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Evaluación de la técnica de fusión de sensores para la detección de ocupación en una oficina universitaria

Assessment of the Sensor-fusion Technique for Occupancy Detection in a University Office

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RESUMEN– Dado que el éxito de desarrollar edificios con mayor eficiencia energética tiene una dependencia quirúrgica del comportamiento de los ocupantes y el uso de los sistemas, la necesidad de tener en cuenta su comportamiento correcto en la simulación del diseño de los edificios en etapa inicial y la evaluación del consumo de energía, aumenta rápidamente. Para abordar esta necesidad, se está implementando ampliamente una técnica llamada fusión de sensores en el dominio del edificio, para desarrollar primero modelos descriptivos precisos para los perfiles de ocupación y, en última instancia, para poder predecir los perfiles típicos. En este contexto, una oficina está instrumentada para monitorear la calidad del aire interior, el consumo de energía y el uso de la ventana y la unidad de aire acondicionado. El estado de ocupación real fue monitoreado manualmente. El análisis de datos permitió resaltar los parámetros más relevantes asociados con el estado de ocupación, basado en el coeficiente de correlación de Spearman. El uso de histogramas permitió identificar una combinación óptima de sensores para detectar el estado de ocupación de la sala de oficina. La combinación óptima identificada agrupa los sensores de CO_2, energía y estado de la ventana, que detectaron la ocupación con un 91.5% de precisión.

Palabras clave– *Ocupación, técnica de fusión de sensores, modelado de ocupación, edificio de oficinas, histogramas.*

ABSTRACT– Since the success of developing more energy efficient buildings has a surgical dependence on the occupants' behavior and systems usage, the necessity of accounting for their correct behavior in the simulation of the early-stage buildings' design and energy consumption evaluation, is increasing rapidly. To board this necessity, a technique called sensor-fusion is being widely implemented in the building domain, to first develop accurate descriptive models for occupancy profiles, and ultimately, to be able to predict typical profiles. In this context, an office is instrumented to monitor the indoor air quality, the power consumption, and the use of the window, and air conditioning unit. The real occupancy state was monitored manually. The data analysis allowed to highlight the most relevant parameters associated with the occupancy state, based on the Spearman's correlation coefficient. The use of histograms allowed to identify an optimal sensor combination for detecting the occupancy state of the office room. The identified optimal combination groups the CO_2, power, and window state sensors, which detected the occupancy with 91.5% of accuracy.

Keywords– *Occupancy, Sensor-fusion technique, Occupancy modeling, Office building, Histograms.*

1. Introducción

According to the international energy agency [1], in 2017, buildings and appliances were responsible for around 30% of global energy use. Building energy use increased by 0.8% from 2016 and rose 20% between 2000 and 2017. Since the success of developing more energy, efficient buildings and equipment have a surgical dependence on the occupant´s behavior and systems usage.

Now with the implementation of new technologies oriented to energy saving and green building certifications, a new approach related to how they affect the use of energy due to occupant behavior has emerged [2].

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Include the occupant behavior is fundamental to quantifying the savings in energy consumption. For commercial buildings, behavioral change can reduce energy use by 5% to 30% [3].

Occupant movements and presence are fundamental to occupant behavior simulation by providing information about whether a room is occupied, the number of occupants, or the specific individual in the room, depending on the sensor or combination of sensors.

The real occupancy patterns in buildings may differ significantly from each other. Existing research includes various data collection approaches, including non-invasive occupant observations, observing occupants that have had perturbations applied, surveys, and laboratory studies [4]. Gathering data on human-building interaction is a new approach for achieving energy efficiency in the building sector, and the research groups are focusing into evaluating the impact of occupant behavior in the building design and operation as a new horizon [5].

Measurements of energy-related behavior are collected using a) physical sensing, and b) non-physical sensing methods [6]. Data gathering to investigate occupant behavior studies in thermal comfort, occupancy, windows, shades and blinds, and lighting and electrical equipment were categorized by [7]. The indoor and outdoor environmental data are in the physical sensing category, and the authors identified the most significant as air temperature, air humidity, CO_2, occupancy, window state, door state, and others. The authors in [8] monitored some environmental parameters as CO_2, carbon monoxide (CO), total volatile organic compounds (TVOC), outside temperature, dew point and small particulates (PM 2.5), air temperature, relative humidity, motion detection, and acoustic to determining which parameters have significant correlation with the occupancy level. The results show the most significant correlation for CO_2 and acoustic parameters with the number of occupants in the space.

