A RECOMMENDATION SYSTEM FOR ENERGY SAVING AND USER ENGAGEMENT IN EXISTING BUILDINGS

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ABSTRACT

This paper presents an IT system that provides building users with hands-on executable recommendations in order to reduce their energy consumption. For that purpose, it analyses building operation data in real time in order to identify energy wastes as well as suitable energy conservation measures that shall help saving energy without compromising comfort and indoor environmental quality. One main goal is to provide a highly scalable solution that can be easily replicated and used in a wide range of buildings thus enabling resource saving at a large scale.

INTRODUCTION

Building users and facility managers often need guidance to change their behavior towards energy efficiency because of their lack of energy awareness and knowledge. In last decades, much research efforts have been spent to optimize the efficiency of energy systems. New technologies have been introduced that increase the use of renewable energies, and existing technologies have been optimized to avoid or reuse wasted energy. Moreover, many developments and research have led to enhanced building automation systems embedding data analytics algorithms and performing energy-optimized and automatic building systems control (Oldewurtel et al., 2012; Mayer & Enge-Rosenblatt, 2019; Mehmood et al., 2019). Even if technology has been enhanced, there was not much attention paid to building users themselves who represent a major factor of energy inefficiency and waste due to energy-unaware behavior. In contrast to the classical goal of building automation that tends to achieve a fully automated and autonomous energy management, the proposed approach relies on the interactions between the building and its users. In particular, it aims at increasing the awareness and engagement of building users with regards to their energy consumption and building operation costs.

This work is part of an on-going EU-funded project called eTEACHER. The eTEACHER project aims at empowering energy end-users to achieve energy savings and improve comfort conditions within buildings by enabling behavioral change. The behavioral change is addressed by means of ICT solutions that connect building energy monitoring systems with end-users. The proposed solutions focus on providing end-users with tailored recommendations which were designed with engagement methods and gamification concepts based on the results of social studies. In this way, end-users (householders, facility managers, staff, teachers, etc.) are able to identify energy efficiency and comfort improvements that they can undertake by themselves and integrate in their usual activities.

To achieve this goal, the presented system analyses building data in order to identify suitable energy conservation measures (ECMs) as formally defined in (EVO, 2014). These ECMs are meant to be applied by building users or facility managers to save energy. In view of that, the system translates ECMs into tailored recommendations in text form that are provided to end-users through a graphical user interface for engaging their actions towards more energy efficiency and for bringing them more energy awareness. The core algorithms follow a rule-based approach for best addressing the goals and constraints that are encountered. Among the main constraints, the availability of building data is a common issue. Indeed, many buildings do not have a monitoring system. Moreover, the system has to be applied in real time during building operation. Thus, it must have restricted computational time and be executed continuously in a proper runtime environment. Furthermore, one major constraint is the ability to be applied to any kind of building regardless of their type, size, usage, users and existing facilities (heating, ventilation, air conditioning, lighting, etc.). Reprogramming or reconfiguring the tool according to singularities of each building should be avoided in order to have a scalable system.

ENERGY SAVING ANALYSIS AND STRATEGY

Use Cases Overview

Twelve use cases i.e. buildings, that involve about 5000 people and are located in 3 climate areas, have been used to identify the requirements of the recommendation system and test the resulting tool. The 12 use cases are real buildings and are listed in Table 1 below.

Table 1: List of buildings introduced as use cases

Type	*Key figures*	*Country*
kindergarten	built in 1976, 905 m2 gross area, 1 floor, 20 users	Spain
high school	built in 1965, 5307 m2 gross area, 3 floors, 120 users	Spain
office building	built in 2011, 3211 m2 gross area, 3 floors, 130 users	Spain
residential building	built in 1984, 4540 m2 gross area, 5 floors, 95 users	Spain
healthcare center	built in 2000, 1270 m2 gross area, 2 floors, 577 users	Spain
healthcare center	built in 2002, 2180 m2 gross area, 2 floors, 915 users	Spain
residential complex	built in 2009, 67900 m2 gross area (4 buildings), 1500 users	Romanaia
secondary school	built in 2005, 9163 m2 gross area, 2 floors, 800 users	United Kingdom
municipal building	built in 1927, 5826 m2 gross area, 7 floors and 40 users	United Kingdom

