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An IoT sensor network to model occupancy profiles for energy usage simulation tools

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***Abstract*—The development of IoT devices has allowed to install large amounts of sensors in different environments. Consequently, monitoring small houses and entire buildings has become possible. In addition, buildings are one of the biggest energy consumers, so the monitoring of the energy waste, and its sources, is gaining attention. Human behaviour has been reported as being the main discrepancy source between energy usage simulations and real usage, thus being able to easily monitor such behaviour will bring greater insight in the building usage. In this paper, an IoT sensor network is proposed to model occupancy profiles at room level. Such measurement of users' behaviour along with additional information such as temperature or humidity can be used to develop strategies to save energy, especially regarding heating, ventilating and air-conditioning (HVAC) systems. The proposed equipment has been gathering data for some months in a workplace containing several meeting rooms. Four of those rooms were monitored and later analysed to test the validity of the proposed approach. The results show that it is possible to obtain occupancy profiles by using simple IoT equipment.**

***Keywords*-behaviour modelling; data analysis; IoT; occupancy profiles; sensor networks; smart building**

I. Introduction

The integration of Internet of Things (IoT) devices in the environment is rapidly increasing and it is expected to continue increasing in the following years; different entities have forecasted different increase levels for the next years, but most estimations forecast between 20 to 30 billion connected devices by 2020 [1]. The development of the smart building paradigm has made necessary the development of devices that operate without human intervention by using on-line data of the buildings assets.

There exist multiple research paths in the smart building framework; the area is gaining increasing attention as buildings are responsible for about 40% of the energy consumption in developed countries including both residential and non-residential buildings [2]. Moreover, such energy usage is expected to grow 45% over the next 20 years [3], thus gaining knowledge about such usage and trying to reduce it is a common goal sought by researchers and practitioners.

The most energy consuming equipment in buildings are clearly heating, ventilating and air-conditioning (HVAC) systems, which account for nearly 37% of the total building energy usage in commercial buildings. The ability to decrease the energy usage in such systems should result in a clear reduction in the energy usage of buildings. Several research paths are opened regarding smart and efficient control of HVAC devices.

Usually energy usage simulation tools use a pre-assumed fixed maximum presence profile for HVAC control designing, which results in large discrepancies between predicted and measured energy usage [4]. Several studies have proved that identifying the occupancy patterns results in having better energy usage simulations as their results are improved by using on-line information [5][6].

We present a solution for obtaining occupancy profiles, such system being easily installable and scalable. The proposed solution makes use of PIR sensor raw data readings, which after a modelling process gives valuable information about use percentages of a limited space. With the proposed hardware solution, several meeting rooms were monitored by using wireless multipurpose sensors and a main node receiving all the inputs. In addition, the system measures other variables such as temperature or humidity for example. All the gathered information is valid as input for many energy usage simulation tools, which in combination could lead to important energy usage reductions.

The paper is organized as follows. Section II will introduce the state of the art regarding the IoT networking in smart buildings and occupancy monitoring. Afterwards, in section III, our proposal for an IoT sensor network to measure such usage and additional parameters is shown. Then, the data analysis performed over the acquired data as well as the acquired knowledge will be shown in section IV. Some results regarding the predictive capabilities of the occupancy profiles are discussed in section V. Finally, the main conclusions are presented in section VI.

II. State of the Art

The development of wireless networking and advances in data analytics and machine learning algorithms have resulted in advances in many fields including smart buildings. The smartization of buildings requires to gather data from various sources, this usually requires placing a considerable number of sensors in the different assets of the building which

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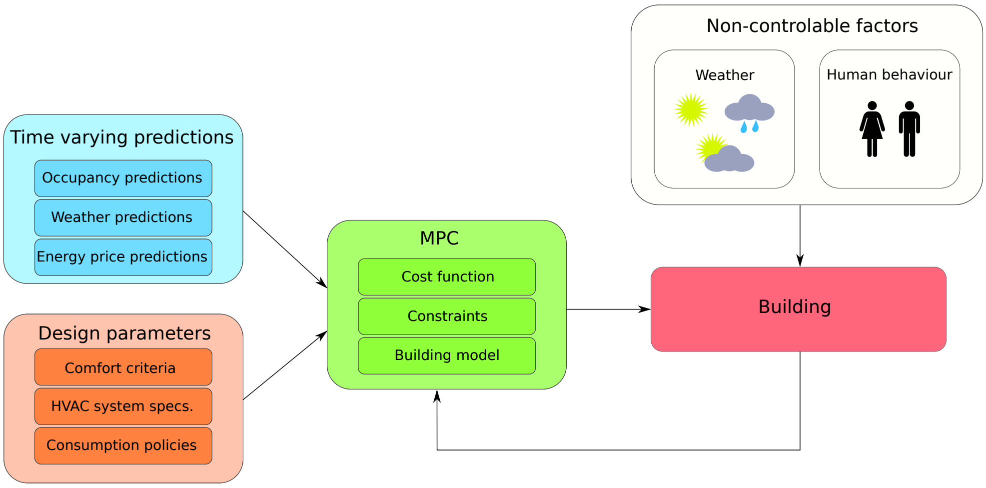