Sensor fusion approaches are built upon the use of multiple sensors or sensing modalities in an attempt to combine their advantages while canceling out their disadvantages as much as possible [9], [10]. In general, to overcome the disadvantage of an individual detection system, a fusion of multiple sensors is encouraged in occupancy detection.

2. Experimental setup and monitoring parameters

The experimental apparatus was designed to monitor the occupancy in an office at the University of Calabria (Italy), as well as collecting data from the indoor environment such as air quality, occupancy state and behavior, and electricity usage; this data collection started in February 2016 is ongoing.

2.1 Description of the office room

Within the University building, submitted to Mediterranean climatic conditions, the instrumented office room has a surface area of $19m^2$ and 2.50m height. This office has a Westward-facing external wall and a two-wing window of 0.68 x $0.76m^2$ (Figure 1 (a)). The equipment within the room includes desktop computers and printers, where the heating and cooling system are autonomous (Figure 1 (b)). Normally, the office is generally used by one person, where the information about how the office is used, was collected by personal interview.

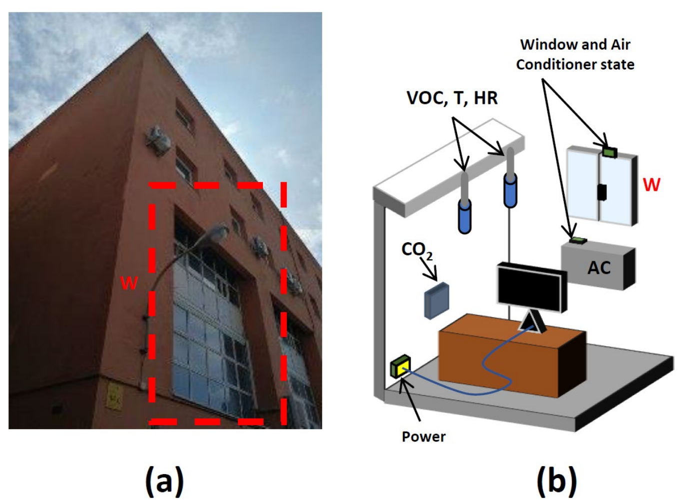

Figure 1. The university office: (a) external wall, (b) schematic with sensors location.

The detected variables for data collection were divided into two groups, binary and continuous:

1) Binary variables: Occupancy state (vacant = 0, present = 1), Window state (closed = 0, open = 1), Air conditioning usage (off = 0, on = 1).
2) Continuous variables: CO_2 (ppm), Power (W), VOC (ppm), Indoor air temperature (°C), Indoor air relative humidity (%).

2.2 Equipment for internal variables measurement

Sensors were installed to obtain information regarding user presence and absence intervals. Data were automatically queried every one-minute and stored in central embedded MySQL database.

The experimental apparatus was designed to monitor the presence and movement of the occupants in the office, as well as thermophysical properties of the internal environment and the electricity consumption connected to the use of computers [11].

The sensor's location was carefully selected to ensure that the sensors were triggered when occupants are inside the office. The indoor environment sensors were placed on internal walls at the height of 1.8m above the floor, as suggested in [12] to avoid any perturbation from direct sunlight.

The WuTility Version 4.30 tool was used for management and inventorying [13]. Indoor VOC and CO_2 sensors for concentration levels and temperature/humidity sensors were the first installed. The results were checked, and clock synchronization was set up. Preliminary tests for window/door position and air conditioning usage sensors were successively conducted before actual data collection.

The CO_2 sensor was installed near the desk at nose level (when sitting, 1.1m above the ground) [8], at this position more stable CO_2 values are ensured during the unoccupied periods. Table I shows the characteristics of the sensors used in the experimental apparatus.

3. Experimental results and data analysis

Fig. 2 and Fig. 3 show hourly data of the occupancy state in relation to CO_2, VOC, air temperature, relative humidity, window state, power, and air conditioning usage for two summer days (1st – 2nd June. As shown in the graphs, just after the first person arrives in the office, all sensors indicate a change in their measurements. In the first day, the CO_2 sensor (figure 2 (a)) seems to have a morning maximum reading around 11:00 and window closed. From about 11:30 to 14:30 (when the room is not occupied), all sensors register a decrease in their readings, except for the temperature.