The users of these buildings are facility managers, householders, office/medical staff, cleaning crew, security team, teachers and students. The technical systems are mainly HVAC systems, appliances and lighting systems which consume electricity, gas, fuel oil or waste depending on the specific building and system. The appliances depend on the type of building and are computers, printers, beamers, electric radiators, medical equipment, lab equipment and home appliances such as TVs, fridges, ovens, etc. The lighting systems are mainly fluorescent lamps and have sometimes central control and sometimes manual control. The HVAC systems include several types such as heating and cooling based on VRF heat pumps (Variable Refrigerant Flow) and compact air handling units, splits, district heating and radiators, boilers and radiators, boilers and underfloor heating, electric chillers and cold ceilings, air-water heat pumps and fan coils, air-air heat pumps (multi-splits), etc.

According to a study carried out in the use cases before the deployment of the tool, typical energy-wasting bad habits of users and corrective target behaviors have been identified. This study has been based on on-site surveys and monitoring data. The energy-related behaviors that the recommendation system aims at influencing are among others:

- Lighting use behavior: Turning off lights when leaving a room or at the end of the day; reduce use of unneeded lights checking lighting levels and needs during the day
- Appliance use behavior: Turn off appliances (computers, TVs, medical equipment, etc.) at the end of the day; turn off appliances when away
- HVAC use behavior: Reduce thermostat temperature for heating when overheating; increase thermostat temperature for cooling when undercooling; ensure that windows and doors are kept closed if heating/cooling is on; turn down HVAC system if room/building is not in use for more than one hour; ensure that air-conditioning and heating are not working at the same time; Take advantage of passive solar energy

Energy Conservation Measures

The ECMs have been defined taking into account the energy systems of the buildings, how they can be actuated by the users to save energy, as well as the target behaviors. Specifically, the procedure to define the ECMs consisted of: 1. Identifying energy systems of the buildings that can be manipulated by the users to save energy; 2. List potential ECMs related to those energy systems and applicable by users; 3. Organize ECMs and document their requirements in terms of required data from the systems; 4. Enrich and prioritize the ECMs with the target behaviors; 5. Translate the ECMs into knowledge-based rules. As a result, 4 groups of ECMs that can be carried out by end-users such as householders, staff, teachers and facility managers have been defined:

1. ***ECM1 - Save cooling energy using HVAC control, windows and blinds:*** Building users can save energy by controlling HVAC consumption by means of temperature set-point and fan speed as well as external energy factors (external gains from solar radiation or air flows) by opening/closing windows and blinds. In summer, solar radiation has a negative effect (increase building, zone or room temperature) that should be mitigated closing blinds when necessary; indoor temperature and humidity can also be controlled by opening/closing windows when convenient. Cooling unused spaces should be avoided.
2. ***ECM2 - Save heating energy using HVAC control, windows and blinds:*** End-users can save energy by controlling the HVAC consumption by means of temperature set-point and fan speed as well as external energy factors (external gains from solar radiation or air flows) by opening/closing windows and their blinds. In winter, solar radiation has a positive effect (reduce heating demand) that should be taken advantage of by opening blinds when it is necessary; closing windows also helps to reduce heating losses. Heating unused spaces should be avoided.
3. ***ECM3 - Save lighting energy using natural lighting or power-off when there are no people using it:*** Lighting energy consumption can be reduced taking advantage of natural lighting by opening blinds and turning off lights when there are no people in the room or building.
4. ***ECM4 - Save electrical energy turning-off unnecessary appliances, devices or equipment:*** Powering off electric devices (computers, printers…), home appliances (TV, laptops…) when they are not in use is a common practice to save energy.

