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Estimating Occupancy Using Interactive Learning With a Sensor Environment: Real-Time Experiments

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ABSTRACT Interactive learning plays a key role in extending the occupant behavior implementation toward smart buildings. Efficient feedbacks can be obtained from the end user by involving occupants and increasing their awareness about energy systems. Working in highly energy-efficient buildings can be a great opportunity, but users need to feel empowered. This means making them aware of the building features and allowing them to manage some of the appliances. In this way, disorientation or annoyance is avoided, and people feel more in control. This paper proposes a solution to interact with occupants to estimate the number of occupants. A novel way of supervised learning is analyzed to estimate the occupancy in a room where actual occupancy is interactively requested to occupants when it is the most relevant to limit the number of interactions. Occupancy estimation algorithm relies on machine learning; it uses information gathered from occupants with the measurements collected from common sensors, for instance, motion detection, power consumption, and CO_2 concentration. Two different classifiers are investigated for occupancy estimation with interactions: a decision tree C4.5 and a parameterized rule-based classifier. In this paper, the question of when interacting with occupants is investigated. This approach avoids the usage of a camera to determine the actual occupancy. A complete real-time interaction environment has been developed and is used to estimate the occupancy in an office case study. The graphical user interface has been designed to carry out a real-time experiment.

INDEX TERMS Activities recognition, building performance, data mining, human behavior, machine learning, office buildings.

I. INTRODUCTION

Smart Building services are an important provider of technology systems. Services focus on constructing, operating and maintaining buildings in the most effective and cost-efficient manner. At the most fundamental level, smart buildings deliver useful services that make occupants comfortable and productive (by providing them proper illumination, thermal comfort, air quality, physical security, sanitation, and many more), at the lowest cost and environmental impact over the building life-cycle. Reaching this vision requires adding intelligence from the beginning of the design phase throughout the end of the building's life. Smart buildings use information technology during operation to connect a variety of subsystems, which typically operate independently so that these systems can share information to optimize total building performance. Smart buildings are connected and responsive to the smart power grid, and they interact with building operators and occupants to empower them with new levels of visibility and actionable information.

Figure 1 shows the state of the building system which includes: a- physics with the buildings possible devices and envelopes, b- human part related to building occupants.

In order to define the state of building, non-measured values should be known in both parts: physical and human (i.e. occupancy and activities). Measuring these variables

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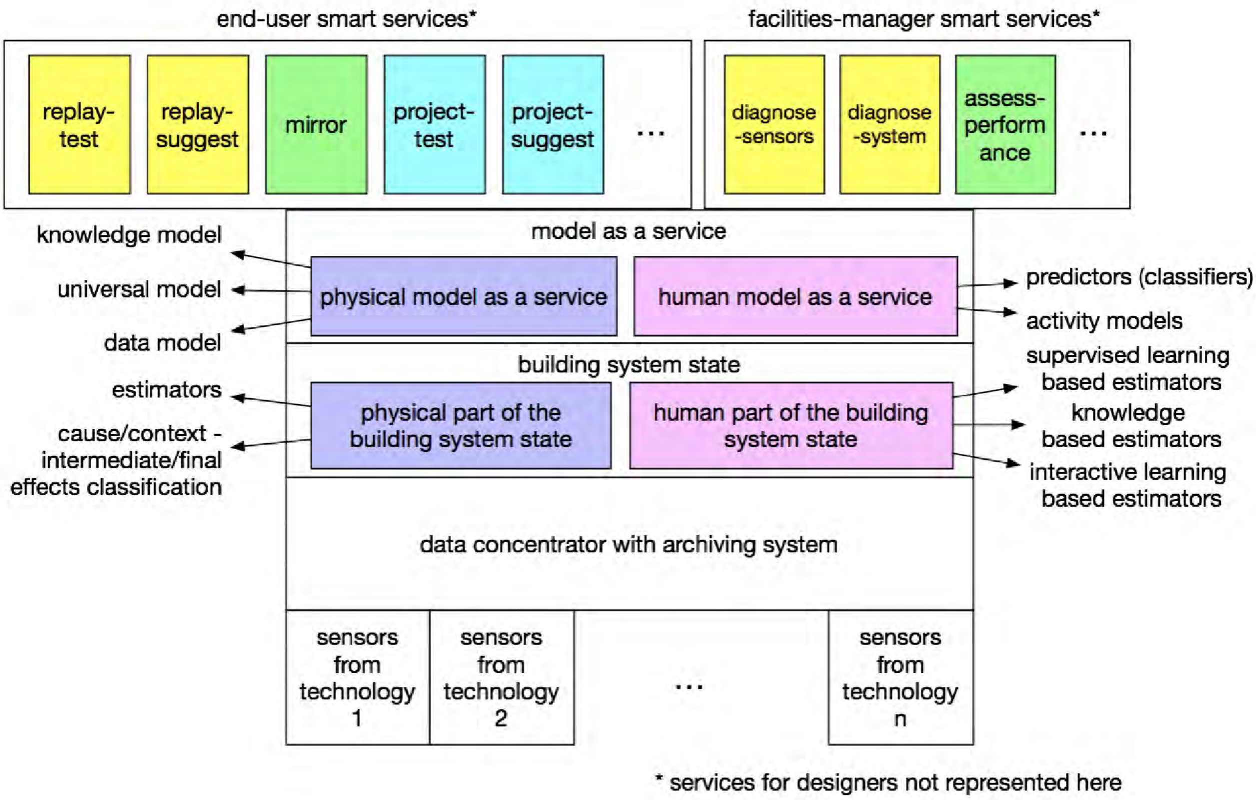

FIGURE 1. Layers of energy management system.

will open the gate to different applications in the design and operating phases of smart buildings (table 1).

In this paper, an interactive technique has been investigated, in order to solve the problem of getting the required labels used in supervised method. In practical applications the limitation arises due to the occupant's privacy issues. Accurately estimating occupancy with a set of sensors and self-labeling by interaction with occupants are the main goals of this work.

The rest of this paper is organized as follows. Section 2 presents a review of the research about occupancy estimation. Section 3 investigates the proposed methodology of interactive learning that interacts with occupants to collect the actual occupancy. Section 4 discusses the decision tree classifier. Section 5 focuses on parameterized classifier for interactive learning. Section 6 compares the two classifiers with interactive learning in an office context, and section 7 points out an implementation and experimentation with the real-time interactive learning application and section 8 concludes the paper.

II. STATE OF THE ART

Recent advances in smart building methodologies have focused on human occupancy in order to increase the performance of buildings. Several approaches have been proposed by researchers in the field for activity recognition and occupancy analysis. The learning generally involves creating a probabilistic or statistical model trained via large training or learning dataset. The aim of the model is to learn and recognize patterns that differentiate classes in the training data and apply this knowledge for the prediction/classification of test data in order to solve the problem without necessarily providing it with domain-specific knowledge. Since the problem emanates from pattern recognition, or data analysis such methods are termed data-driven. Reference [6] identifies such data-driven approaches and classified them into (a) a generative modeling [7], (b) discriminate modeling [8], and (c) heuristic-based modeling [9]. Recently, some hybrid generative discriminative approaches have been proposed, also (see for instance, [10]).

