Abstract—The dense instrumentation of future smart buildings enables the implementation of advanced control techniques which are aimed at the dual objectives of energy efficiency/cost savings and occupant comfort. One of the essential functions and prerequisite consists of robust dynamic occupancy detection and prediction which allows improved estimation of active thermal zones and internal loads, as compared to static schedule-based approaches. The paper presents the design and preliminary evaluation of a wireless system for embedded monitoring of occupancy states across the thermal zones of the building. The challenges of calibration, detection and prediction algorithms are discussed along with experimental outcomes. The infrared array sensor within the system offers improved detection performance compared to conventional PIR sensors while preserving user privacy in comparison to image processing approaches using security cameras. Several advantages of the proposed solution are also highlighted such as the low cost, flexibility, scalability and integration towards the building-wide automation system.

I. INTRODUCTION

Reducing the energy footprint of the built environment represents a key engineering challenge with broad environmental, economic and social impact. Through recent advances in networked embedded systems, intelligent information processing and control algorithms, new developments are facilitated allowing fine-grained monitoring and control of building subsystems which leverage increased availability of computing and pervasive communication resources at the building level. Most common approach to building automation, implemented as proprietary solution from various providers, currently assumes some type of rule-based control (RBC) in combination with conventional PID control loops at the local level for heat/cooling delivery and ventilation. The overview of the building is aggregated at a central level through a software-based Building Management System (BMS) implementation which offers the building operators and administrators visualisation, alarming, logging and manual actuation functionalities. More advanced control techniques that apply chiefly to energy management at the Heating, Ventilation and Air Conditioning (HVAC) subsystem layer have seen an increase in interest from academic research groups and academia-industry collaborations, providing reference tools and baselines [1].

A suitable example of advanced model based control technique is model-predictive control (MPC). This embodies a thermal model of the building dynamics to solve a suitable optimisation problem yielding the optimal heat/cooling inputs to the network of thermal zones that make up the buildings [2]. The receding horizon control technique forecasts the control input over several sampling periods, with the first few inputs being applied followed by updating the results at the next sampling step. Key issue in MPC is deriving dynamic models under a trade-off between complexity and fidelity with reference to the actual building. Common approaches include: modelling based on first principle equations and system identification, grey-box methods which revert to simplified equivalent electrical RC networks analogies and black-box input-output models. Recently, purely data-driven approached for black-box model generation e.g. decision trees [3], have gained traction with some limitations related to observing the building behaviour under a sufficiently large spectrum of operating and environmental conditions. The constraints of the problem result from limitations of the HVAC subsystem components, acceptable temperature ranges and construction regulation and laws. External disturbances such as predicted weather, solar radiation and internal loads are also considered.

In this context, as argumentation of the work in the context of smart building control, occupancy detection and prediction represents a highly relevant feature of the control system as it enables the departure from statically assumed occupancy schedule or rough estimates using single Passive Infrared (PIR) detectors and inference based on data from the access control logs. The potential for energy savings results in switching the heating/cooling on/off for the target thermal zone, pre-conditioning the zones with regard to forecasted occupancy, more accurate estimation of internal thermal loads due to human activity and equipment usage. Leveraging improvements in miniaturisation, power consumption and cost of sensors, electronic subsystems and modules [4], allows for a network of wireless infrared array sensors to be efficiently deployed at the floor level and reporting the data to a central gateway which runs the detection and prediction algorithm. The gateway in turn feeds the binary outcome to the BMS for evaluation of the control algorithm.

The paper is structured as follows. Section 2 discusses related work and alternative approaches to accurately detect and estimate occupancy in residential and commercial buildings. Section 3 describes the design and arguments for the
proposed wireless occupancy detection system, highlighting technical aspects and core functionality. We present the experimental study carried out along with the results achieved and associated discussion in Section 4. Conclusions and focus improvements for ongoing and future development are listed in Section 5.

II. RELATED WORK

A brief overview of related papers with key contributions is carried out next, establishing the context of the work.

In [5] demand conditioning strategies based on occupancy models are discussed in depth. The prediction system uses Markov chains to forecast the likelihood of thermal zone occupancy at given time samples and assure efficient pre-conditioning. The energy savings are estimated up to 42% while observing ASHRAE comfort standards applicable to office buildings. Subsequently in [6] the Thermosense system is presented. This integrates a low-power, embedded, multi-sensor node for dynamic occupancy observations. Main advantage is derived from using both a conventional PIR sensor and an infrared array sensor, triggered by the former, to detect persons. The authors argue a overall 25% in energy savings compared to static scheduling methods.

