language (SWRL) which are applied into a reasoner (Pellet) to identify such risks in an air handling unit (AHU) according to its built-in components (e.g. heating coil, cooling coil, fans, humidifier...). As a result, specific fault detection rules are affected to such AHUs to identify issues from real operation data.

### Table 2. Examples of rules used for risk identification

<table>
<thead>
<tr>
<th>Nr</th>
<th>Rule definition in human-readable syntax</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>brick:AHU(?ahu) ∧ brick:Heating_Coil(?hc) ∧ brick:Cooling_Coil(?cc) ∧ brick:hasPart(?ahu, ?hc) ∧ brick:hasPart(?ahu, ?cc) → risk:hasRisk(?ahu, risk:SimultaneousAirHeatingAndAirCooling)</td>
</tr>
<tr>
<td>(2)</td>
<td>brick:AHU(?ahu) ∧ brick:Heating_Coil(?hc) ∧ brick:Cooling_Coil(?cc) ∧ brick:hasPart(?ahu, ?hc) ∧ brick:feeds(?hc, ?cc) → risk:hasRisk(?ahu, risk:SimultaneousAirHeatingAndAirCooling)</td>
</tr>
<tr>
<td>(4)</td>
<td>brick:AHU(?ahu) ∧ brick:Cooling_Coil(?cc) ∧ brick:Supply_Fan(?sf) ∧ brick:hasPart(?ahu, ?cc) ∧ brick:hasPart(?ahu, ?sf) → risk:hasRisk(?ahu, risk:AirCooledButNotVentilated)</td>
</tr>
<tr>
<td>(5)</td>
<td>brick:AHU(?ahu) ∧ brick:Humidifier(?h) ∧ brick:Supply_Fan(?sf) ∧ brick:hasPart(?ahu, ?h) ∧ brick:hasPart(?ahu, ?sf) → risk:hasRisk(?ahu, risk:AirHumidifiedButNotVentilated)</td>
</tr>
<tr>
<td>(7)</td>
<td>risk:hasRisk(?e, ?ri) ∧ risk:assessedBy(?ri, ?ru) ∧ so:Rule(?ru) → so:hasRule(?e, ?ru)</td>
</tr>
</tbody>
</table>

**RECOMMENDATION SYSTEM**

**System Components.** The previous chapter introduced the ontology which represents only one part of the overall recommendation system. This linked data system is only in charge for building metadata processing and for configuring further algorithms for data processing. The whole expert system is composed of three main components: (1) a base of facts or use cases, (2) a knowledge base and (3) an inference module that takes information from (1) and (2) as input in order to derive new facts. In our case, these new facts consist principally of corrective procedures or control actions which can be applied in a building by end-users. Figure 2 illustrates the whole workflow of the proposed recommendation system which integrates these three main components:

- The fact base encompasses information about the building, its topology and its technical systems inside the ontology, as well as operation data gained periodically from a pre-existing building data acquisition system.
- A knowledge base that contains several axioms and rules that are splitted into different computer-readable languages and that describe conditions for potential faults and energy conservation measures (ECMs).
- An inference module that consists of algorithms that execute the analysis using both the information model from the fact base and the knowledge base in order to generate warnings and recommendations.

The illustrated building and monitoring metadata consist of information from the OWL ontology which is imported from RDF/XML syntax into Python at runtime using RDFLib library. The first kind provides the description of the building structure together with its technical systems (heating system, cooling system, etc.) while the second describes the types of sensors and meters installed, the quantities they measure, their units, etc. In contrast to metadata, actual measurement data are not stored into the ontology but are regularly cached into Pandas data frames from a database prior to each inference run. On the basis of the fact base and with the help of the knowledge base, the inference module can then characterize the building as it is built and assess its operating conditions.
Metadata and Data Processing. The logical axioms and rules used by the inference module are divided into three inferencing levels, as illustrated in Figure 2, which are executed sequentially. The first level consists of metadata processing whose goal is to characterize the existing building systems. For that purpose, the ontology system and logical reasoning as presented in previous chapter are involved. It is executed once at monitoring setup or periodically when metadata i.e. building information changes over time (retrofitting of HVAC system, addition of sensors…). This system characterization step is run in Python using Owlready2 library and delivers for each room, HVAC subsystem or component a list of potential energy risks and energy conservation measures (ECMs) that should be checked for validity in the second inference level. Additionally, it provides for each element a list of data checking rules together with the required measurement points that should be queried from the existing data acquisition system. As an example, if a room hosts e.g. radiators, it will be considered for checking potential overheating, and if it really occurs, the next inference levels will provide the end-user with the advice to reduce local indoor temperature.