For the recommendation system to evaluate these ECMs in each building and in real time, it requires some information related to building topology and energy systems, as well as data provided by e.g. energy meters (cooling/heating, electricity), pyranometers or weather stations, occupancy sensors or presence sensors, indoor temperature sensors, outdoor temperature sensors, etc. These requirements are discussed in chapter MONITORING SYSTEM.

RECOMMENDATION SYSTEM

The recommendation system that has been developed can be assimilated to an expert system that relies on a certain control logic implemented with the help of rules. Contrary to classical control systems which operate actuators, this logic is used to perform a so-called indirect control (Shigeyoshi et al. 2011) relying on handlings of building users.

System Components

An expert system is a computer system that emulates the reasoning ability of a human expert. It is composed in general of three main components: (1) a base of facts or use cases, (2) a knowledge base and (3) an inference engine that takes information from (1) and (2) as input in order to derive new facts. In our case, these new facts consist principally of procedures or control actions which are applicable in a building by end-users. The preliminary facts are real building data which are provided by the monitoring system presented in next chapter. Figure 1 illustrates the internal workflow of the proposed recommendation system which integrates the following three main components:

- A fact base that encompasses information about the building, its topology and its technical systems, as well as operation data gained from the monitoring system.
- A knowledge base that contains different rules that are expressed in computer-readable language and that describe the energy conservation measures (ECMs), their effect and several underlying building operational states that condition their validity for some specific use cases.
- An inference module that consists of algorithms that execute the analysis using both the data model from the fact base and the knowledge base in order to generate recommendation objects that describe ECM procedures including estimations of their energy saving potential.

The core data model in the fact base consists for each studied building of metadata about the building and its built-in monitoring system, as well as actual measurement data which are regularly cached into the fact base prior to each inference run. A building metadata model provides a static description of the building structure together with its technical systems (heating system, cooling system, etc.). In contrast, a monitoring metadata model describes the types of sensors or meters installed in the building, their measured physical quantities, their units, etc. Accordingly, these metadata are used to annotate and locate real measurement data that consist of time series. For describing these different metadata, an overall metadata model has been built as an ontology using the Semantic Web data standards RDF (Resource Description Framework) and OWL (Web Ontology Language) (W3C, 2020). On the basis of the metadata and with the help of the knowledge base, the inference module can then characterize the building as it is built together with its available monitoring data. After this first characterization step, the inference tool can then continuously analyze actual operational conditions and identify proper ECMs that are further provided to a Front-End application through an API (Application Programming Interface) using the REST (REpresentational State Transfer) architectural style (Fielding & Taylor, 2002).

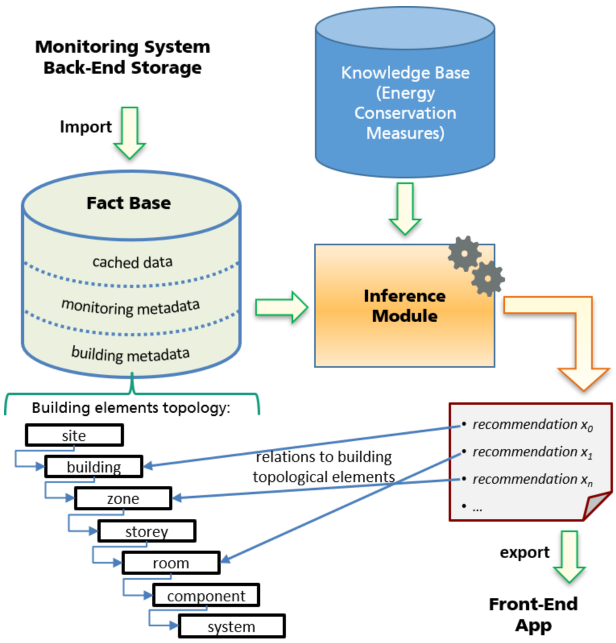

Figure 1: Data flow of the expert system

In addition to the expert system part of the recommendation system, another module is used for evaluating and storing the energy saving potential of each ECM. This estimation module consists of a set of algorithms that compute absolute and relative values of energy consumption in certain units e.g. kWh, kWh/d, kWh/a. For that purpose, the time series data from the monitoring system are again used and especially values from submeters that allow for differentiating the energy consumed for cooling, heating, lighting and appliances in specific zones. Each of the computed results represents the amount of energy that can be saved when users apply some ECM action. The estimation module runs on daily basis and independently from the expert system. It provides estimations which are then written into the recommendation objects delivered to the Front-End App. Since the estimation module requires a sufficient data history, the energy saving estimation process is differentiated into two usage phases of the recommendation system:

- Commissioning and first operation period: the energy saving potential consists of reference values which were taken from experimental surveys and benchmarks about energy saving in reference buildings by means of similar ECMs. These values are also used for the case that a building does not dispose of the data points required by the estimation module.

- Second operation period: when the tool has been used for a sufficient period of time, the corresponding historical data (1 month till 1 year back depending on the ECM) is processed by the estimation algorithms to compute energy saving values.

Data processing

The ECMs are formalized in terms of rules that can be formulated in natural language as IF-THEN statements. These rules must be translated into a computer-readable form in order to be processed by the inference algorithms. For that purpose, there exists a certain number of possibilities ranging from boolean expressions in classical procedural programming languages to rule languages usually used in the field of artificial intelligence and logic-based systems. An overview of some rule languages is given in (Rattanasawad et al., 2013). Once translated into specific computer-readable objects, the ECM rules can be stored into the knowledge base. Even if a rule can be formulated into one IF-THEN expression in natural language including boolean operators (OR, AND, NOT) and predicates, their implementation in computer-readable form necessitates nesting them in several atomic rules. Consequently, for each ECM several single atomic rules have been defined and written into the knowledge base. In runtime, these atomic rules are checked sequentially following a forward-chaining principle in order to allow the recommendation system to identify if one ECM is valid and a recommendation can be triggered for a certain building location at a certain time.

The atomic rules are classified into three different execution levels. During runtime, the inference engine processes the rules in a sequence starting from the first level till the third level. The levels are defined as follows:

- **1st level: system characterization rules**
  - These rules are used for characterizing the building and its technical systems: cooling / heating system, distribution system, shading system, actuable systems, etc
  - They are based on the building and monitoring metadata contained in the core data model of the fact base
- **2nd level: state interpretation rules**
  - These rules are used for interpreting the operational conditions and energy performance of the building: weather conditions, systems status (on/off), indoor conditions, occupancy, openings status, etc
  - They are based on the monitoring data respectively time series which are cached into the fact base
- **3rd level: procedural rules**
  - This last layer checks if an ECM is valid or not for the current time and building use case
  - They use as premises the results from the system characterization and state interpretation levels

Because of the specific type of data each level processes, the rules have been for one part implemented into some logical axioms and rules inside the ontology, and for another part into the Python programming language. More specifically, the first rule level (system characterization) relies on the ontology for processing metadata. The second (state interpretation) and third (procedures) levels are based on the programming language for processing time series and boolean expressions. As a result, the inference module consists of these distinctive rule checking levels, each implementing a proper technology. Indeed, ontology is rather 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 of expressing procedural rules. Figure 2 provides a simple example of 1st level rule for identifying if a space is an heating zone. It consists of an equivalent class axiom defining a heating zone as a building spatial element that contains some energy distribution component from the building heating system.

```
Class: HeatingZone

    EquivalentTo:
        SpatialStructureElement
         and (hosts some
            (EnergyDistributionComponent
             and (composes some HeatingSystem)))

    SubClassOf:
        ConditionedZone
```

Figure 2: Some logical axiom for classifying heating zones


```
{
  "location": {
    "site": {
      "id": "6",
      "name": "Badajoz",
      "ifcGuid": null
    },
    "building": {
      "id": "10",
      "name": "Residential Building",
      "ifcGuid": null
    },
    "zone": null,
    "storey": {
      "id": "21",
      "name": "Fifth",
      "ifcGuid": null
    },
    "space": {
      "id": "48",
      "name": "5oB",
      "ifcGuid": null
    }
  }
}
```


