Energy Reduction Platform based on Occupant Behavior Pattern Detection in Enhanced Living Environments

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***Abstract*—The increasing of device interoperability creates a new way to design smart houses and to support enhanced living environments having as main aim the increasing of quality of life. In this context more supporting platforms for smart houses were developed, some of them using Cloud systems for remote supervision and control. An important aspect, which is an open issue for both industry and academia, is represented by how to reduce and estimate energy consumption for a smart house. In this paper we propose a modular platform that both increases device interoperability and uses machine learning models to detect occupant behavior patterns. This platform describes the data collection and aggregation procedures, monitoring and control algorithms, batch training of machine learning models, and offers internal and external (based on Cloud services) access point for the user. In this way we create a model and use it with the purpose of creating energy-awareness by advising the user on how he/she can improve daily habits while reducing costs at the same time.**

***Index Terms*—Energy Reduction, Occupant Behavior, Pattern Detection, Smart House, Enhanced Living Environments.**

I. Introduction

Designing a functional smart house implementation is a cumbersome process mainly because of the large number of different competing protocols on the market. There isn't an easy way for different manufactured devices to inter-communicate, and the competition can become more of a barrier in the long-term evolution of the market than promoting the innovation.

Big names from the industry launch smart hardware every year that can be used in intelligent house implementations. They rarely offer an open communication protocol or expose a viable way of integration. The majority uses proprietary applications or set-top boxes to interact and control their devices, which further reduces the interoperability of smart hardware that exists on the market.

The main challenges that we had were to design the platform in a way that is able to facilitate a high degree of interoperability between the heterogeneous systems that currently fill the domotic market, and to find a way to transform the gathered data into a series of messages that facilitates the training of the behaviour pattern detection model.

The main contribution of this paper is represented by a novel platform that gathers two streams of data composed out of raw data gathered from sensors and a new message format. The message is composed of data collected from multiple sensors, and used to determine objects usage scenarios and their energy consumption. Secondly, we used the power of the cloud to schedule model recalculation based on the latest gathered data and push it to the smart house system.

The paper is structured as follows. Section 2 highlights similar existing solutions and their limitations. Then, in Section 3 we describe the proposed platform and the main components. In Section 4, the main use-case used for experimental validation is presented together with experimental methodology, which is supposed to be generic. In Section 5 we analyse the experimental results. The paper ends with conclusions and future work, presented in Section 5.

II. Related Work

An exhaustive survey of existing Ambient Assistance Living (AAL)/ELE solutions was compiled by Rashidi *et al.* in [1]. The authors describe the paradigm of "ambient intelligence" as "*Ambient intelligence is a new paradigm in information technology aimed at empowering people's capabilities by the means of digital environments that are sensitive, adaptive, and responsive to human needs*", then they talk about why AAL/ELE solutions are needed and how this type of solutions can offer to elders the comfort of still living in their homes without the need of home nursing.

In his paper [2] Duong *et al.* addresses the problem of recognizing human daily activities using a two-layered extension of the Hidden Semi-Markov Model (HSMM) named Switching Hidden Semi-Markov Model (S-HSMM). He splits the activity recognition in two parts, one for atomic activities and one for high-level activities composed of a sequence of atomic activities.

Furthermore, Nguyen *et al.* showed yet again that using a derivation of the Hidden Markov Model (HMM), the Hierarchical Hidden Markov Model (HHMM) [3] can be used for human activity recognition. They use an integrated system for detecting and modelling both low-level and high-level activities proposed by Nguyen *et al.* [4]. To model the behavior hierarchy, the abstract hidden Markov memory model (AHMEM) [5] is used.

Stepping into machine learning area, the Nest thermostat is one of the few successful intelligent products available on