Existing methods for occupancy estimation depend on different sources of data. Reference [11] proposed an occupancy detection using sensing by proxy, where the inference depends on proxy measurements such as CO2 concentration, and indoor temperature. In [12] the authors investigated a solution for occupancy and activity prediction (eating, sleeping, and taking medicine) by imitation learning and reduce it to a simple regression problem. Moreover, data coming from sensors have been used in this work (i.e. location sensors, window and position). Numerous studies in smart homes have used sound processing for activities recognition such as [13] which used Gaussian Mixtures Model (GMM) and

TABLE 1. New service requiring occupancy/activity.

Application	Occupancy or activities	Mean	Objective
1-Performance guaranty and simulation during the design phase [1]	occupancy and activities	fill conditional probability tables of Bayesian networks consisting of nodes concerned with occupants	design occupants behaviour
2-Simulating building behaviour [2]	occupancy and activities	calculate heat gains from bodies for estimating internal thermal gain	parameter estimation
3-Replay/determine best solution for past or future [3]	occupancy	use occupancy and physical models for anticipated plan	energy and comfort management by having the best solution for the future
4-Explanation [4]	occupancy	use model including gains due to metabolism	help occupants to understand their energy management strategies
5-Determine best solution without model	occupancy	cluster historical data including occupancy	occupants can be assisted to understand the impact of actions by experimenting with different actions and monitoring how they are affecting their habitat
6-Diagnosis and failure detection [5]	occupancy	use physical model	increase the comfort and reliability of the building.
7-Key performance indicator	presence, occupancy and activities	calculate indicator depending on presence or indicators related to some activities	summary of some information that occupants would not be able to understand separately

Support Vector Machine (SVM), in order to classify sound data sequences in order to be used in elderly people monitoring systems. While, in [14] the researcher has proposed an algorithm for audio-based occupancy analysis, which depends on GMM and Hidden Markov Model (HMM). Moreover, [15] proposed an action recognition approach based on Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). This model is suitable in case of using wearable sensors. Besides, it does not require expert knowledge to design the required features, but still suffers from the drawback that deep learning algorithms need a large quantity of training data.

Many studies depend on classification from vision-based data, they use image processing and computer vision techniques. According to [16], detecting humans using images is a hard task because of their variable appearance and the many variables involved in. The first need is a robust feature set that allows efficient human detection, even in cluttered backgrounds under difficult illumination conditions. There have been several other studies of presence/absence detection. For instance [17], describes a technique to detect the presence of computer users. It relies also on ultrasonic sonars using hardware already present in laptops. It leverages the fact that human bodies have a different effect on sound waves than air and other objects.

Interactive learning is proposed to develop smart devices for buildings. Efficient feedbacks can be obtained from the end user by involving occupants and increasing their awareness about energy systems [18]. Working in highly energy-efficient buildings can be a great opportunity, but users need to feel empowered. This means making them aware of the building features and allowing them to manage some of the appliances. In this way, disorientation or annoyance is avoided and people feel more in control. Reference [19] has indicated an improved user experience results when users regulate their environment. In addition, the concept of interactive learning allows to evaluate the quality of the database. One major problem in term of communication with the occupant is the availability of the user which can be different from one situation to another, occupancy recognition approaches can be a practical solution to solve the problem of occupant availability (Amayri *et al.*, 2019).

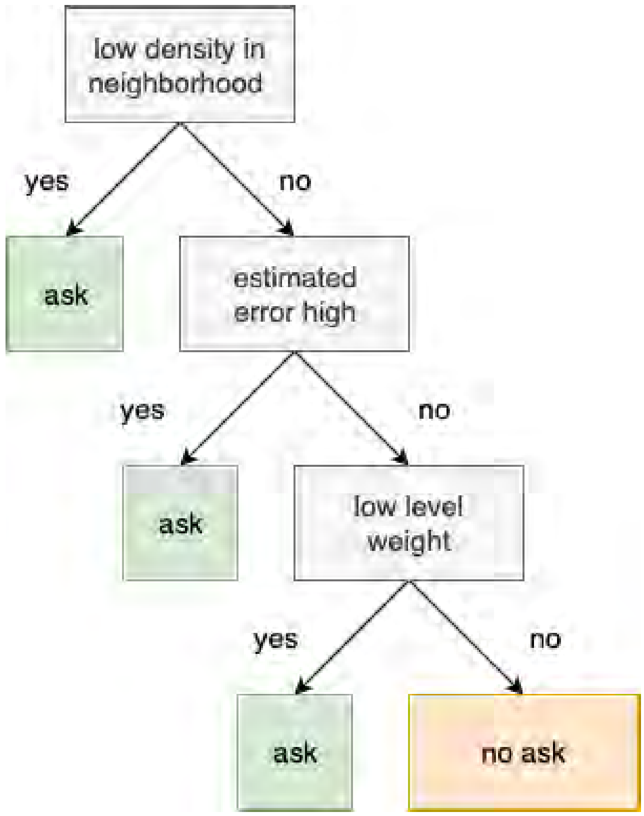

FIGURE 2. Asking problem.

TABLE 2. Number of asks.

Day	1	2	3	4	5	6	7	8	9	10
Number of asks	9	3	1	0	0	0	0	1	0	0

III. THE PRINCIPLE OF INTERACTIVE LEARNING

In this section, a new approach for occupancy estimation is proposed: the interactive learning methodology.

Interactive learning is a process involving an exchange of information with the users in order to collect some important data according to the problem context. In supervised learning methods, which are widely used in a lot of applications, the problem of the required target arises in the determination of the number of occupants i.e. the labeling issue is usually

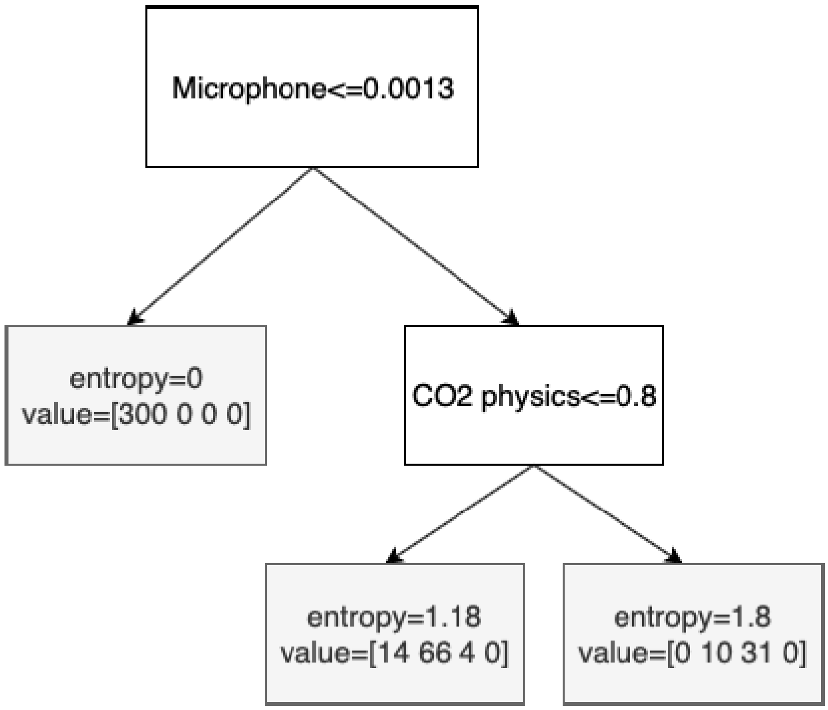

FIGURE 3. Decision tree.