Figure 1. Architecture of Model Predictive Control in buildings

should be done making as few changes as possible. So, using systems which allow wireless communication is a must, while it is also important to develop a scalable architecture which allows to easily include new sensors and actuators without much effort [7].

IoT based sensing equipment is widely being used in buildings for monitoring various behaviours, usually comfort and energy usage related parameters [8][9]. The multiple possible inputs and architecture configurations create a wide variety of configuration possibilities. Those systems which allow scalability are the ones which have a brighter future as they allow to easily deploy new nodes in the installation [10].

Regarding the energy consumption reduction and control, several strategies are being developed. Among them the Model Predictive Control (MPC) is receiving attention since it considers not only the energy efficiency criteria but also the indoor comfort [11]. This multiple goal optimization process is sought by using online measurements such as temperature, humidity or occupancy schedules, predictions about occupancy, weather and more; and a model of the building, which provides knowledge about the buildings physics [12]. Therefore, a basic idea of an MPC system is that of a classical control model which is fed with on-line information, the model of the building and predictions about weather, occupancy, energy price, etc. [13] (see Figure 1).

The main advantage of MPC with respect to other energy efficiency seeking techniques is the ability to use a model of the building to gain information about the buildings physics. There exist also models based entirely on AI techniques, but the lack of the information provided by a model of a building makes those models to lose physical insight and therefore they do not deal well with varying occupancy in the building [12]. Moreover, there exist multiple studies which prove that there is a great difference between the predicted and current energy usage, mainly produced by the interaction between users and the building [3][14][15]. Thereby, being able to model such usage of the users regarding window opening, occupancy patterns, etc. can result in huge improvements regarding to a building's energy usage estimations and predictions [16][17].

As previously mentioned, discrepancies between common energy usage simulations and real usage happen mainly because of human interaction. This interaction can take a variety of forms, from simple occupancy in a room to window opening/closing, temperature fixing, etc. [18]. Research in occupancy monitoring is the most active one among other interactions between the built environment and humans. Several solutions have been proposed to handle different scenarios. The presence and occupancy monitoring can be performed by direct or indirect means. The direct methodology groups detection of movement by PIR sensors [19], detection by chair sensors (which detect if a person is sitting or not) [20], placing sensors in different elements of computers (mouse, keyboard, etc.) [21], detection by cameras and computer vision etc. [22]. Indirect detection methods are less in number but are gaining attention as they make possible to detect presence reusing other variables, in this group we find detection methods based in environmental values such as temperature, humidity, CO_2, etc. [23][24][25].

III. Proposed IoT Network

One of the main advantages of the development of IoT equipment is that there is no need for a wired installation between devices, that way the effort when deploying such a network is considerably reduced. Continuing with the idea of non-intrusiveness and easy installing, we propose a setup which consists in IoT sensors as nodes, with at least one node connected per room, and a microcontroller responsible for receiving the data from the nodes and uploading it to a

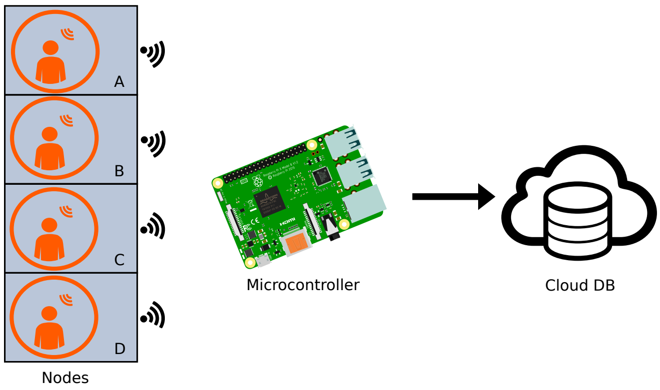

Figure 2. Configuration of the IoT sensing equipment

database in the cloud. The proposed configuration is shown in Figure 2.