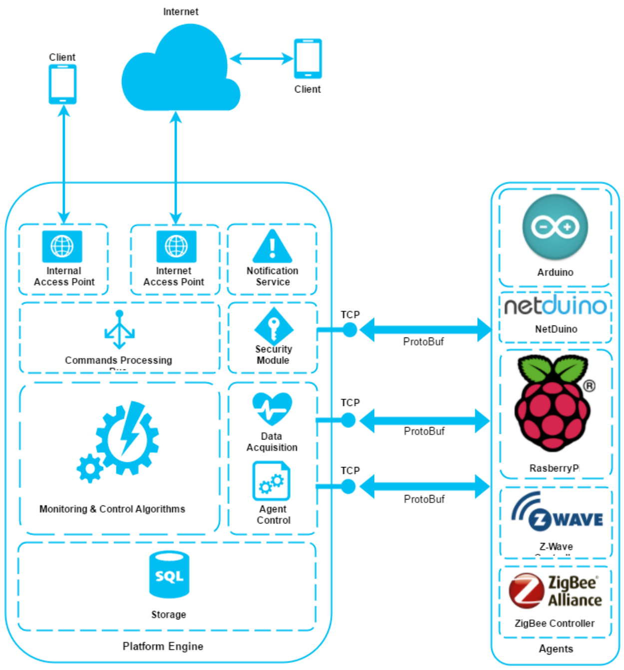

Fig. 1. Platform architecture.

the market that is using algorithms to learn based on how the users are interacting with their smart-house environment. Yang *et al.* studied in his paper [6] the "*experience of living with an advanced thermostat*" and revealed the challenges and the implications of intelligent systems in smart-house environments [7].

III. Platform Description

Currently in the smart-house environment there isn't any standard related to hardware communication protocol or sensor data format [8], [9]. An AAL/ELE application should reuse the majority of existing systems and hardware and in the same time offer interoperability between the available systems on the market by implementing and accepting as many existing protocols as possible.

From all the requirements that define an AAL/ELE application: dedicated Service Level Agreements (SLA), upfront costs, usability, security, interoperability [10], we will focus mainly on interoperability and reducing the upfront and running costs. The other requirements, although they are not on our primary focus, they will be kept as a requirement for our platform.

A. Platform Architecture

We consider that increasing device interoperability also reduces costs. For this we proposed a platform that is able to receive sensor data, control devices that use different technologies, and is also able to create a bridge between them by adding an abstraction level between platform and devices. All the hardware used by the platform is abstracted to the level of a generic Agent, each with its own set of capabilities.

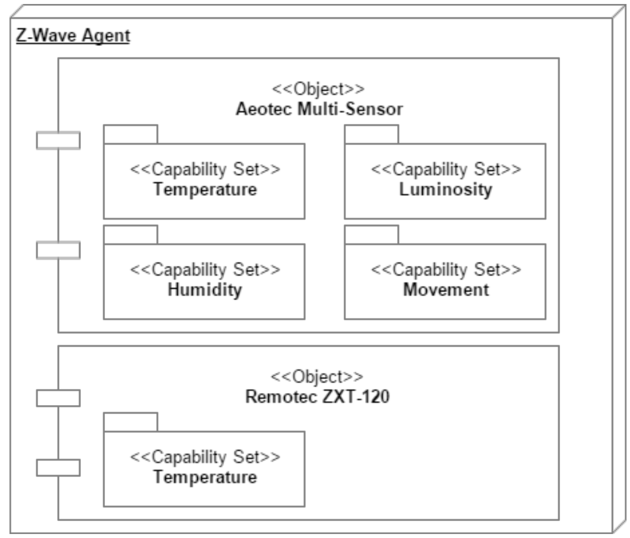

Fig. 2. Agent architecture.

Figure. 1 illustrates our system, composed from the platform engine - the component that gathers agents data, stores the data, uses machine learning algorithms and models to give input to the agents, and the agents - components that use a single type of communication protocol to read sensor data and control actuators. The platform engine is the component that creates bridges between agents and assures protocol interoperability.

B. Agent Description

An Agent is composed of multiple Objects, components that can be physically moved and placed in different rooms. Every Object can have one or multiple capability sets as seen in Figure. 2. Every capability set refers to a specific measure and it will contain one or multiple capabilities such as: read, control, warning. The *Read* capability tells the platform that this Object is able to read the *MeasureUnit*, the *Control* capability tells the platform that the Object is able to control the *MeasureUnit*. While the *Warning* is a special capability that will send a signal to the platform when an event occurs and when it ends. The capabilities are depicted in Figure 3.

C. Model Training

All the machine learning trained models used by the platform are being retrained periodically by a Cloud batch service using all the gathered historical data [11], [12]. For this all sensor data is sent to a Cloud message queue and then saved into a NoSQL database. There is a scheduler in-place that will start a batch training of the defined models and when the batch process completes its training, the models are pushed to the smart-house platform.