A data mining approach is proposed by [7] where information from arbitrary deployed networks of spatially distributed sensor networks is leveraged to infer the sensor placement through their data traces. Walking trajectories are used for evaluation which point to an accuracy range of 77-100%.

Previous work has been concerned deploying and evaluating wireless sensor networks as for residential monitoring and ambient assisted living [8] and designing MPC-based controllers using static scheduling assumptions [9]. The current contribution extends these towards dynamic occupancy models using a suitably designed system.

A software framework supporting occupancy based application is presented by [10]. A technology agnostic API is provided for efficient retrieval of occupancy relevant information, operational across heterogeneity typically encountered within the built environment and suppliers of proprietary automation technology for this domain. Alternative approach to infer room-level occupancy from light, temperature, humidity and CO2 is presented by [11]. This can serve as a validation technique in relation to direct measurement of occupancy using PIR sensors, security cameras, or as in the current paper, thermal infrared sensing arrays. Several methods for data-driven extraction of occupancy states are described, while the authors conclude that the best accuracy, in the 95-95% range is obtained using either Linear Discriminant Analysis (LDA), or through tree-based methods: CART and random forests (RF).

In [12] the authors evaluate the impact of shifting from static occupancy schedules to online occupancy detection and prediction upon the baseline building energy consumption patterns. The proposed system leverages sensors already available throughout the BMS to infer coarse-grained occupancy metrics. Main finding of the study is stated as a 38% reduction in reheat energy consumption for the same indoor comfort level, through better forecasting of occupancy patterns.

III. SYSTEM DESIGN

The system architecture of the wireless system for occupancy detection and prediction is structured on three layers:

- Zone-level: wireless sensing nodes (WS) are deployed across the thermal zones, depending on the zone size and the desired granularity of occupancy detection, one or several nodes can be assigned to each zone. The sensing nodes provide the infrared array readings on demand to the next hierarchical level;
- Floor-level: an embedded gateway (G) collects synchronised raw data from the sensing nodes and runs the pre-processing and detection algorithms which yield the occupancy state of each zone;
- BMS integration: the occupancy states are aggregated at a central level, to run the prediction algorithms in conjunction with the advanced model-based control strategy e.g. MPC.

Within a given room the wireless nodes are placed either with a vertical or horizontal field of view, in relation to the space layout which would yield the best readings for occupancy detection e.g. above an entry or an office, across a hallway, etc. The temperature measurement range of the infrared array sensor is between -20 and +100 degrees Celsius, with good accuracy and up to 10 fps rate. Through sensor fusion at the gateway level additional existing sensors can be used for more robust detection, such as temperature and humidity measurements and information from the access control system logs.

The architecture is illustrated in Figure 1. Communication is performed through low-power Bluetooth connections in a star topology between the sensing nodes and the floor gateway. The gateway communicates with the BMS using the ubiquitous WiFi connections or through the wired Ethernet backbone of the building.

Figure 2 illustrates the reference hardware devices for implementation: Panasonic Grid-Eye sensor board with Bluetooth connectivity as wireless sensing node and the gateway implemented by means of a Raspberry Pi 3 Model B embedded development board, with the Sense HAT extension module. The advantages that this solution presents are considerable in terms of energy and costs: while commercial solutions are very expensive, our proposal consists of a Raspberry Pi model B (for the need of Bluetooth transmission possibility) which is around $40 with a 512 MB memory card and a Panasonic Grid-Eye infrared array, which consumes approx. 230 mA (1.2W) and respectively 4.5 mA in normal mode. The solution implemented in this case for occupancy monitoring is different from the previous ones in terms of usage of a web server to see in real time the presence detection transmitted from the Raspberry Pi module. Even more, for a physical representation on hardware, a Sense HAT could be attached on top of the PI module (not necessary for occupancy detection, but nice to have for visualization), using the 8x8 RGB LED matrix.
for the temperature representation in the monitored area, within the observation field of the Grid Eye sensing matrix. The Sense HAT brings additional cost of $40. This feature of adding the Sense HAT is presented in the Fig. 2. The functionality and specifications within the proposed system are further described in the following section.