The second and third inference levels consist of data processing. The inference module executes these inference levels in real time. The rules from that levels mainly consist of IF-THEN statements including boolean operators (OR, AND, NOT). These rules are used for interpreting the operational conditions of the building technical systems (weather conditions, systems status (on/off), indoor conditions, etc). They are based on the measurements time series which are cached into the fact base. The cached time series range from the most recent value to a few hours in the past. As a result, if a fault or ECM is validated at a certain time, a warning or recommendation is triggered by the expert system. In constrast to the first level, these rules have been implemented directly as boolean expressions into the Python programming language. One reason for the distinct inference levels is that ontology-based reasoning is more adapted for semantic processing of metadata and less for time-series analysis, while a programming language like Python provides a fast and efficient way of processing large time-series data and for expressing procedural rules.
A first prototype of the recommendation system has been implemented for twelve buildings. In that context, a common database schema has been defined to store and continuously update all sensors and meters data. The metadata required to populate the ontology has been defined into that database schema and implemented in SQL (Structured Query Language). A simplified version of this schema is illustrated in Figure 3 in the form of an Entity-Relationship Diagram (ERD). The resulting relational model applies a modeling construct used in building information modeling (BIM) that consists of nesting building elements into a spatial hierarchy (BuildingSMART, 2020). The building information contained in these metadata is reused in the fact base mentioned in previous chapter together with the measurements time series from sensors and meters. Thanks to this information, the recommendation system has the ability (1) to unambiguously locate each measurement within or outside a building, and (2) to characterize the building, its HVAC system and available data points. As much more metadata can be extracted from BIM models like the ones produced in CAD planning tools, an integration into a BIM workflow represents the next release of the prototype. The instantiation of metadata inside the ontology system from BIM data is not put in focus in the article, but it is a work in progress that relies on existing data conversion methods from the Linked Building Data field (Bonduel et al. 2018).

The recommendation system runs as a cloud service remotely on a virtual machine that is hosted at our premises. For synchronizing data from the existing monitoring system of each building with the fact base, a universal communication interface was chosen. It consists of an OPC UA interface (Open Platform Communications Unified Architecture) which shall increase, as one of the established automation standards, interoperability possibilities with BACS systems of future buildings (OPC Foundation, 2020). The results from the recommendation system are sent as JSON (JavaScript Object Notation) payloads to a RESTful server which provides users with recommendations through a web front-end application.

Figure 3. Communication between monitoring and recommendation systems
CONCLUSION

The building sector has been assessed as the main contributor to world-wide energy use. An important amount of this energy is wasted or consumed unnecessarily through wrong or suboptimal building operation. To avoid this, we have proposed a rule-based and model-based expert system that shall support automatic energy system monitoring, fault detection and energy advices. The main added value of the proposed system is its ability to be applied at a large scale on the basis of its self-configuring mechanisms relying on semantic modeling. It can be used remotely as a cloud service thus easing its deployment. Two main constraints remain i.e. the availability of monitoring data and of metadata for the analysed buildings. Metadata issues can be addressed by the use of BIM models which would unleash the full potential of the system by providing more comprehensive information and possible use cases. In that context, it was noticed the need for uniformized monitoring database systems, which could be solved by normalizing and generalizing database schemas and ontologies as the ones introduced. With the emancipation of smart buildings, IoT (Internet of Things) and smart home systems, even in retrofitted buildings, data availability and interoperability should increase in near future. Further extensions are the support of more BACS communication protocols (e.g. MQTT, BACnet) for easing integration with more buildings.

REFERENCES