IV. Use Cases

We are aiming to reduce the costs by reducing the energy consumption in an smart-house environment. We are going to achieve this by using the collected sensor data that we will

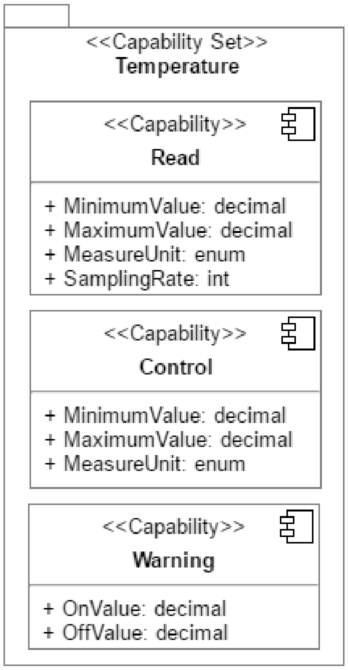

Fig. 3. Capability set.

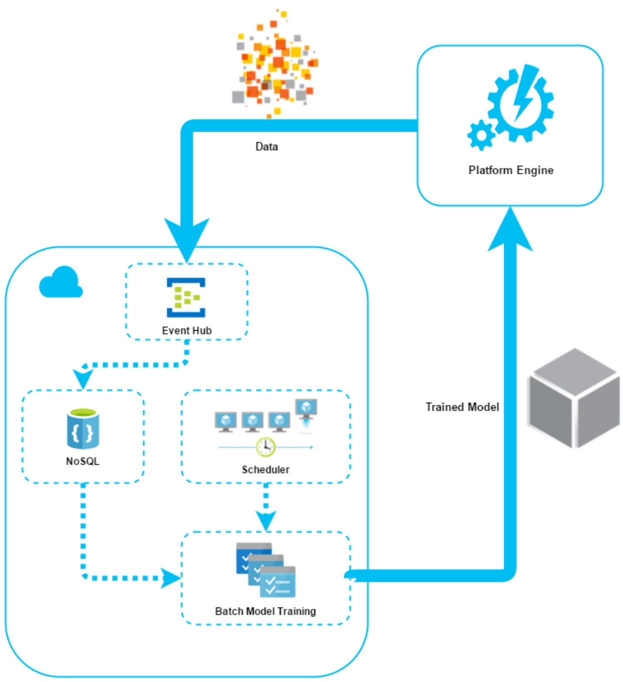

Fig. 4. Model training architecture.

further analyse it for the purpose of detecting usability patterns that wastes energy.

To obtain the best results with the pattern recognition algorithms we will use two different datasets: one containing sensor raw-data for temperature, luminance, humidity, CO_2 concentration, and one containing messages that describes an user activity step (considered interaction with an Object) together with the value of the energy consumed by it.

In Figure 5 we monitored a kitchen from a smart-house environment over a period of 48 hours and collected raw-data from temperature, luminance and humidity sensors. We then marked where user activity happened in the kitchen and observed how the environment responded. For the data collection we used the Z-Wave sensor Aeotec Multisensor Gen5 (which is considered an Object in our platform) that sent data to an Aeotec Z-Stick S2 (which is considered an Agent in our platform). The exterior temperatures ranged between -5°C and 5°C, the temperature for the whole environment was controlled by a central heating with the reference temperature set to 22°C. The sampling rate that we used to collect data was 4 minutes.

To extract user activities and energy consumption data we defined a new message format that uses data received from the Agents grouped based on the Object location. The message is composed of data collected from multiple sensors and grouped together in a way that describes an user activity step. E.g. for the message where a user opens the refrigerator door we will use: a camera to identify the user, a sensor to detect the door state and another sensor that measures the energy consumption.

A. Activity Message Structure

We considered a user activity as having multiple steps, each of the steps having its own measured energy consumption. The structure of an activity step is presented in Picture 6 and it contains important data like: the activity it's part of, the type of the step and the associated energy consumption (in mWh). All this messages compose our data stream that is being pushed in real time to a Cloud message queue from where they are stored in a NoSQL database, while also used as input data in the pattern recognition algorithm.

V. Conclusion

The current hardware segment of domotics is well developed but it lacks the platforms and algorithms that will allow those devices, that are merely simple switches at the moment, to step to the next level where they are able to understand the environmental context and take decisions for the benefit of residents based on their behaviour.