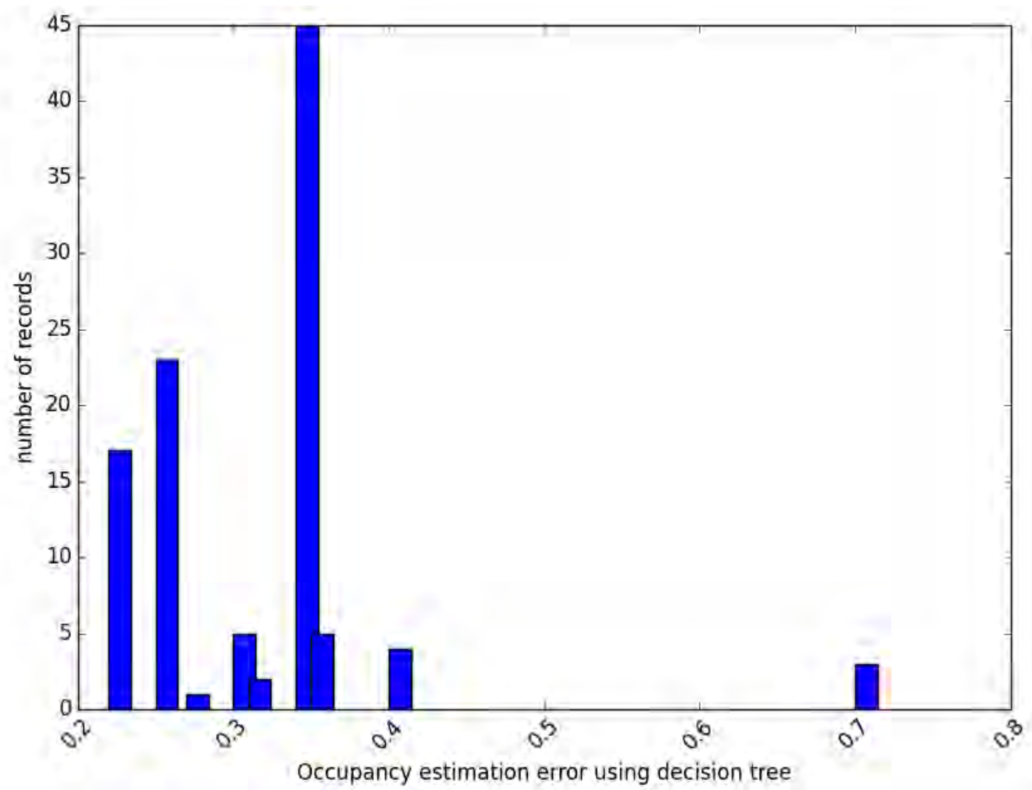

FIGURE 4. Distribution of decision tree error with 14 *asks* $\epsilon = 0.5$, error ratio is $E_r = 1.5$, and the weight of each class $C_W = 2$. 14 *asks* are not enough to build an acceptable decision tree estimator, with an average error equal to 0.32. The estimation error lies between 0.22 to 0.7 which is decreased by collecting more number of answers for building the estimator model. The interactive learning process has been performed 100 times to show the distribution of the error because of the randomness.

tackled using video cameras. Using camera is generally not acceptable in many places to respect the privacy of occupants. Interactive learning is an extension of supervised learning that determines the occupancy by collecting the required labeling from the occupants themselves. The problem statement of occupancy estimation has been explained in [20].

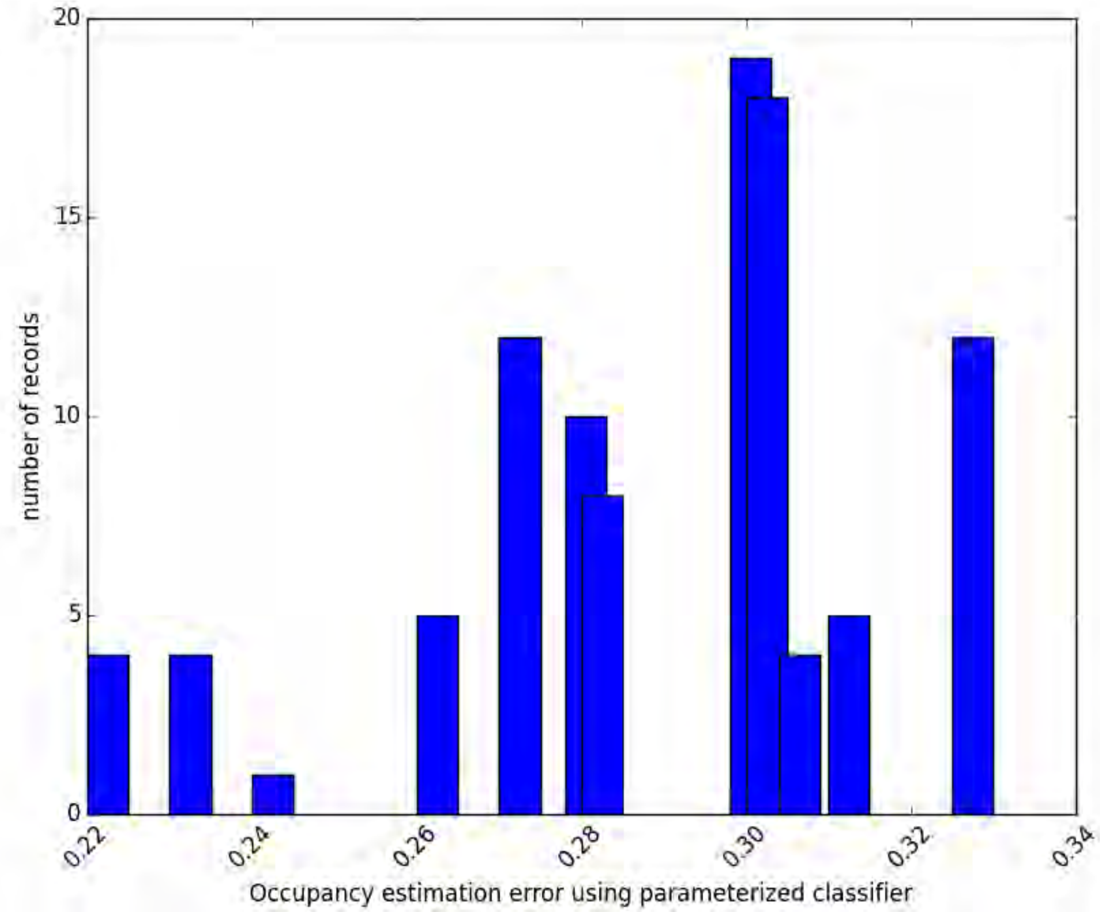

FIGURE 5. Distribution of parameterized classifier error with 14 *asks* $\epsilon = 0.5$, the error ratio is $E_r = 1.5$, and the weight of each class $C_W = 2$, the parameterized classifier is giving better results than the whole decision tree, with an average error equal to 0.288. The estimation error has been changed a slightly between 0.22 to 0.33 because of the optimization process. The interactive learning process has been performed 100 times to show the distribution of the error because of the randomness.