In our deployment, a multipurpose sensor was placed in each of the four monitored meeting-rooms. Each of such nodes contains motion, temperature, and humidity sensors. In our setting, the communication between the nodes and the microcontrollers is performed via the Z-Wave low power wireless communication protocol, allowing to make few changes in the environment. The nodes have enough smartness to send the data when there is a change in the measured value, this way the power consumption is lower, which is necessary as the nodes are powered by batteries, and in addition the database does not increase with redundant data.

In our case, the used microcontroller has been a Raspberry Pi 3 running GNU/Linux based Raspbian 8.0, but it can be any other embedded system with similar capabilities. The main role of this node is to receive the data from all the rooms via wireless communication and store the data in an easily accessible way, in this case a database in the cloud which can be accessed from outside to perform whatever analysis needed.

IV. Data Analysis

The previously mentioned sensing equipment were placed in four different meeting rooms, where temperature, relative humidity, and motion were measured by using the cited nodes. The monitoring period lasted for five months. As previously mentioned, the measured values are saved to a database in the cloud where each record consists of a timestamp, the address of the node, the code of the measured variables and the measured value. The analysed database contains around 200,000 entries.

As previously seen in Figure 1, an MPC control takes some measurements and predictions as input, for example: temperature, relative humidity and occupancy or the occupancy patterns. As the monitored meeting rooms are in a workplace with a fixed time-table, it is expected that the measured variables are influenced by such condition.

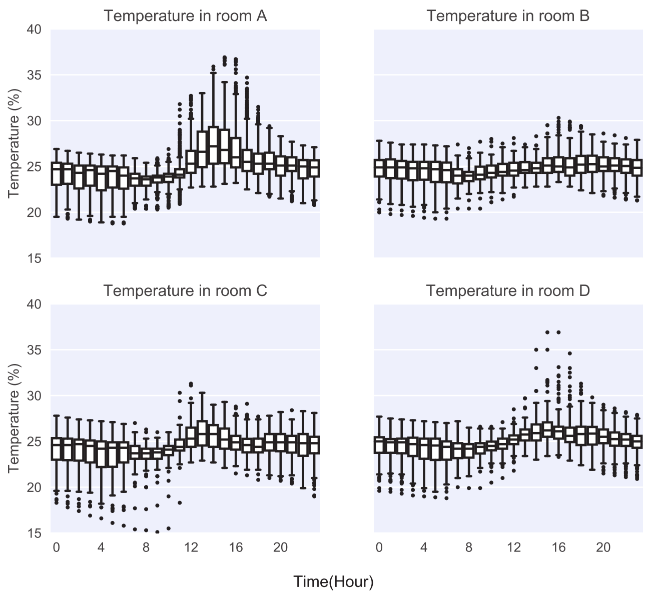

Figure 3. Temperature ranges per hour in the monitored zones

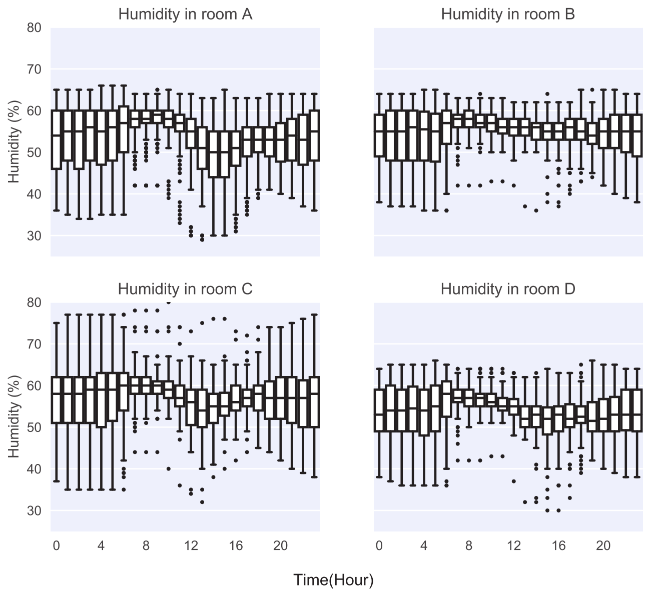

Figure 4. Humidity ranges per hour in the monitored zones

In order to analyse if such behaviour appears in the data, two different visualizations have been performed one for temperature values (see Figure 3) and another one for humidity values (see Figure 4).

