A semantic approach towards implementing energy efficient lifestyles through behavioural change

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ABSTRACT

Residential and office buildings have the largest share in energy consumption, followed by transport and industry. At the same time, many buildings do not leverage all feasible opportunities to increase their energy efficiency. Particularly, the solutions influencing the behaviour of the end-users are lacking. In this paper, we present a novel semantics-empowered approach for motivating end-users towards the adoption of energy efficient lifestyles, based on recommendations provided through personalised applications and serious games. As a foundation of our approach, we have designed two semantic models to represent energy consumption and behavioural characteristics of consumers. The Energy Efficiency Semantic Model represents energy consumption data collected from a heterogeneous sensor network, while the Behavioural Semantic Model focuses on energy consumption profile of end-users. These models are being validated in the reference architecture and use cases of EU H2020 project ENTROPY.

Keywords

Energy efficiency, behavioural change, semantic modelling

1. INTRODUCTION

A recent report [6] shows that buildings are responsible of 41% of total energy consumption in Europe in 2010. It is the largest energy consuming end-use sector, followed by transport (32%), and industry (25%). Furthermore, as stated in the Smarter 2020 report [5], majority of the buildings have not reached their potential to increase their energy efficiency.

The significance of this end-use sector is also supported in the Energy Efficiency Plan 2011 by the European Commission, that the greatest energy saving potential lies in buildings [4]. In order to exploit this potential, innovative solutions have to be implemented taking into account the main energy consumption factors and trends, including citizens' energy consumption behaviour.

Thus, the deployment of energy efficient ICT solutions has to be accompanied by active engagement of the occupants to increase the overall environmental friendliness of buildings. A study conducted in several developing countries [8] shows that providing timely interventions adaptive to user's behaviour create significant impact on energy saving.

Under the light of the aforementioned findings, we take the existing research on the utilization of ICT for energy efficiency one step further and propose the ENTROPY[1] platform which consolidates Internet of Things and semantic technologies in a pervasive system, in order to provide timely interventions through personalised applications and serious games (i.e. games that do not primarily aim to entertain [3]). Following University of Murcia (UMU) use case provides an example scenario for the motivation of ENTROPY: *A faculty or staff member arrives to his/her office in the morning. The HVAC (Heating, Ventilating and Air Conditioning) system equipped with sensors and smart meters are available in the offices. We observe the average temperature every hour from the weather station in the campus as well as the HVAC state in the offices. For instance, in a summer day, we create a personalised recommendation to persuade a faculty or staff member to turn the HVAC system off and open the window instead, if the external weather conditions and user's traits are suitable.* UMU's existing IoT infras-

[1] http://entropy-project.eu

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tructure and mobile crowd-sensing techniques allow us to obtain energy consumption measurements giving indications about consumer's behaviour. Our aim is creating effective interventions targeting energy consumption behaviour in an iterative fashion. We expect our approach to have a significant effect on general energy efficiency of UMU only by motivating the campus inhabitants.

Throughout the paper, we will review the literature and state our contribution (Section 2), introduce the semantic models (Section 3) and reference architecture (Section 4) in which the semantic models will be utilised. Finally, we will conclude the paper with closing remarks and next development steps for our approach (Section 5).

2. STATE OF THE ART AND CONTRIBUTION

Utilization of ICT for energy efficiency has drawn high interest from computer science community. A plethora of research projects address energy efficiency with human users' actions, and for many of them semantic technologies are a key element. Here we review recent projects focused on energy efficiency domain that utilise semantic technologies and explain our contribution. Naturally, many of these projects produced various ontologies and we reuse several concepts of those in our ontologies when suitable. The SEMANCO [7] project has aimed to create an ontology-based energy information system to enable policy makers, engineers and citizens to make guided decisions on reducing CO_2 emissions in cities. The ThinkHome ontology, the Smart Appliances REFerence Ontology (SAREF) and the Energy Efficiency Ontology (EEOnt) [2] cover several aspects regarding energy efficiency in buildings. OPTIMUS [12] is a EU funded project that aims to optimize the energy consumption in public buildings. It proposes a semantically enabled decision support system based on an assessment framework [1], in order to guide public administrators to create more energy efficient cities. OpenFridge [13] has delivered a simple and scalable Internet of Things data infrastructure for providing data services that create value for user communities. Powered by semantic technologies, the OpenFridge platform explores the potential of opening and linking fridge energy consumption data.