Three rules are considered to determine whether an interaction space (*ask*) is potentially useful or not:

1) The density of the neighborhood: It is the number of existing records in the neighborhood of a potential *ask*. The neighborhood is defined by the infinite distance with radius equal to one, because of the normalization. The record is a vector of features obtained which values are obtained from the sensors. The neighborhood can be modified according to $\epsilon \in [0, 1]$
2) The classifier estimation error in the neighborhood of the potential *ask* leads to the concept of neighborhood quality. If the classifier estimation error is too high for a record, this record is removed from the neighborhood because of the poor quality. $E_r \in [1, 2)$ typically, is an error ratio which can be adjusted. However, a value smaller than 1 means a record is considered as good. Conversely, if E_r is big, equal to 2 for instance, it means you accept error twice as big as the average error. Theoretically E_r belongs to $[0, \infty)$ but it is limited in our experiments to 2.
3) The minimum class weight: i.e. the minimum number of records for each class. The minimum class weight, weight(classx) < C_w which can be adjusted according to the problem.

All the potential *asks* that satisfy the above three rules are asked to the occupants in order to possibly become an additional record. The three previous rules have been checked with each new record according to the flowchart, in figure 2.

As a first validation, occupant reaction has to be taken into account as a response probability whether the occupants answer or not. In a given context, the number of asks relies on the classifier used for estimation occupancy.

Decision tree and a parameterized classifier together with the proposed *ask* mechanism are presented in the next two sections.

IV. DECISION TREE WITH INTERACTIVE LEARNING

In order to evaluate the interactive approach, we deploy decision trees which is one of the most valuable supervised learning methods for occupancy estimation. According to our study in [20], decision trees gave human-readable results which can be analyzed and easily adapted for building managers. In addition, it is possible to limit the depth of the tree in order to simplify the analysis of the (if - then) rules,

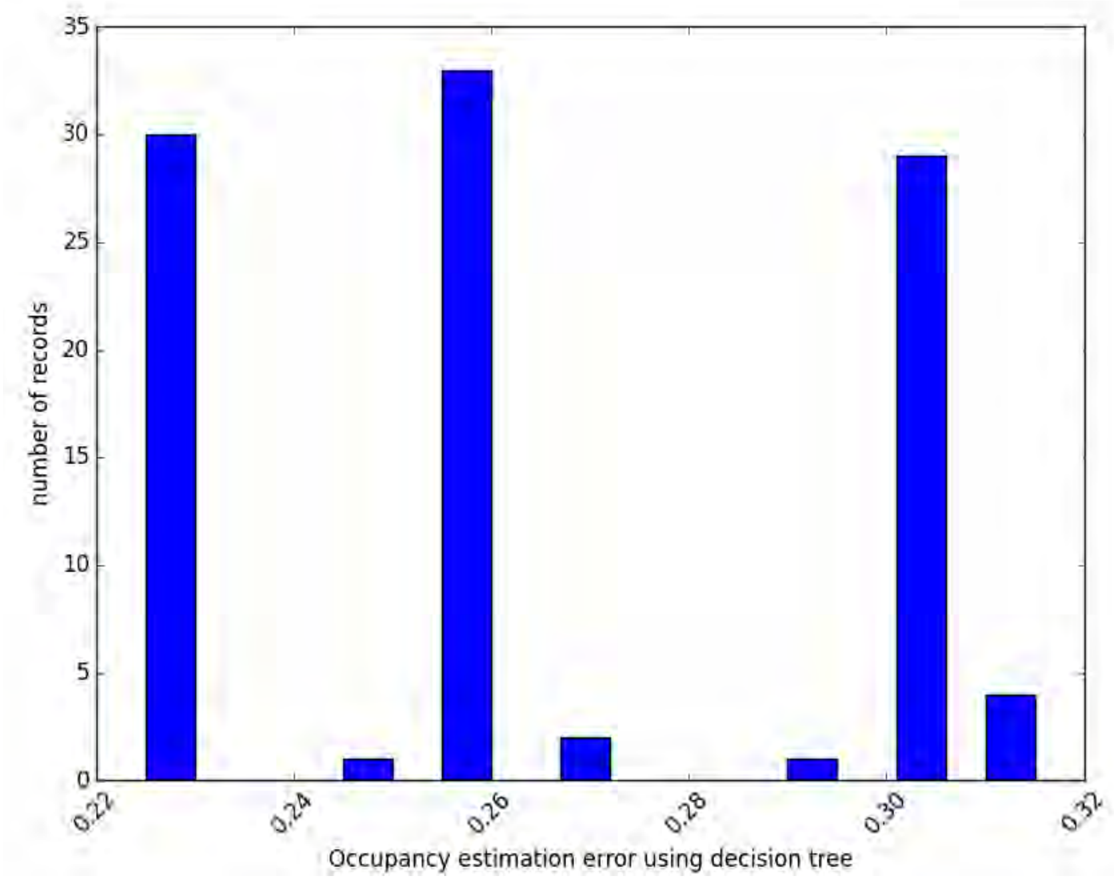

FIGURE 6. Distribution of decision tree error with 50 *asks* $\epsilon = 0.5$, error ratio is $E_r = 1.5$, and the weight of each class $C_W = 11$. 50 *asks* are enough to build an acceptable decision tree estimator, with an average error equal to 0.24 person which is better than the case of 14 *asks*. The estimation error has been changed between 0.22 to 0.8 which is decreased by collecting the required answers for building the estimator model. The interactive learning process has been performed 100 times to show the distribution of the error because of the randomness.

enable users to quickly extract useful information about occupancy estimation. Decision tree needs a training period (labeling) which is usually obtained from video cameras. Due to privacy issues, installing video cameras is not acceptable in many contexts. Using interactive learning solves this problem by sending questions and collecting answers from the end users. Figure 3 shows an example of a decision tree.

V. PARAMETERIZED CLASSIFIER WITH INTERACTIVE LEARNING

The parameterized classifier uses a predetermined classifier structure with parameters to be adjusted according to the incoming records. Tuning problem can be solved by adjusting the classifier parameters (node thresholds of the decision tree) in the final structure according to each updated recordset and how much it's different from the previous one. An objective function is determined to minimize the distance between actual (coming from an *ask*) and estimated (coming from the classifier) number of occupants in the room [20]. An example of the classifier parameters using if-then rules to read the decision tree is displayed in figure 3.

if microphone is less than 0.0013 **then**
  $\approx$ 0 person
else if microphone is more than 0.0013 and CO2 physical model is less than 0.8 **then**
  $\approx$ 1 person
else if microphone is more than 0.0013 and CO2 physical model is more than 0.8 **then**
  $\approx$ 2 persons
end if

VI. CASE STUDY FOR ONE ZONE OFFICE

A one zone office is used for interactive learning experiments. This office is equipped with 30 sensors. The data cover 11 days from 04-May-2015 to 14- May-2015. During these days a simulation has been done to evaluate the proposed approach. At this step, Human Machine Interface (HMI) interaction with end users in the office is simulated, while the answers of asks are coming from the data label obtained from video cameras. The effective replies of the occupants are also modeled using a random process with a reply probability equal to 50% i.e. only half of the *asks* get replies. Decision tree and parameterized classifier have been applied. The interactive learning process has been performed 100 times (random replies to the *asks*) to show the distribution of the error for both methods (see figure 4).