Figure 3 shows that the temperature remains quite stable during the morning but it increases during the afternoon, this is most notorious in room A. The time-table effect is more notorious in Figure 4, the plots show how the variability is smaller in the central hours of the day when the building is used, while the variability is higher outside those hours when the rooms are not occupied, and the HVAC systems are not working, so the effect of the activation of HVAC systems is notorious according to the indoor comfort levels. The used sensor network is able to correctly determine different temperature and humidity behaviours, which in this case are clearly influenced by the activation of HVAC systems.

Even if the temperature and relative humidity values show the climatic inertia of the building, the provided information is not the main focus of this paper. As mentioned before, the main limitation regarding predictive control systems is the occupant behaviour modelling. In this case the performed monitoring provides the data of a PIR sensor for each room. Those PIR sensors trigger a value of 1 when movement is detected in the detection range and the value returns to 0 when no movement is detected. The value obtained from the sensor is not directly the existence of occupancy but it is directly related to it.

The first step when performing any analysis over PIR raw data is to pre-process it to obtain more consistent features and time intervals [26]. A modelling must be performed to convert the movement detections to occupancy, that way there is a conversion from a sometimes rapidly changing 0-1 sequence to time fixed and consistent binary occupancy or presence intervals. First of all, the functioning of each of the PIR sensors must be analysed to understand its behaviour. Figure 5 shows an example of the output of one of the installed PIR sensors, three different behaviours can be observed in it: continuous 0, continuous 1 and intervals with various changes from 0 to 1 and vice versa.

In this case an algorithm was developed to cast the raw PIR data to binary presence in two-minutes intervals, this is performed considering the values measured and changes detected by the PIR sensors. Such intervals of two minutes are not very representative of what is happening in the building so a second modelling step is performed. In this case the two-minute interval binary occupancies are the input, and percentages of occupancy for every half hour time intervals are calculated (e.g. 12:00-12:30, 12:30-13:00, etc.), which gives an idea of the usage of a room in such half an hour range. An example of this second modelling step is shown in the plot at the bottom in Figure 5.

The obtained percentages give an idea of the usage of the rooms, which makes possible to detect the periods of the day in which they are more used, and at the same time it is possible to detect under or over usage of the meeting-rooms. Being able to obtain such information with the proposed system has great advantages as it allows to deploy the solution in any closed space with a limited cost and with limited computational needs.

An example of the mentioned room usage is shown in Figure 6, in which the mean percentages per room (it has to be mentioned that in this case there are not values which can distort the mean value as they are all limited to a 0-1 range) are displayed for each weekday, giving some valuable information about the usage of the monitored meeting-rooms. First, mean percentages during weekend days, as expected, are null as the building is closed those days. Second, the fixed time table appears clearly on the values, so the system at least can determine regular work-ours from the data. Third, the pattern for all weekdays is very similar except for Fridays where it seems that the buildings usage decreases before in the afternoon. Fourth, room A is the most used one by far, especially in the morning. Finally, smaller usage is detected during lunchtime. Some of the obtained results were expected, but the ability to obtain them in an automatic way makes it possible to deploy the system in