Figure 3: Example location object in JSON format

Accordingly, if a room or a flat hosts e.g. radiators, it will be considered for checking some ECM which relate to saving heating energy (ECM2) by acting on local indoor temperature. On the 2nd and 3rd levels, the measurements data which are relevant to this location are analysed in real time to compute operating conditions which are used to detect if energy is being wasted and some recommendation can be triggered. Besides OWL and Python, the JSON format (JavaScript Object Notation) has been used to manage metadata in the fact base and to support the data flow presented in previous section. Figure 3 shows an example location object used to represent a flat in a residential building.

MONITORING SYSTEM

Hardware Installation

The recommendation system requires some dynamic data as input that is normally provided by a monitoring or building automation and control system (BACS). The number and type of sensors, their position, connection (wire or wireless), data transfer and frequency, energy supply, cost and communication protocol must satisfy some requirements. For the identification and evaluation of energy conservation measures, the monitoring system needs to collect following data related to the use of lighting, appliances, HVAC systems, windows, shadings, etc. at each specific time interval (e.g. 10 minutes):

At building level

- Outdoor conditions: temperature (ºC), relative humidity (%), light level (lux), solar radiation (W/m2)
- Energy consumption (kWh): lighting, HVAC, appliances

At room/apartment level:

- Energy consumption (kWh): lighting, HVAC, appliances
- Indoor conditions: temperature (ºC), CO2 (ppm), relative humidity (%), light level (lux)
- Other binary measurements: presence and windows opening

Other important technical requirements for the monitoring system consist of easy installation, cost-effectiveness, system security and easy integration in standard server and database systems.

Table 2: Monitoring system in one use case

Qty	*Sensor type*	*Measurement type*
1	Z-Wave weather station	Irradiance at the rooftop of the building (W/m2)
		Luminance at the rooftop of the building (Lux)
		Ambient temperature in the outside (ºC)
		Relative humidity in the outside (%)
1	Circutor Mini (CVM MINI-ITF-RS485-C2)	Energy consumption of the building (kWh)
4	Circutor Mini MC (CVM MINI-MC-ITF-RS485-C2)	Energy consumption of the lighting (kWh)
3	Circutor Mini MC (CVM MINI-MC-ITF-RS485-C2)	Energy consumption of the HVAC system (kWh)
1 per room	NEO COOLCAM for opening of doors and windows (NEOEDS01Z)	Binary, window opened/closed (adimens.)
1 per room	Schucko Everspring with energy measurement (EVR_AN1812)	Energy consumption of the appliances (kWh)
1 per room	Qubino Flush 1 Relay with energy measurement (ZMNHAD1)	Energy consumption of the lighting (kWh)
1 per room	Fibaro Z-Wave Plus multi-function motion sensor (FIBEFGMS-001-ZW5)	Binary, presence detector at the room (0 no detection)
		Luminance in the room (Lux)
1 per room	Z-Wave plus MCOHOME sensor for CO2, Temperature and Humidity (MH9-CO2-WD)	CO2 concentration in the room (ppm)
		Temperature in the room (ºC)
		Relative humidity (%)
2 per room	Fibaro Universal Binary Sensor (FIB_FGBS-001)	Fan coil input/output temperature in the room (ºC).

In the 12 use cases i.e. buildings, data were collected from existing BACS systems when it was possible. Otherwise, new monitoring systems were installed when the required data were not accessible or missing in the existing system. There are many options for monitoring systems on the market that include wire and wireless sensors.