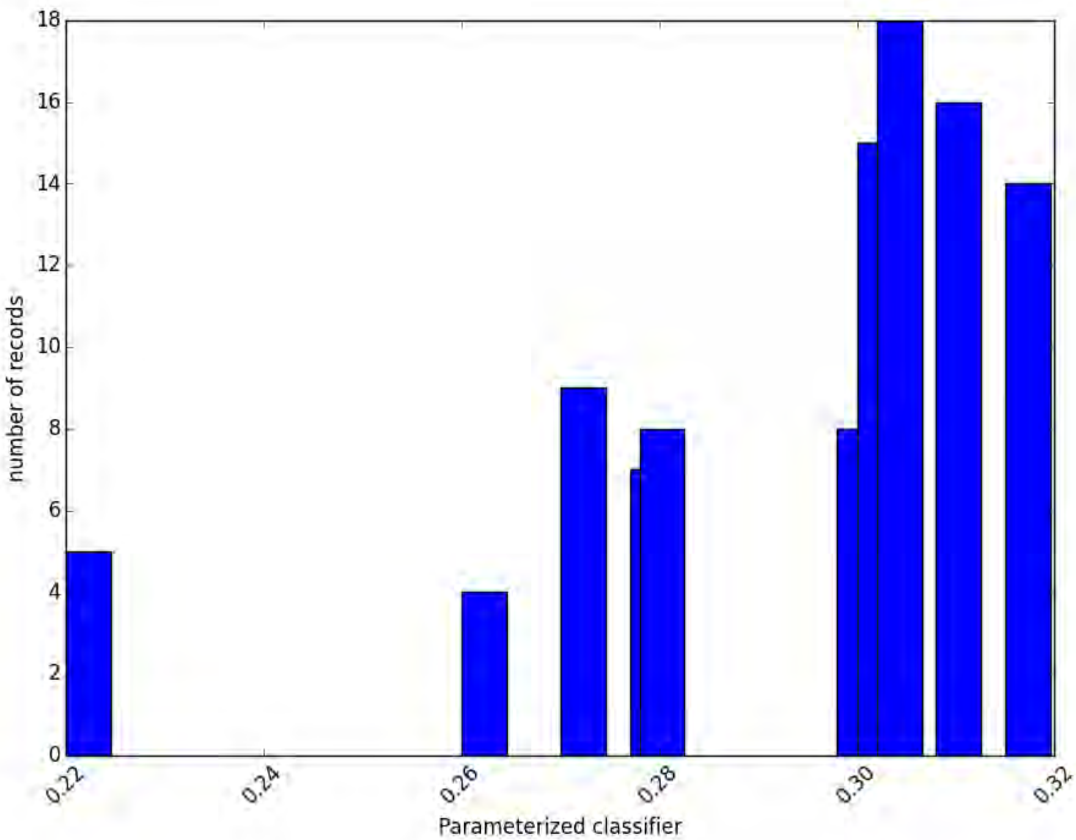

FIGURE 7. Distribution of parameterized classifier error with 50 *asks* $\epsilon = 0.5$, the error ratio is $E_r = 1.5$, and the weight of each class $C_w = 11$, decision tree gives better results than the parameterized classifier, with an average error equal to 0.27 and 0.24.

Table 2 illustrates how the 14 *ask* are distributed along the days with parameterized estimator. Asking process with decision tree leads to almost the same results depending on the run that contains randomness because of the *ask* replies.

The estimation error has been changed between 0.22 to 0.32 because of the optimization process. The interactive learning process has been performed 100 times to show the distribution of the error because the randomness see figures 4 and 5.

By comparing the occupancy estimation results in the case of 50 *asks* (average error is 0.24 person) with the estimation results of the decision tree using labels from video cameras (average error was 0.19 person), it is found that they are quite similar, see figures 6 and 7.

For more robust validation of interactive approach, different scenarios have been investigated by changing their parameters (ϵ, error ratio, class weight), see table 3. In order to compare the change in average error and find the best values of:

- The distance of the neighborhood $\epsilon \in [0, 1]$
- The error ratio is $E_r \in [1, 2)$
- The weight of each class C_w

Five case studies have been investigated, therefore the interactive learning process has been performed 100 times in each case study to show the distribution of the error because of the random replies of the *asks*.

TABLE 3. New service requiring occupancy/activity.

case study	neighborhood distance ϵ	error ratio E_r	class weight C_w	average error decision tree	average error parameterize classifier	number of *ask*
1-initial case study	0.5	1.5	4	0.24	0.28	38
2- decrease ϵ	0.2	1.5	4	0.245	0.27	72
3- increase ϵ	0.8	1.5	4	0.292	0.288	26
4- increase E_r	0.5	2	4	0.256	0.282	35
5- decrease C_w	0.5	1.5	10	0.24	0.27	46

- Case study 1: is considered as an initial one with ($\epsilon = 0.5$, $E_r = 1.5$ and $C_w = 4$) and occupancy estimation average error equal to 0.24 for decision tree and 0.28 for parameterized classifier.
- Case study 2: the neighborhood distance is decreased from $\epsilon = 0.5$ to $\epsilon = 0.2$ that leads to increasing the number of *asks* from 38 to 72 and the average error is kept 0.24 for decision tree and is decreased a little for the parameterized classifier with 0.27 average error. It means no value is noticed by increasing the number of *ask* over 38 *asks*, while it has a small effect on the parameterized classifier estimator and its optimization method.

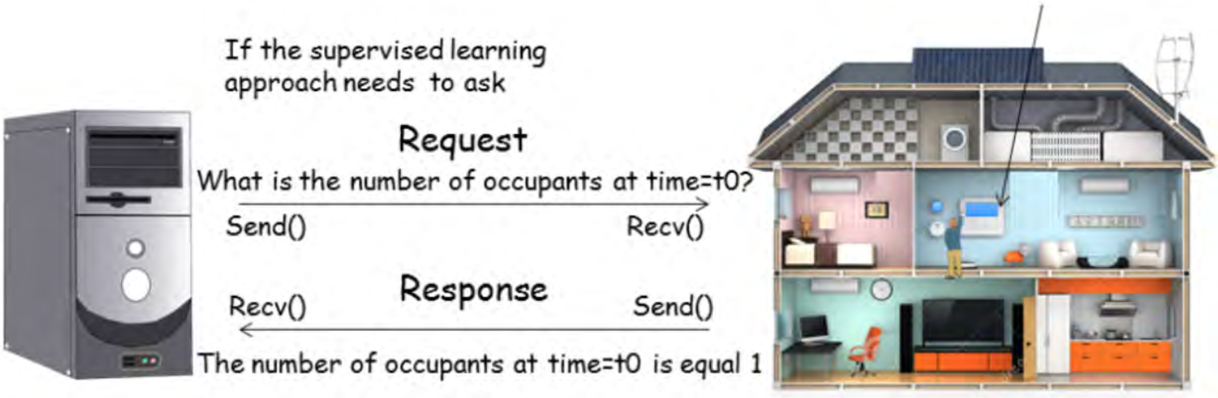

FIGURE 8. General principle of interactive learning approach.