Current literature accommodates an abundance of ontologies, and applications that facilitate semantic technologies. However, they mostly represent infrastructural aspects of energy efficiency domain and target policy makers. In the scope of ENTROPY project, we address individuals' energy consumption characteristics and use the infrastructural elements such as sensor and smart meter measurements as a supporting factor. To the best of our knowledge, *a holistic approach in energy efficiency domain that applies semantic technologies in terms of rules and reasoning on semantically lifted sensor and crowd-sensing data and puts it into the recommendation and serious gaming context* would be an innovative and unprecedented set-up. Additional to the contributions to the energy efficiency field, *our main contribution to the semantic technology field is the development of an ontology that represents the knowledge about behavioural characteristics and lifestyle of people, and its population and evolution principles.* This task is not trivial, considering the velocity and variety of sensor data, as well as varying nature of human behaviour.

3. SEMANTIC MODELS

We have developed two semantic models[2] to represent the data collected from a heterogeneous sensor network and to semantically enhance the behavioural aspects of users' energy consumption.

3.1 Energy Efficiency Semantic Model

Energy Efficiency Semantic Model represents the information from different type of sensors and building infrastructure from an energy efficiency perspective. Such type of sensors refer mainly to energy consumption, production and storage. In addition to the sensor-oriented information, the semantic model represents also entities relevant to the spatial elements. Thus, information on buildings, rooms, floors or even open areas is also included. The main concepts of the current version of the model are depicted in Figure 1.

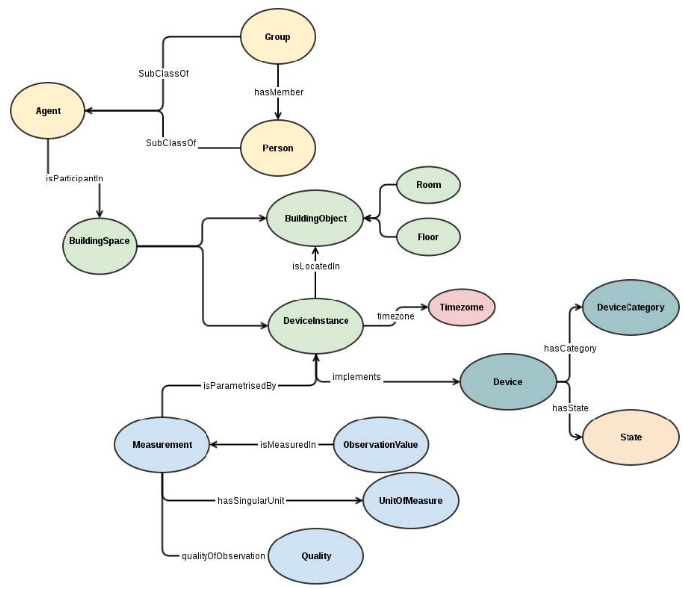

Figure 1: Energy efficiency semantic model

The design of ENTROPY Energy Efficiency Semantic Model is based on the reuse of concepts in well-known ontologies and extending them when appropriate, in order to fulfil the objectives of the model. Our model borrows concepts from SAREF[3] ontology for *Device* and *Building*, the DUL[4] ontology for *Agent* as well as the SSN[5] ontology for *Sensor Observation*.

3.2 Behavioural Semantic Model

From a context-driven point of view, there are many ontologies including user activity modelling. The work in [11] surveys these ontologies comprehensively. However, as stated in the survey, human behaviour and user activity do not imply the same notion. Our model focuses on representing

[2]Link to models: http://vocab.sti2.at/entropy
[3]SAREF: the Smart Appliances REFerence ontology: http://ontology.tno.nl/saref/
[4]DOLCE+DnS Ultralite ontology: http://www.loa.istc.cnr.it/ontologies/DUL.owl
[5]Semantic Sensor Network Ontology: https://www.w3.org/2005/Incubator/ssn/ssnx/ssn

interventions aiming behavioural change rather than simple activity recognition. This forms a basis for the information transferred to the personalised applications and serious games.