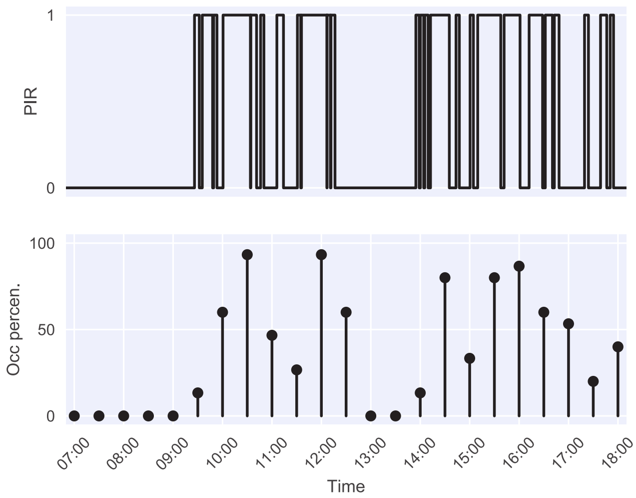

Figure 5. PIR raw data and occupancy percentage after modelling

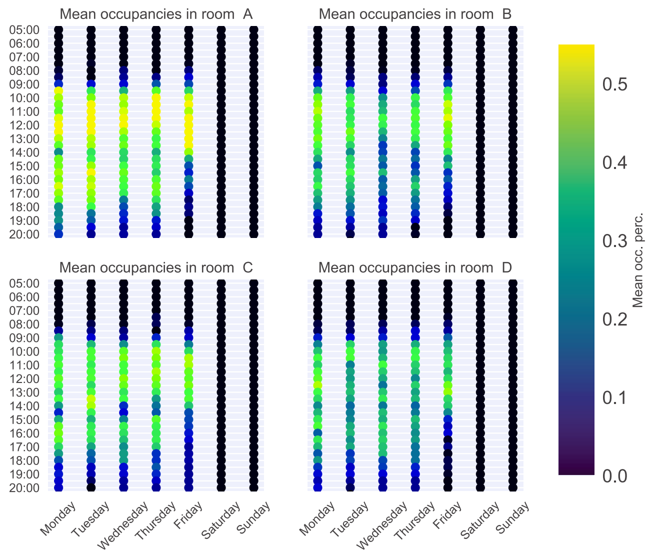

Figure 6. Mean occupancy percentages per day

any place, without previous knowledge, and obtain similar information.

As seen in Figure 6, there are some hour ranges in which it is common to have the room occupied, while there are other hour ranges in which the room is always unoccupied. For many purposes, for example energy saving, having previous knowledge and being able to predict future usage by using the knowledge acquired is beneficial, and could lead to a better performance.

V. Results

Occupancy profiles in Figure 6 show that some valuable information can be obtained with the performed modelling. As mentioned, being able to predict future behaviour by using previous knowledge is beneficial for many purposes, so it has to be tested whether the proposed approach, based in the occupancy profiles, is useful for such purpose.

For doing so, the values in the occupancy profiles shown in Figure 6 were first converted into a binary variable according to a threshold. Such threshold was set according to the distribution of the values shown in Figure 6. As the aim is to develop an independent solution which works at room level, the occupancy profiles were independently obtained for each of the rooms. Once the occupancy patterns are obtained, they can be used to compare them with new data. With the defined approach there is a predicted value for each hour range per day, such value is based in the experience obtained from previous data. So, even if machine learning based models have not been extracted, the occupancy profiles can be used to predict the occupancy of a room at any given moment.

The predictions obtained with the occupancy profiles obtain an overall acceptable accuracy of 82% when using them on data not used to make the profiles. Even if the accuracy is correct it should be mentioned that the predictions based in the occupancy profiles tend to predict continuous occupancy intervals, which sometimes do not correspond with the reality. Examples of the predictions made for a given day in the four monitored rooms are shown in Figure 7.

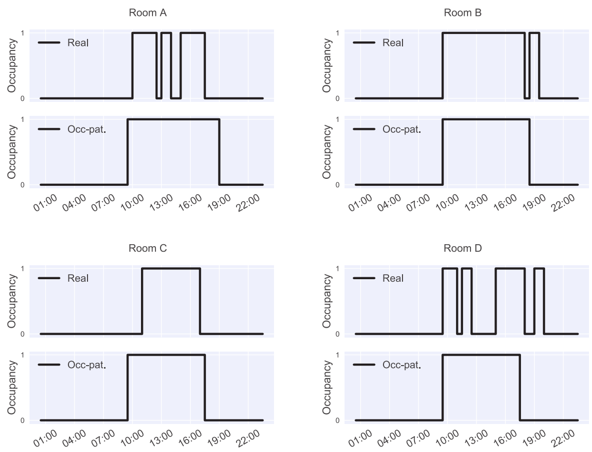

Figure 7. Real values and predictions based in the occupancy profiles

As shown in the plots in Figure 7 the occupancy profiles give valuable information about regular use, but do not manage well particular changes for a day. Considering that the aim is to use these models for HVAC system controlling, or similar purposes, the general occupancy profiles are enough for feeding such systems with valuable information.

VI. Conclusions

The exploitation of the facilities and opportunities that IoT sensor networks provide for building comfort and occupancy monitoring have been shown. Moreover, the proposed approach can be deployed without much effort and without extensive equipment, yet the information obtained is valuable. On the one hand, it has been shown how the sensing equipment network allows to monitor temperature and humidity levels in a way that the effect of the activation of HVAC systems and human interaction with those can be evaluated. On the other hand, it has been proved that a single PIR sensor is enough for obtaining a simple but significant occupancy profile for the rooms of a building.

The acquiring of the occupancy profiles does not require big computational resources, so the solution can be embedded in the microcontroller used for receiving the data of the nodes. The obtained occupancy profiles, despite of their lacks, are valid for various purposes which benefit from the knowledge of the building use, as it is the case of HVAC systems control.

The proposed system is not only valid for feeding HVAC predictive control systems, but it could also be used as a sensing infrastructure for smart meeting rooms, obtaining information not only of the air quality, but also of the usage of the assets of the building. Moreover, the aquired measures could be used to create Markov chains which can model the transitions in the room and allow to make predictions.

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