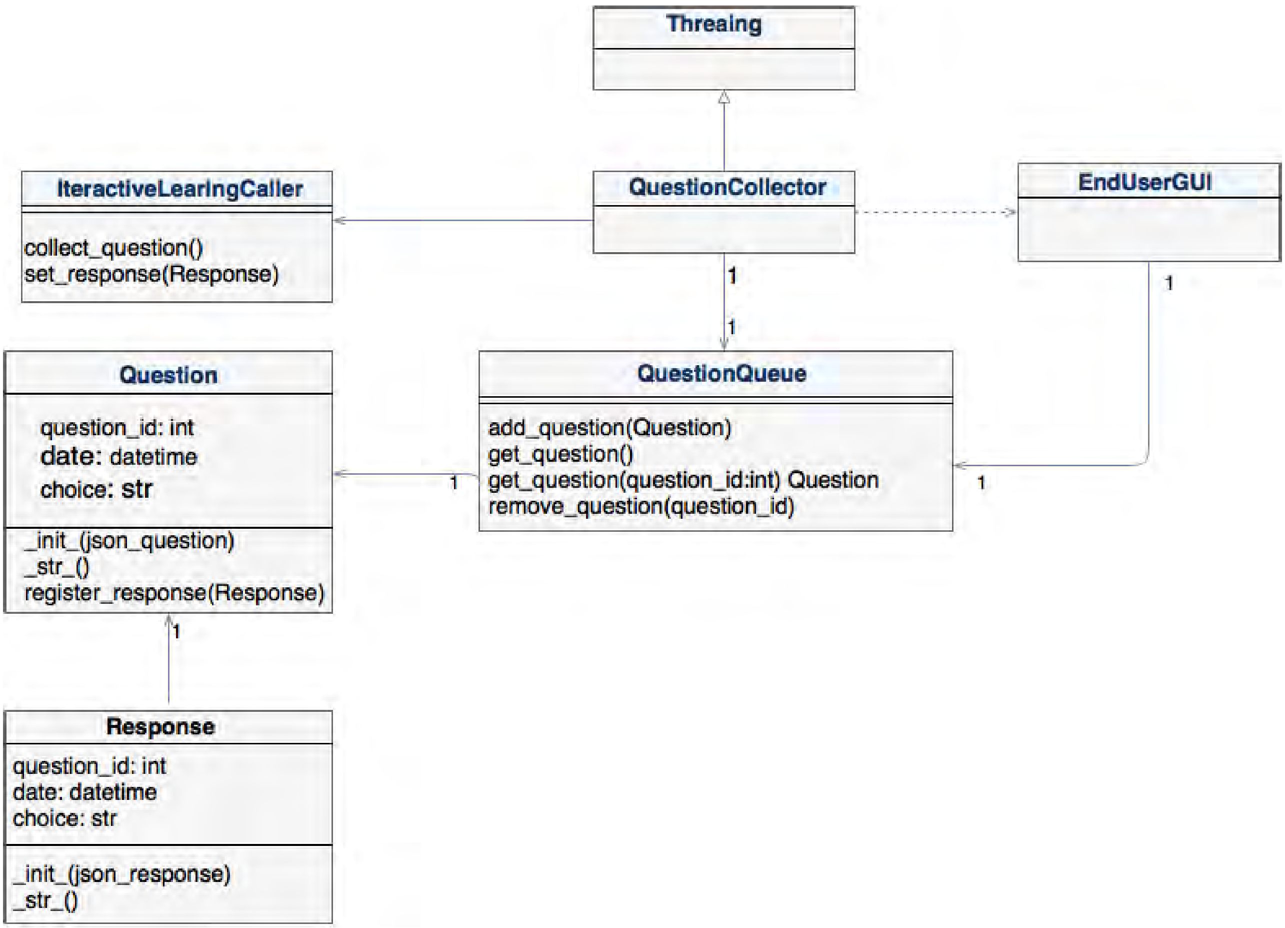

FIGURE 9. Class diagram of occupancy estimation using real time interactive learning approach.

- Case study 3: the neighborhood distance is increased from $\epsilon = 0.5$ to $\epsilon = 0.8$ that leads to decrease the number of *asks* from 38 to 26 and the average error increased from 0.24 to 0.29 for decision tree and increase a little from 0.28 to 0.288 for the parameterized classifier. It means the increase in ϵ value made the number of *asks* less and not enough to build an acceptable estimator for the decision tree, and it has a small effect on the parameterized classifier estimator.
- Case study 4: the error ratio is increased from $E_r = 1.5$ to $E_r = 2$ that leads to decrease the number of *asks* a little from 38 to 35, with a slight increase in average error for decision tree 0.256 and 0.282 for the parameterized classifier. It means this increase has no

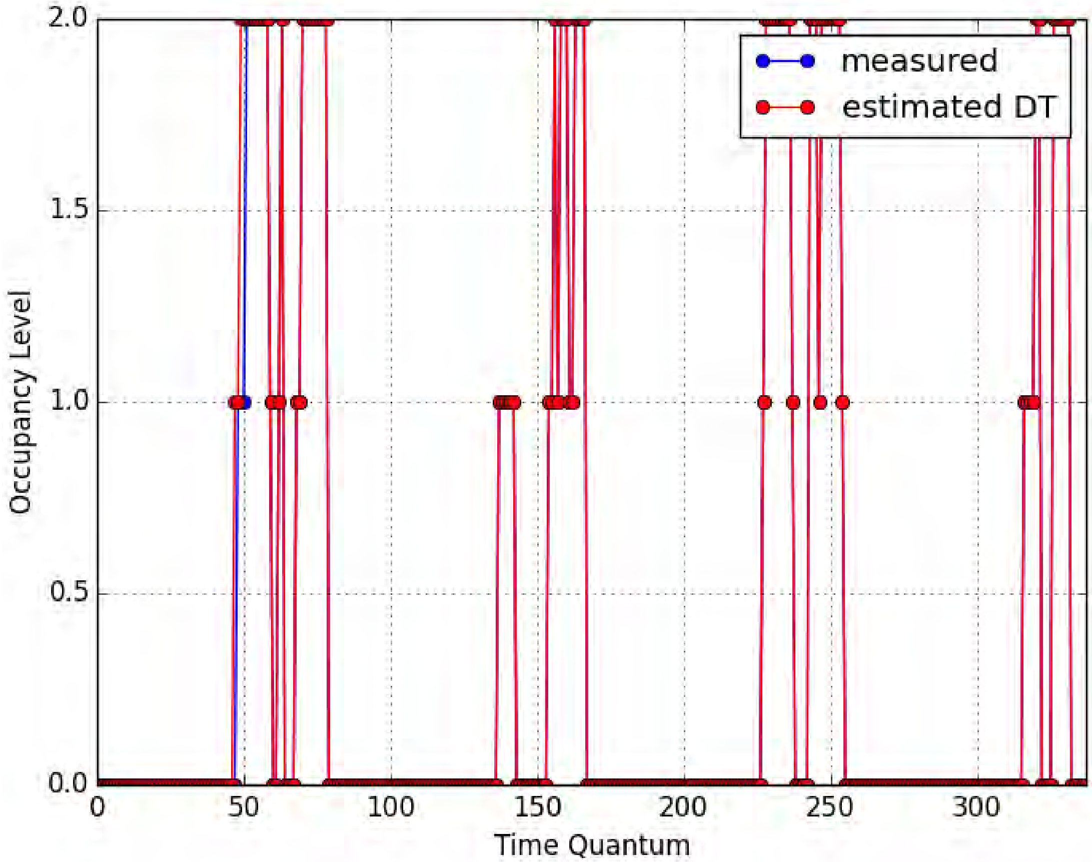

FIGURE 10. Occupancy estimation from DT with 3 occupancy levels and using interactive learning, time quantum =30 minutes. $\epsilon = 0.5$, $E_r = 1.5$, $C_w = 3$ and 16 asks.

much effect on both decision tree and parameterized classifier.

- Case study 5: the class weight is increased from $C_w = 4$ to $C_w = 10$ that leads to increasing the number of *asks* from 38 to 46 and the average error is almost the same for decision tree 0.24 and little decrease from 0.28 to 0.27 for the parameterized classifier.