When the office is left vacant after 18:00, all sensors measurements drop except for the humidity. Clearly, this behavior is strongly related to the occupancy state and also to the number of people that might have been in the room at the moments were CO_2 levels reached high values even though windows remained open (Fig. 2 (a) with figure 3 (a), for the second day at 12:00).

Moreover, there appears to be a stable value for CO_2 concentration level and the power, when there is no occupancy. The same consideration can not be said for indoor air temperature, relative humidity, and VOC.

Table 1. Characteristics of sensors employed for data collection

Sensor	Variable	Range and accuracy
57018[a] CO_2 sensor	Carbon dioxide [ppm]	0–2000 ppm ±30 ppm, ±5%
57645[a] AC Device	Electricity power	0–50 A AC, 30–6000 Hz (all waveforms)
ABUS FU7350W Abus rectangular, NC,0.2 A Reed Switch	Window/door position (open/closed) Air conditioning (on/off)	Contact sensor
57618[a] Web-Graph Air Quality	Volatile organic compounds [ppm]	450–2000 ppm VOC as CO2 equivalent
	Air temperature [°C]	typ. @ 25 °C ±0.3 °C max. @ 0–50 °C ±1.2 °C
	Relative humidity [%]	typ. @ 25 °C ±3% rH max. @ 0–50 °C ±7% rH (0–100% rH)
57613[a] Web-Thermo-Hygrobarograph	Pressure [hPa]	typ. @ 25 °C ±0.8 hPa (750 – 1100 hPa)
	Air temperature [°C]	typ. @ 25 °C ±0.3 C max. @ -40–85 °C ±1.5 C
	Relative humidity [%]	typ. @ -20–60 °C ±1.8% rH max. @ -20–60 °C ±4% rH (0–100% rH)

[a]Wieseman & Theis.

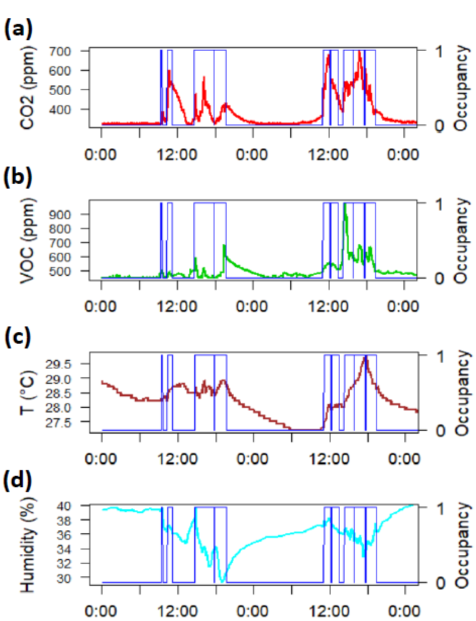

Figure 2. Real occupancy (dashed line) and measurements for two summer days (1st to 2nd June): a) CO_2 (ppm), b) VOC (ppm), c) air temperature (°C), d) relative humidity (%).

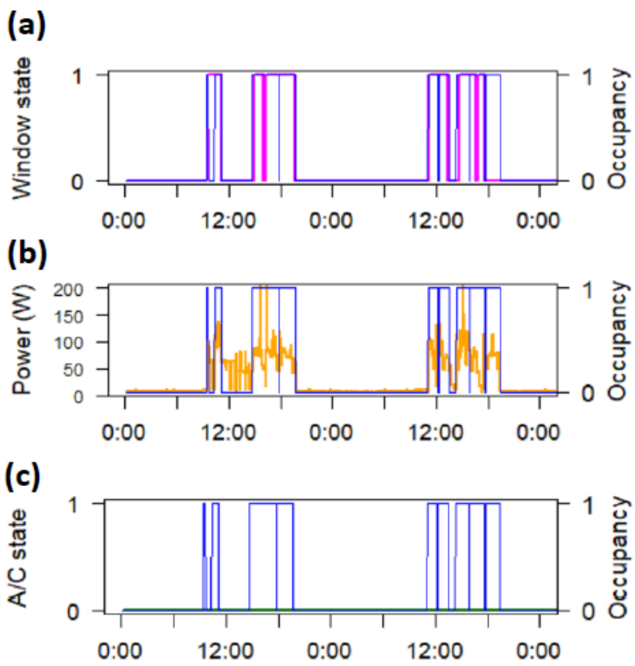

Figure 3. Real occupancy (dashed line) and measurements for two summer days (1st to 2nd June): a)) window state, b) power (W), c) air conditioning usage.