We build the model around *User* and *Recommendation* concepts. Since user's interaction with ENTROPY ecosystem mostly performed via mobile devices, we reuse user and device modules of mIO! ontology network[9] which itself reuses FOAF[6] concepts. In our pilot sites, users might have different roles (e.g. faculty, student) and these roles should be considered for the creation of recommendations. Another high-level concept that is relevant to recommendations is user's *Situation*. A situation is an inferred state that represents user's current context (e.g. a student in UMU can have InClassroom, Commute situations). In order to determine the situation of a user, we will utilise context reasoning techniques (e.g. [10]).

The *Recommendation* concept on the other hand is the core of the model. A recommendation consolidates a sequence of activities and a target user. Since the interactive nature of ENTROPY allows the users to give implicit or explicit feedback to recommendations, we also model the *Feedback* concept in relation to *Recommendation*. Although it is not visible in the excerpt, additional to task form, we include a *Message* concept as a subtype of recommendation that allows us to represent persuasive messages targeting a simple behaviour.

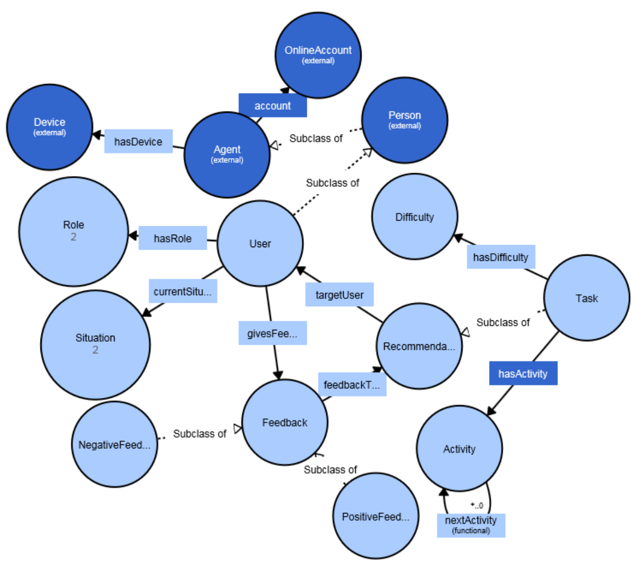

Figure 2: An excerpt of behavioural semantic model

4. REFERENCE ARCHITECTURE

The ENTROPY architecture consists of four layers. Namely, the Communication Layer, where all collected data are aggregated, the Data Fusion Layer, where data mapping to the semantic models and data storage occur, the Analysis Layer, where data are queried and analysed leading to specific recommendations and finally, the Application Layer, that consists of personalised applications and serious games available to the end-user.

[6]http://xmlns.com/foaf/spec/

4.1 Communication Layer

Following a bottom-up approach, the basis of the architecture is the Communication Layer, which is responsible for collecting the data coming from sensors, mobile devices and social media. The IoT Data Aggregation Component and Crowd-sensing Data Aggregation Component comprise the Communication Layer and are depicted with yellow colour in Figure 3. The IoT Data Aggregation Component facilitates the registration of sensor devices and collects the measurements obtained from registered devices. On the other hand, the Crowd-sensing Data Aggregation Component is responsible for communicating with social media APIs in order to collect various information about end-user as well as the data obtained from mobile applications.

4.2 Data Fusion Layer

The Communication Layer forwards the collected data to the Data Fusion Layer, specifically to the Semantic Enrichment Component. As the name indicates, the component realises the mapping between collected data and two aforementioned semantic models: the Behavioural Semantic Model and the Energy Efficiency Semantic Model. The semantic enrichment of collected data augments the expressiveness of information and enables semantic reasoning. The Semantic Enrichment Component feeds the core big data repository with the semantically enhanced data in the form of JSON-LD documents. The big data repository constantly synchronizes relevant views of the data with a triple store where the data reside in RDF format, available for the Analysis Layer.