Table 2 shows a summary of the 5 case studies, it concludes that the increase of the neighborhood distance (ϵ) leads to increasing the number of *asks*, also reduces the error (complex context), while it depends on collecting the *asks* to build the estimator model. The occupancy estimation of parameterized classifier will not be affected. It can be explained because the decision tree estimator depends on the number of *asks* to build an acceptable estimator. Increasing the error ratio E_r will decrease the number of *asks* but with more sensitivity to fake replies, and Increasing the level weight C_w will increase the number of *asks* but will also confirm the replies (redundancy). It has been found that the number of *asks* equals 38 can be achieved by taking ($\epsilon = 0.5$, $E_r = 15$ and Cw $= 4$) i.e case study 1. Its good enough in decision tree with an average error equal to 0.24 and parameterized classifier estimators with an average error equal to 0.28. However, no added value is noticed when increasing the number of *asks* (i.e case study 5 and case study 2). Conversely, it will bother the users to be involved in the estimation process. It is important to mention that decision tree estimators in all case studies start occupancy estimation with a high average error corresponding to a little number of *asks* (training data) with an average error almost 0.7, and improve the estimation process by collecting replies, which leads to decrease the average error to 0.2. On other hand, parameterized classifier does not need a big number of *asks* comparing with the number used in decision tree. The estimation error is between 0.22 to 0.35 smoothly in each case study. It can also be noticed that the asking process is dependent on the classifier used because of the estimation error intervenes.

All these results lead to consider interactive learning approach as an acceptable solution to avoid the camera use to determine occupancy.

VII. IMPLEMENTATION AND EXPERIMENTATION WITH THE REAL-TIME INTERACTIVE LEARNING APPLICATION

A real interactive learning system is proposed based on a discrete feedback from occupants using a screen/keyboard device. It suggests a client-server architecture to implement this application. A system makes it possible to a server to send questions for the occupants (client side) in order to obtain the occupancy (labels). After deciding to send a question, it appears on the client side with an alarm to attract his/her

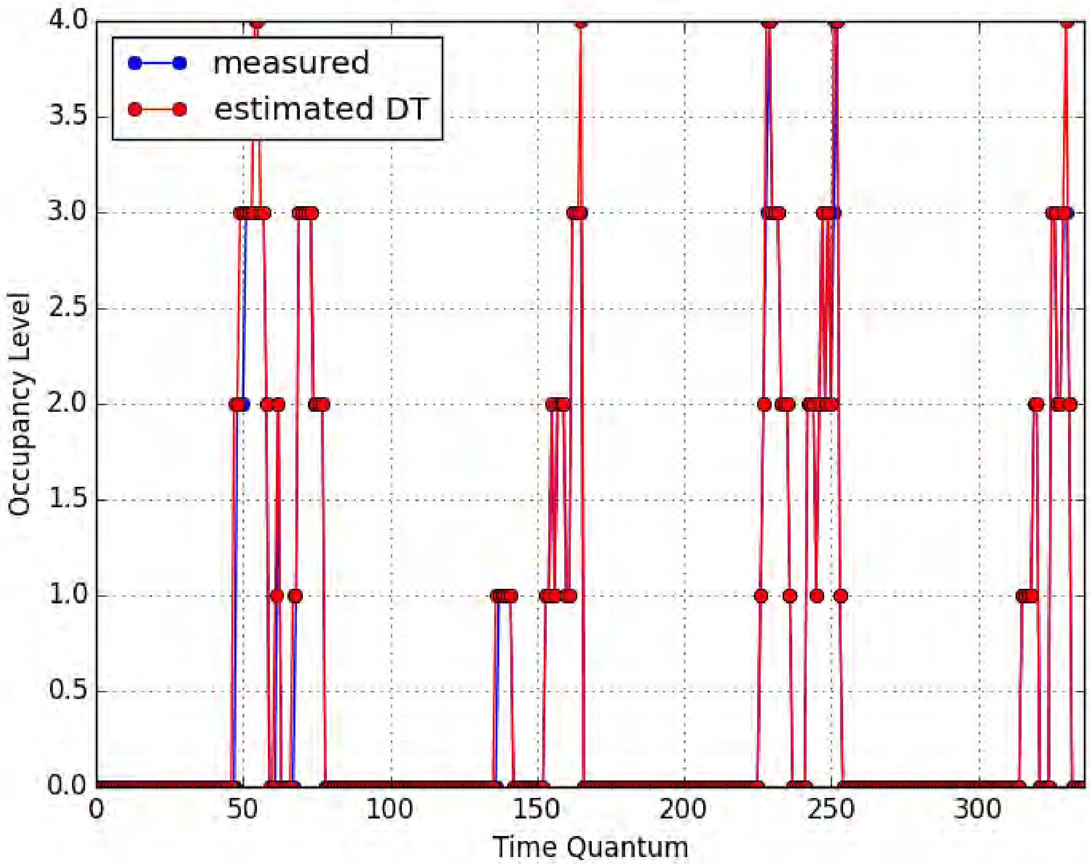

FIGURE 11. Occupancy estimation from DT with 5 occupancy levels and using interactive learning, time quantum =30 minutes. $\epsilon = 0.5$, $E_r = 1.5$, $C_W = 3$ and 21 *asks*.

attention for answering a new question. The occupants have the right to reply by sending the number of occupants among the available options or to cancel it. Collecting the replies will be used by a supervised learning method (i.e decision tree) in a training data or parameterized classifier in the optimization process. Figure (8) presents a general idea of the proposed real interactive learning system.

For interactive applications, a human-machine interface (HMI) allows humans to interact with the occupancy estimation. HMI is displayed with a machine with touch display, a computer with a keyboard, a push button or a mobile device. Choosing the right HMI can be as important as considering the capabilities of the process behind it. The proposed human-machine interface is easy to understand and gives clear options to end users. With a laptop device, a Python based human-machine interface has been proposed for interactive learning application to be used by the end users in a very easy way see (figure 9). Each question is displayed on the screen with it is order, date and time i.e. (Q1, 02/05/2017 14:38:18 How many occupants in last 30 minutes? (0...6)), while in a response area, there are 7 options to answer, defined accordingly to a minimum and a maximum possible number of occupants with a timeout of 3 hours for each question. The user has to select the question, choose one option and click on the send button, or occupants can cancel the question by clicking on cancellation check box. Many questions could appear on the screen if the user is not available for answering. In this case, the user has to choose among the questions or he could answer all of them.

For more details of the proposed approach, (see figure 9). It shows a class diagram of the interactive learning system.

In addition, a question is removed from the screen after a specific time i.e. 6 hours here, in order to avoid confusing the user by many questions, in case he could not reply for long period. Human-machine interface (HMI) has been built using Tkinter in a Python environment.

Day	1	2	3	4	5	6	7	8	9	10
Number of *asks*	10	5	0	0	1	0	0	0	0	0

A. RESULTS

Considering the same case study of the office, the real-time system launched from 07/04/2017, (see figure 8).

Different experiments have been done using the following thresholds $\epsilon = 0.5$, $E_r = 1.5$, $C_w = 4$. The first experiment is occupancy estimation using 3 occupancy levels to generate decision trees, the results have been obtained till 13/04/2017 with an average error 0.008 person, (see figure 10).