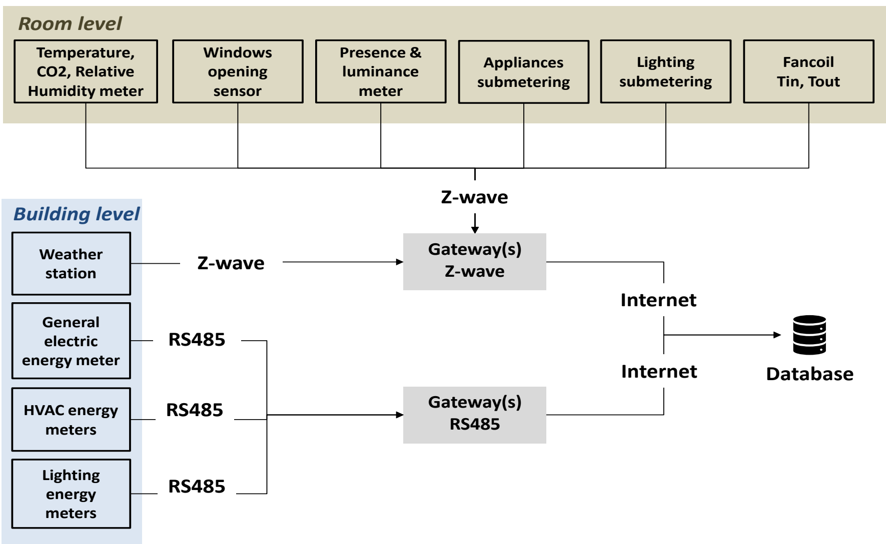

Figure 4: Monitoring network in one use case

Several technologies have been used in the 12 use cases. In general, low cost and wireless sensors were prioritized to avoid big investments and intrusive installations, but wired sensors have also been used. As an example, Figure 4 illustrates the monitoring network in one of the use cases. The building has 2180 m2 gross area with 43 rooms and it is conditioned by an air-water system (3 central heat pumps and fan coils) and 5 air handling units (AHU) used for ventilation. Table 2 summarizes the monitoring system used in the same pilot building.

According to the experience in the 12 use cases, the existing wireless monitoring technologies require a continuous maintenance of the sensors (batteries, network connection, etc.) to ensure data quality which is key for the recommendation system.

Data Storage and Transfer

A common and centralized relational database has been implemented to store all sensors and meters data located in the 12 use cases. This database is continuously updated over time with actual data. That way, all data remain available and up to date as well as accessible to the recommendation system through a single interface. It was necessary to harmonize all data and metadata into a proper database schema since part of the data is provided by some pre-existing on-premise monitoring systems that use own database management systems (DBMS) and data structuration. This schema has been implemented into SQL (Structured Query Language) as it is the most used database standard in existing building monitoring systems, which enabled the replication of pre-existing data points into the common database. A simplified version of this schema is illustrated in Figure 5 in the form of an Entity-Relationship Diagram (ERD). This schema describes the metadata i.e. the entities that are represented within the database together with their relationships. The resulting relational model applies a modeling construct that is commonly used in the field of building information modeling (BIM) and which is called spatial decomposition (BuildingSMART, 2020). It consists of decomposing the topological structure of a building into a hierarchy of containing and contained elements. For example, a site contains one or more buildings; a building contains floors; one floor contains rooms; a room contains technical equipment; etc. The building information contained in these metadata is reused as input for the fact base described in the previous chapter together with the measurement 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.

In order to identify ECMs that are relevant to a specific location within a building, the recommendation system has to recognize its topology and built-in systems. Key characteristics are for example the presence or not of heating and cooling systems, the type of energy distribution components or terminals (e.g. radiators or AHU outlets), type of sensors, etc. This kind of information can usually be contained in a building design model like the ones that are produced in CAD planning tools and that can be serialized in BIM-compliant data formats. The use of such BIM models represent further extensions of the recommendation system like proposed by Stenzel et al. (2013) and Schneider et al. (2020).

Because the relational database is hosted in another network and it can become an interchangeable component inside a specific on-site monitoring ecosystem, a universal communication interface was chosen. It is built on top of the database for enabling the monitoring system to communicate data over the web to the recommendation system which is run as a cloud service at Fraunhofer.