Figure 3 (a) and (c) show the relationship between occupancy and window state, and between occupancy and air conditioning usage (A/C state), respectively. In this case, the office is occupied, it can be observed that the air conditioning remained off during the presented period. Thus, it can be inferred that merely the action of opening the window is enough to maintain occupants' comfort. It seems that they are variables more related to occupant preferences than to presence.

It can be inferred from Fig. 2 (a) and Fig. 3 (b) that there is a limit value, for both CO_2 and power, when there is no occupancy: around 368ppm and 14.1 W, respectively. Therefore, the following is considered: when the CO_2 value falls below 368ppm there is no occupancy, and if the CO_2 level stays above this value, the office will be considered as occupied. The same criterion was applied concerning power. This "threshold value" for each continuous variable was obtained by calculating the average value when there is no occupancy in the office.

Regarding the window state and the air conditioning usage, it was assumed that when the air conditioning is on, then the room is occupied, in accordance with the information collected by the interview and collected data; this assumption is also valid for the window state. These assumptions and considerations are of vital importance at the moment to decide which sensors should be combined to determine the occupancy state in the room accurately.

3.1 Determination of the significant variables

As shown in the figures above, some variables showed a stronger affinity to the occupancy state than others. Thus, to objectively determine which are these variables, a correlation study was conducted using the software R and its corrplot library, based on Spearman's Correlation Coefficient (SCC). The correlation plot (or corrplot) is presented in figure 4. A sample of 45 days (from February 2016 to September 2016) with a sample rate of an observation every minute was used in this correlation study, which results in 64,800 observations in total.

The highest SCC values are in agreement with the relations observed in the behavior of CO_2, power, air conditioning, and window state (figure 2 and figure 3). The SCC value between CO_2 and occupancy state resulted in 0.61. As expected, a similar SCC value is encountered for the correlation between occupancy state and power (SCC equal to 0.64). Window state and air conditioning usage presents a SCC value of 0.46 and 0.42, respectively in relation to the occupancy state. Only for the relationships between occupancy state and temperature and humidity, the Spearman's correlation coefficient returns values of negative correlation.

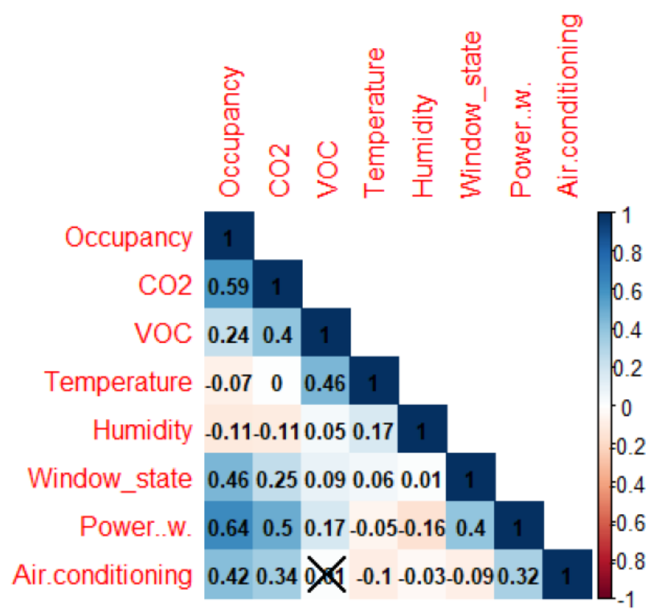

Figure 4. Correlation plot using Spearman's correlation coefficients.

3.2 Difficulty in correlating discrete and continuous variables

Since the occupancy state behaves as a discrete variable and parameters such as the CO_2 and VOC levels, temperature, humidity, and even the power consumption, all behave as continuous variables, inquiries may arise at the moment where the most relevant parameters are identified by using a simple correlation analysis based on Pearson's and Spearman's coefficients. The reason lays in the weak values presented in the correlation coefficients.

For example, the correlation between Power and Occupancy state (figure 3 (f)), compared with other plots, at a glance, it seems that the Power should present a strong correlation coefficient value with the occupancy state, just by observing these figures. In fact, the correlation analysis shows that this is indeed the case, where the correlation coefficient value equals 0.64 (figure 4), which is the highest value in the correlation plot. However, from the point of view of statistics, expected strong correlation coefficient values might lay around or higher than 0.97.