Decision tree needs 16 *asks* for training data to build an acceptable estimator. The following table illustrates how

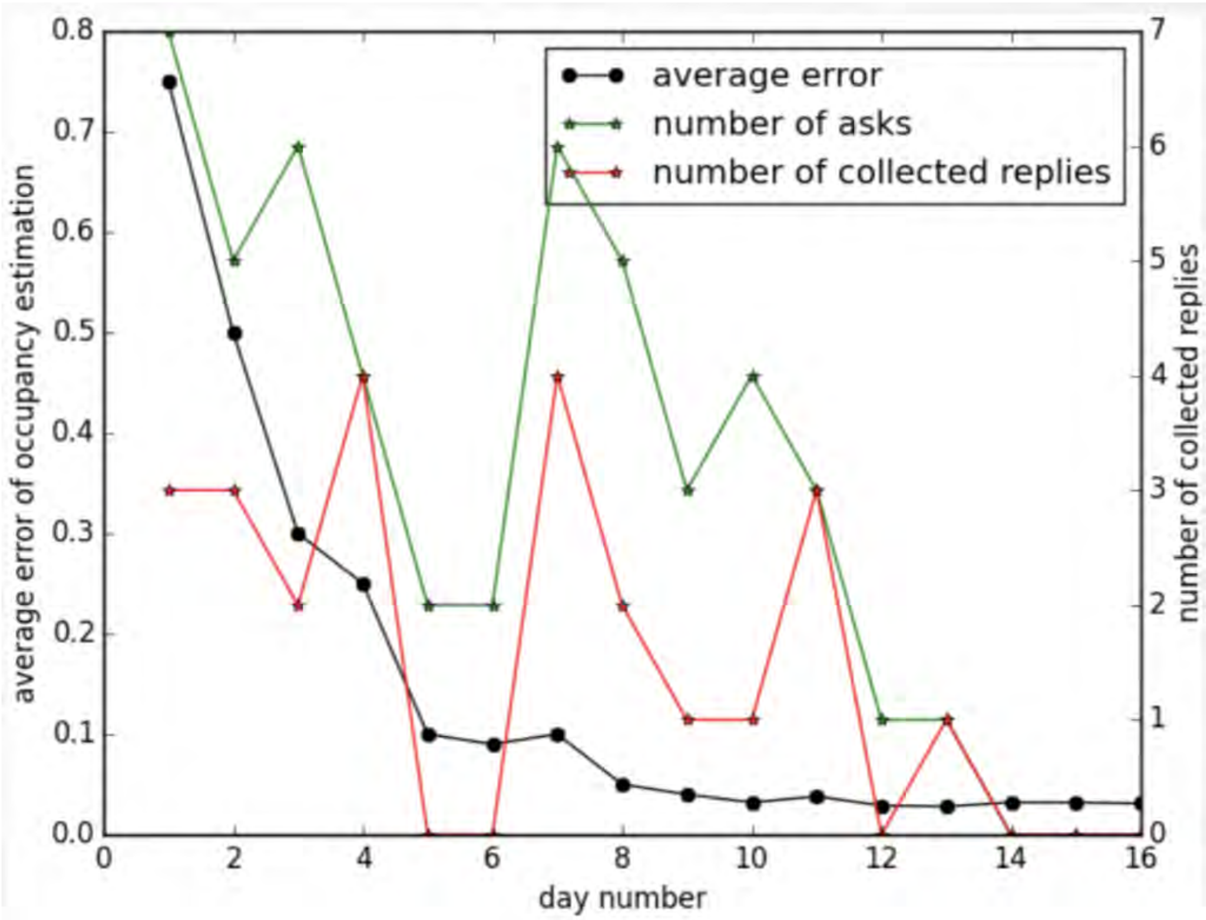

FIGURE 12. Black plot refers to occupancy estimation error each day using decision tree with interactive learning. Green plot refers to the number of *asks* each day. The decision tree has been deployed for 5 occupancy levels, time quantum =30 minutes. $\epsilon = 0.5$, $E_r = 1.5$, $C_W = 3$ and 24 *asks*.

the 16 *asks* are distributed along the days with decision tree.

The second experiment continues in estimating occupancy using 5 occupancy levels to generate decision trees with an average error of 0.03, (see figure 11). Decision tree needs 21 *asks* for training data to build an acceptable estimator see the following table.

Day	1	2	3	4	5	6	7	8	9	10
Number of *asks*	10	4	0	0	2	1	2	1	0	0

Occupancy estimation using decision tree and interactive learning with an average error 0.03 person is more efficient than using decision tree and manually labeling from the video camera with an average error of 0.2 person [20]. This improvement in occupancy estimation results can be explained by the precise answers to all the questions which have appeared on the HMI. They have been replied by an occupant during a training period of decision tree. While in manually labeling from a video camera, average values of occupancy have been obtained, with some human mistakes during labeling. Probably the average error will decrease if the end user does not feel concerned by the estimation process. The final experiment has been proposed to analyze the estimation process in case of implementing the interactive process where the users who are not really involved by this research. The following table needs more days for collecting the required answers (20 *asks*) as compared to the second experiment. This result proves that the time of collecting the training data depends on the end user interest. Figure 12 shows the improvement in an average error of occupancy estimation each day during 14 days with 24 *asks*, which is directly related with collecting the training data. Green plot shows the number of *asks* during the interactive process each day, while the red plot shows only the collected replies from the end user each day during the interactive process.

Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Number of *asks*	3	3	2	4	0	0	4	2	1	1	3	0	1	0	0

The estimation process starts with a high average error on the first day which is equal to 0.75. After collecting the required training data, it starts to improve the estimation results with an average error equal to 0.1 person at the fifth day. After obtaining all the required answers (training data) the average error of occupancy estimation decreases and starts to be almost stable with an average error equal to 0.032 person.

VIII. CONCLUSION

An interactive learning methodology has been proposed in this paper to avoid the manual labeling of actual occupancy from a video camera in a room for a supervised learning approach. for privacy preserving purposes, little number of interactions with occupants to estimate occupancy in a zone. Two different classifiers have been deployed together with the interactive learning process: a pure C45 decision tree algorithm and a parameterized rule-based classifier. The approach can be easily extended to any kind of classifier. The C45 decision tree algorithm is very general because its structure is not assumed: it can be discovered from the real data and can be therefore extended to any room with any sensors. It gives the best results after about 14 *asks*. The parameterized classifier yields better results at first but because the number of parameters (2) is much less than the C45 decision tree (about 45 parameters), the C45 decision tree finally estimates better the number of occupants although the parameterized classifier directly minimizes the estimation error and the classification (with C45, classifying in class 2 or in class 3 instead of class 1 has the same impact). Due to the fact that the structure of parameterized classifier is predefined, the adaptation capability to another context is less: a relevant structure has to be proposed. A Real-time application has been developed for occupancy estimation with an average error 0.03 person and 16 *asks* for the training period, this result leads to consider interactive approach as more efficient for occupancy estimation than the other methods taking into account the context. It is the main step to collect knowledge about the relations between user behaviour and energy use. Interactive learning approach can also be combined with estimation activities approach, in order to avoid to send a question in case of estimated activities with non-interaction possibility. Estimation of human occupancy and activities is one challenge for existing and future smart building occupant services. A considerable amount of research work addresses the problem. In general whatever the application is, occupancy and activity estimation should be known to define the state of the human building part. It is useful for performance guaranty and simulation during the design phase, calculate heat gains from bodies for simulation and parameter estimation, replay/determine the best solution for the past or future, explanation to help occupants to understand their energy management system, diagnosis and failure detection, usage performance indicators.

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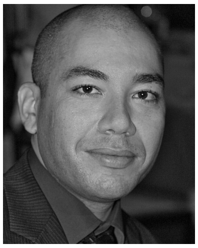

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