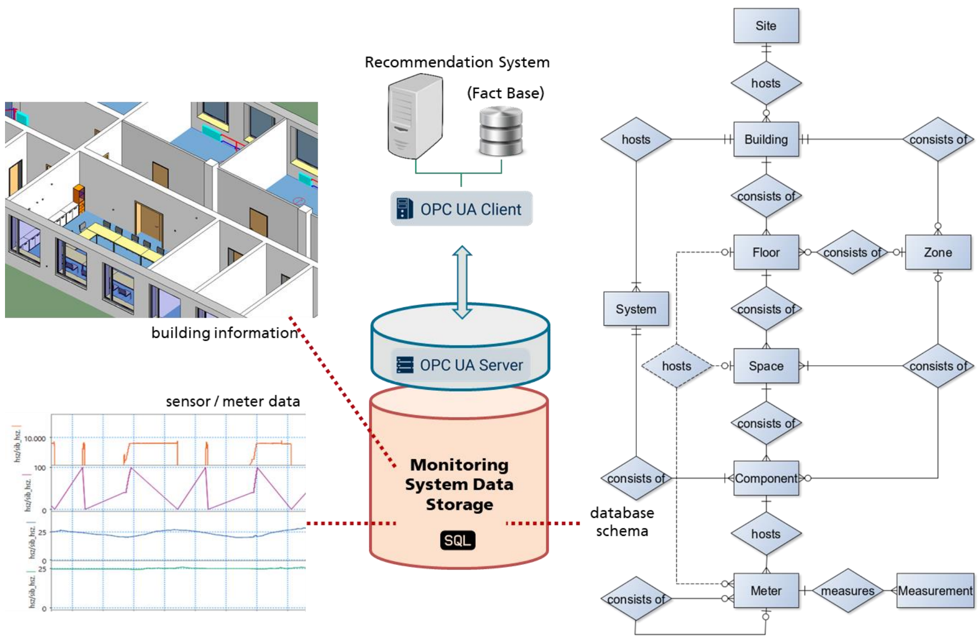

Figure 5: Communication between monitoring and recommendation systems

It is usual to find different types of DBMS in BACS systems, which all offer specific APIs. To avoid implementing database-specific data imports and maximize the chances of interoperability with existing BACS systems in potential further buildings, the choice was made to use a web-capable and standardized communication protocol for the universal interface. To communicate with the central database, our system uses the Open Platform Communications Unified Architecture (OPC UA) which is a machine to machine communication protocol originally developed for industrial automation (OPC Foundation, 2020). It has also spread in automation systems for buildings and provides relevant characteristics for data as well as metadata exchange in real time. OPC UA provides a standardized, open, cross-platform and service-oriented architecture (SoA). An OPC server includes a hierarchical node model that structures all information about the available sensor data following the same Entity-Relationships and metadata models mentionned previously. The OPC client can browse this information model and read underlying data like actual and historical sensor values.

TOOL DEPLOYMENT

At the time of this paper, the overall system presented within previous chapters has been deployed as a research prototype and applied for all building use cases. The monitoring system has been set up and the common database is continuously updated in real time with new sensor and meter data. The corresponding DBMS system has been built into a Docker Container for facilitating its installation on any computer. The incoming data is constantly synchronized through the OPC interface with the fact base of the recommendation system. This latter runs remotely on a virtual machine that is hosted at Fraunhofer premises. The execution of the recommendation system is managed by a Linux scheduler that guarantees the continuous availability of the service over the year. Accordingly, the different algorithms of the inference module and the estimation module run repetitively over time with different frequencies depending on the analyzed ECMs. The execution frequencies range from some minutes to one day.