4.3 Analysis Layer

The analysis layer resides on top of Data Fusion Layer and provides the data to the Analytics Tool, the Recommendation Engine and the Gaming Engine. The analytics tool performs behavioural and energy analysis. The results of the analysis help the platform administrators better understand the habits and patterns of the consumers, as well as detect the positive-negative-neutral effect of gaming and recommendation components on consumers' behaviour. The Gaming Engine receives data from the Big Data Repository and Recommendation Engine, in order to enable a set of serious games that increase energy efficiency awareness of end-users. Whereas the Big Data Repository provides input to the Gaming Engine by simple querying, the Recommendation Engine does it in a personalised way, via applying SPARQL rules and semantic reasoning on the knowledge represented by ENTROPY semantic models. The relevancy of data for a recommendation is determined by several factors such as change of context elements (location, time, device), user's situation (see Section 3.2) and interaction with the application layer which serves as a feedback mechanism.

4.4 Application Layer

The Application layer accommodates a set of personalised applications and serious games that are available to the end-user. This layer receives input from gaming engine as well as from recommendation engine. User's interaction with this layer flows back to the recommendation engine, to be stored in user's behavioural graph as a feedback for the creation of future recommendations.

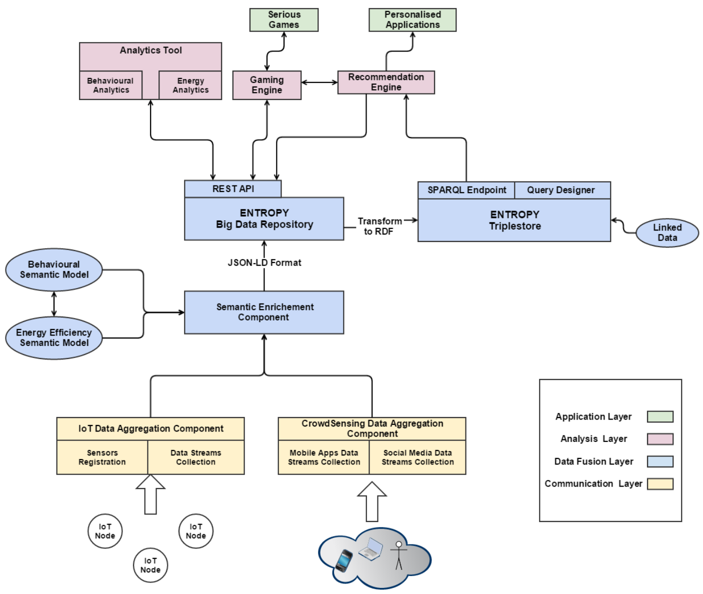

Figure 3: Reference architecture

5. CONCLUSIONS AND FUTURE WORK

We have presented a semantic-based approach for promoting energy efficiency through behavioural change. ENTROPY proposes a holistic ecosystem that is concerned with infrastructural elements and energy consumption behaviour. We have described the reference architecture of our approach, where we make use of our two semantic models. Given the studies on the impact of human behaviour on energy efficiency, the ENTROPY project is expected to achieve a substantial improvement for the utilization of ICT in the energy efficiency domain, as well as the development of the semantics field. The development of the Energy Efficiency Semantic Model will align and extend the existing energy ontologies, while the Behavioural Semantic Model will go beyond the state of the art in activity recognition and represent aspects from behavioural change theories. Additionally, we will create a game elements extension for the behavioural model to provide a base for serious games. As for ongoing work, we are implementing the presented reference architecture and creating concrete behavioural scenarios and key performance indicators based on our three project pilots (located in Murcia, Pisa and Sierre), in order to validate and improve our semantic models and context rules. Furthermore, the adaptive persuasive technologies are being investigated to achieve a more sophisticated intervention mechanism. As it is shown in the reference architecture, we will measure the impact of the semantically supported personalisation of recommendations by comparing it with generic provision of data from the repository.

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