![System architecture](image)

**Fig. 1.** System architecture

- We developed a novel wireless sensor platform for presence detection using a Grid-Eye formed by PIR sensors. This platform was tested in one HVAC conditioning area, focusing data analysis for the period 8AM to 8PM.
- We used the collected data for an off-line analysis which embodies feature extraction, and post processing filtering to detect a human presence in the room. We will use the results for occupancy prediction, testing and comparing the output of several machine learning algorithms.
- We tested 2 different scenarios: when the visual field of the Grid-Eye is vertical, and when this is horizontal, and found that accuracy of transmitted temperature is not reliable when the distance between the sensor and the person in the room is higher than 2 meters. Also, the visual field is 60 degrees when the Grid-Eye is placed on the ceiling, and there is a distance around 2 meters between the person and the ceiling. The accuracy is increasing with the decrease of the distance, but in the same time, also the width of the visual field is reduced. So, for a distance between the person and the Grid-Eye of 20 cm, visual horizon is estimated around 20 cm.

After testing different scenarios, we found that the room temperature is constantly below 26 degrees, and to avoid noise in data processing a static threshold of 28 degrees was set. So, for every frame recorded, from the matrix with the 64 cells indicating temperature, a filter is applied at 28 degrees Celsius. All values above indicate the presence of a significant heat source. This stage is the initial phase of the practical experiment for grid sensor calibration; of course, in a more complex model, we will consider also other external factors such as the increasing temperature during the day, when a person is present in the room.

The algorithm in Table 1 was used to detect presence of a warm body in the HVAC area using a feature vector extraction.

The number of active cells was determined using Algorithm 1 with the steps presented in Table I. Having the output of this algorithm, we use it as sequential input for the second algorithm, the next one presented here, in order to detect the shape of a warm event and classify as a person detected. During the practical experiments we noticed that a person’s presence is represented with a temperature higher than 28
TABLE I
ALGORITHM FOR FIRST FEATURE EXTRACTION

Algorithm 1 - Finding the no. of active cells per frame

1. While read temp(cell)
   do:
     If temp(cell) ≥ 28
       \(\rightarrow\) cell takes value 1
     else
       \(\rightarrow\) cell takes value 0
   2. count(cell = 1)

TABLE II
ALGORITHM FOR 2ND FEATURE EXTRACTION

Alg. 2 - Calculate no. of connected points per frame

connected_region is 0

1. check horizontal neighbor cell:
   if neighbor cell =1
     \(\rightarrow\) then
   connected_region=connected_region+1
1.1. If another connected region on line_i is found
     \(\rightarrow\) then take max(connected_region)
     \(\rightarrow\) take max(connected_region)
2. use max(connected_region) for detection

Celsius degrees on the grid image as is showed in Figure 4.

In Figure 4, the heatmap shows very clear that a warmer region is detected when the person is in the visual horizon of the sensor Grid-Eye. This is a representation using data sampling from the grid sensing platform. Considering the previous algorithms, this image is then transformed into binary values, and the warmest points on the map become 1 and the others take value 0, shaping in this way a zone representing the person. In this manner, the zone, that is a connected region defines one person. Based on this proved hypothesis, the study could be extended to count the persons captured on the visual field of the sensor grid, especially when the Grid-Eye is placed on the ceiling, and they are stationary working on a table, below the grid. In Fig. 4, the heating map contains representations of the temperature values ranged between 24.25 (colder tones of blue) and 30.25° (warmer tones towards red) Celsius. Almost in the center of the figure, the highest values are grouped shaping the representation of a detected person. This map is the image of the case when the sensing module is placed on ceiling, above the target. This is no restricted on a certain place, and the sensing module could be set, for example, on the top door case.

This proposed solution applicable in the context of smart building modeling and control offers the opportunity to learn the occupancy behaviour and patterns of the persons that work in a room and some insights about the characteristics that should be considered in the case of a predictive HVAC model implementation. As is presented in Table III, a fluctuation of the human presence is shaped out of the mean...
value from a single frame stamped considered in the range 8AM to 8 PM, with the coarse step of one hour. The first record of the table represents the initial temperature in the room, at 8AM, when the working day starts. After 12 PM, the temperature decreases, that could signify the lunch time or another break as could be seen from the values after 3PM.