The communication of the results from the recommendation system to the Front-End App occurs through a REST API. REST provides a data exchange architecture that relies on web standards and that uses HTTP Protocol for exchanging data resources. In our case, these data resources consist of recommendation objects that are serialized in JSON according to a specifically defined schema. Each recommendation object contains the following main information:

- a recommendation or advice that is formulated in natural language and that describes a control action that an end-user could perform to save energy
- a location in the building where this recommendation applies. As the system considers different building levels, it relates each output to a specific space, a zone or the building itself.
- a timestamp at which the recommendation has been triggered and is valid
- a validity period that indicates the time duration for which the recommendation is valid. The Front-End App removes it after that period is trespassed.
- the targeted effect associated with the action described in the recommendation
- Estimations of the resource saving potential expressed in different units like the amount of kWh saved by performing one recommended action or the relative yearly saving when repeating this action over a year

Figure 6 below consists of a screenshot of the Front-End App that shows the recommendation view. In the example below, current recommendations for an open space floor of an office building in Spain are listed.

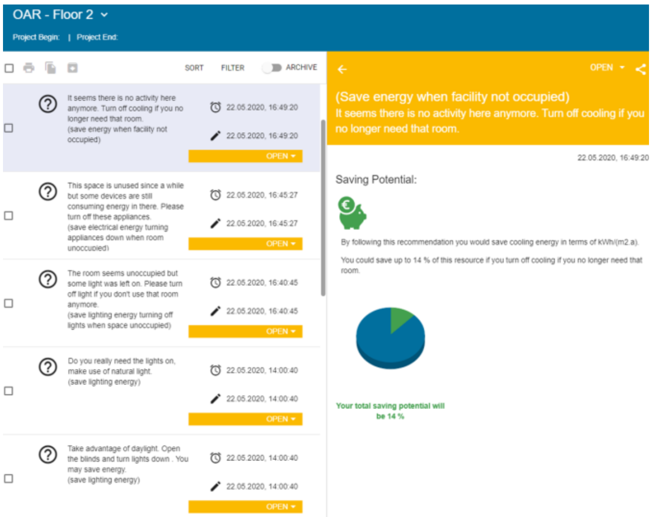

Figure 6: Screenshot of the Front-End App

CONCLUSIONS

So far, the building sector has been assessed as the main contributor to world-wide energy use. Although much of the energy used is necessary, there is an important amount of energy that is wasted or consumed unnecessarily through wrong or suboptimal building operation. To avoid this phenomenon, we have proposed a recommendation system which behaves like an expert system based on knowledge rules. The system analyses buildings data to identify energy conservation measures and provides tailored recommendations to building users in order to guarantee an efficient operation. This system has been deployed in 12 real pilot buildings and is still in testing and evaluation phase.

The main targets of the proposed system are its support to save energy in buildings at a large scale and its scalability. It relies on software tools that can be used remotely as a service and that run on several platforms. A comprehensive monitoring system similar to the one introduced in the paper is necessary to take advantage of all the system features and potential. However, the recommendation system and the related user interface can also be used without such an intensive monitoring system. In extreme cases, the proposed system can work without an installed sensors system by providing general hints instead of detailed recommendations.

The system can be improved in the future in several ways. For example, the use of BIM models can enhance the automation in the configuration of the recommendation and monitoring systems. This can enable a fully automatic characterization of the building and its systems. Indeed, for the moment, the building metadata contained in the DBMS must be manually configured for each building and consist only of few metadata. Accordingly, this implies eroneous or missing metadata that can not be processed. An IFC model could be used instead as input for a computer program to generate these metadata. Moreover, BIM will allow to widely extend the set of use cases and potential ECMs by providing much more precise information about the building (e.g. exact façade orientation, window-to-wall ratio, detailed HVAC system properties…). Furthermore, the recommendation system could be coupled with model-predictive methods relying on simulations for providing more accurate recommendations or estimations based on e.g. weather forecasts, detailed thermal properties of buildings, etc. With regard to energy saving estimations, several machine learning methods can be used for enhancing accuracy by complex correlations between users actions and energy system reactions. Finally, the system will be applied as support for fault detection and diagnosis by extending the knowledge base with new rules and axioms.

ACKNOWLEDGMENTS

This paper is supported by European Union´s Horizon 2020 research and innovation programme under grant agreement No. 768738 , eTEACHER project (End-users tools to empower and raise awareness of behavioral change towards energy efficiency).

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