In this paper we presented an intelligent platform that increases interoperability between sensors and actuators used in the environment and is also able to adjust its models in real-time based on the collected raw data. We focused on reducing the energy consumption, and for this we defined a new message structure that is used to aggregate data [13] in a way that user activities are matched with their associated energy consumption. Using the proposed platform architecture, we are aiming to use the two streams of data: raw sensor data and user activity data together with pattern detection algorithms, to calculate occupant behaviour models that we will use to advise the user on how he/she can improve his/hers daily habits in an energy efficient way.

As future work, we will design the algorithms that will be used to create the occupant behaviour pattern detection model.

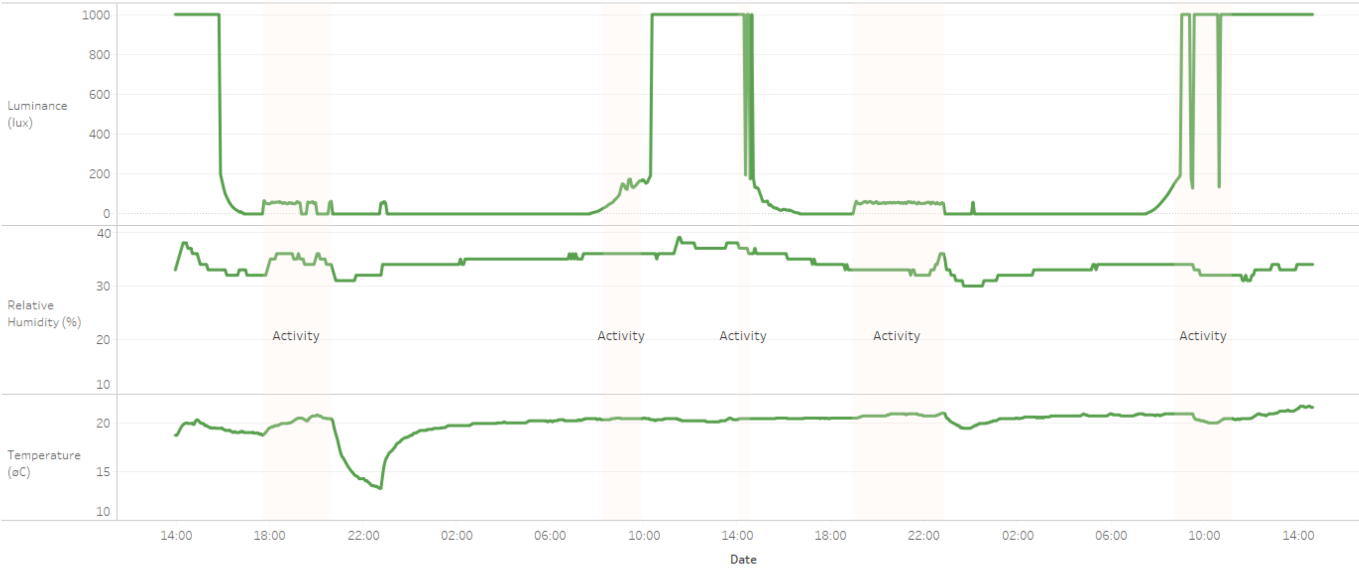

Fig. 5. Kitchen monitoring over a period of 48 hours.

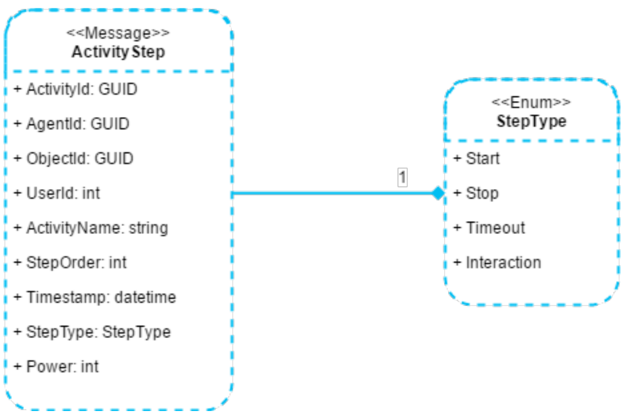

Fig. 6. Message structure.

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