<table>
<thead>
<tr>
<th>Hour</th>
<th>Temp value in Celsius degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>25.60</td>
</tr>
<tr>
<td>9</td>
<td>29.01</td>
</tr>
<tr>
<td>10</td>
<td>27.36</td>
</tr>
<tr>
<td>11</td>
<td>29.80</td>
</tr>
<tr>
<td>12</td>
<td>30.75</td>
</tr>
<tr>
<td>13</td>
<td>27.50</td>
</tr>
<tr>
<td>14</td>
<td>26.83</td>
</tr>
<tr>
<td>15</td>
<td>25.83</td>
</tr>
<tr>
<td>16</td>
<td>26.57</td>
</tr>
<tr>
<td>17</td>
<td>28.40</td>
</tr>
<tr>
<td>18</td>
<td>28.52</td>
</tr>
<tr>
<td>19</td>
<td>28.16</td>
</tr>
</tbody>
</table>

The natural next step is presence prediction, decided on historical data and statistical modelling, but also training and validating several machine learning algorithms. For prediction we will use Markov Chains starting from calculating the moving average of the recorded temperature values from the Grid-Eye. Having it and a histogram of data, resources to find the transition matrix of probabilities are ready. The possible events are 0 and 1, representing the presence detection and respectively, the person detected. We consider this approach due to the advantages of the method by displaying characteristics of steady state, and the probability of every cell to show presence detected does not depend on the initial state of the process. This is fitting very well the application, because in a room, person working after lunch is not conditioned by the first working hours during the day in that room.

A Markov chain is defined as a collection of random variables $X_t$, where the index $t$ runs through a given set $T$. The variable $X_t$ is meant to represent a measurable characteristic, or a point of interest. In this example, it would take the value of the grid cell. The current status of the system can fall in any of a set of $M + 1$ mutually exclusive categories called states. If we continue with the binary filter for occupied or unoccupied, then the states would be: 1 and 0. When the system is observed at a particular points of time, the stochastic process $X_t$ provides a mathematical representation of how the physical system evolves over time. A strong argument for using Markov chains is that it can model a stochastic process and states that the conditional probability of a future event relies on the present state of the process, rather than on a past event. The model is based on transition matrix of probabilities defined as it follows:

$$P\{X_{t+n} = j|X_t = i\} = P\{X_n = j|X_0 = i\} \quad (1)$$

The procedure applied on our collected data from the wireless occupancy detection system, would consist of the following steps:

- Calculating the moving average on the data set for couple of hours, on a time window from 8AM to 8PM for one room;
- A histogram for visualisation on this window, with the classes 0 and 1 for non-presence and respectively detected person;
- Calculate the difference between actual values of cells and the moving average in order to find the transition matrix applying a filter considering a threshold that will be set after several tests to identify its most suitable value;
- Having the transition matrix of probabilities, relying on the Markov chain method, the prediction of the next hour (considering we deploy this scenario, or going towards finer granularity of 10-15 minute sampling rate) for the room occupancy could be achieved.

V. CONCLUSIONS

The paper presented the design and preliminary evaluation of a multi-level wireless system for occupancy detection and prediction in smart buildings. The solution represents a feasible approach to accurately estimate occupancy with direct impact onto the effectiveness of advanced HVAC control strategies. Depending on the deployment layout, calibration and tuning of the detection algorithm is suggested as means of achieving superior performance.

The presentation focuses on a wireless system for monitoring the occupancy levels in various zones and rooms of a building, and discusses how to calibrate it, use it for detection purposes and also how to use the gained information for predicting future occupancy levels. A more advanced experimental scenario would be to include the season factor, in what regards the temperature. Even a person would come from outside in a monitored room, with a 20 Celsius degrees difference between the exterior and the indoor temperature, the system is enough stable and does not focus on a small area; it senses on a whole region, so the person in this scenario would be detected as a body. For this situation, an analysis will be deployed in order to set the temperature threshold of the cells adaptively, and to improve the accuracy in presence’s shaping algorithm.

Another direction to further continue with this work, is to implement other algorithms for forecasting occupancy and correlate the factors which lead to better results; a copula-based approach is a prospective model taken into consideration.

Finally future work is also focused on robust prediction methods for occupancy along with extended experimental evaluation in a real office setting and integration towards the commercial control systems already implemented. A tiered implementation of the algorithms will allow leveraging the computing and communication resources of the embedded gateway for in-situ detection.
REFERENCES