However, when plotting together occupancy state and Power, this strong correlation seems to be difficult to be perceived because, as shown in figure 5, for a range of Power between 0-20 W and 40-60 W, the occupancy state appears to indicate that the office is both occupied and unoccupied.

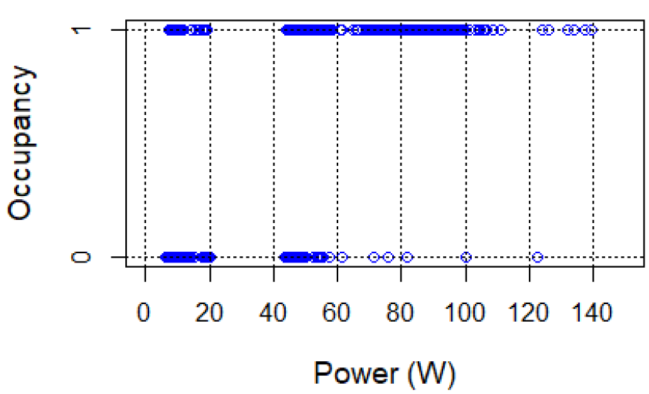

Figure 5. Occupancy state as function of the Power.

Based on the aforementioned, special treatment is procured when estimating the correlation between discrete and continuous variables. The procedure is known as the maximum likelihood estimation (MLE) is used to estimate such correlations [14]. In this method, the discrete variable is assumed as to be a classification of an unobservable continuous variable whose joint distribution with the observed continuous variable is bivariate normal. Such formality is contemplated to be examined in this research within further modeling approaches.

In summary, the identified significant variables are two continuous variables (power and CO_2) and two binary variables (window state and air conditioning usage).

4. Identification of a suitable sensor combination for occupancy detection

After identifying the most significant variables through correlation analysis, these four selected variables are implemented to determine the best combination (or fusion) for detecting occupancy in the office room.

Regarding the window state and the air conditioning usage, it was assumed that when the air conditioning is on, then the room is occupied, in accordance with the information collected by interview and collected data; this assumption is also valid for the window state. For these two binary variables, the authors assumed 1 for occupied room and 0 for an empty room.

Before looking for an optimal sensor combination of the sensors, each of the four variables were analyze as to evaluate their performance on detecting occupancy in the office. figure 6 shows four histograms for such purpose, presenting the occurrence of occupancy when the established values for each of the four variables is reached.

In this case, figure 6 (a) presents the occurrence of occupancy in the office room. This histogram shows that the office remained unoccupied more often than (around 80%) it was occupied. figure 6 (b) shows the occupancy state only when the Power was higher than 14.1 W. This indicates that 70% of the times the office was occupied, the power consumption was higher than 14.1 W. Fig. 6 (c) shows the occupancy state only when CO_2 levels were higher than 368ppm, and finally, figure 6 (d) shows the occupancy state when the window is opened.

In figure 6 (c) it can be observed that the occupancy state of the office is ambiguous based on the CO_2 levels only since the occurrence of presence and absence is nearly 50 % each. However, from figure 6 (d), it can be observed that more than 80% of the times the window remained open, the office was occupied. The other remaining less than 20% can be explained by the fact that sometimes the window might remain opened while the office was unoccupied.

The aforementioned indicates, first, that the occupancy in the office can be somewhat accurately detected by only the knowledge of either the power consumption or the window state (opened or closed), separately. Second, the use of merely CO_2 sensors might not be enough to detect the occupancy accurately. Therefore, it can be inferred that the occupancy state can be accurately detected by combining the power consumption and window state within the office.

The identification of the optimal sensor combination to detect occupancy is based on the Boolean logical theory through AND logical gates. The results presented here (based on an occupied office), has shown that the best arrangement or combination of sensors, is to implement together sensors for the Power consumption, the CO_2 levels and the window state (figure 7) as follows: (Power > 14.1 W) AND (CO_2 level > 368ppm) AND (Window state > 0). In other words, the fusion of only these three sensors describes the best the occupancy state, reaching an error of about 8.5%; meaning that this combination of sensors can describe the occupancy in the office with an accuracy of 91.5%.

Figure 7 also shows that 91.5% of the 20% occupancy presented in figure 6 (a) can be explained by implemented these three sensors together. Finally, since during this period of measurements, the air conditioner was not needed, the results showed that its inclusion to the analysis decreased the overall accuracy (not presented here).

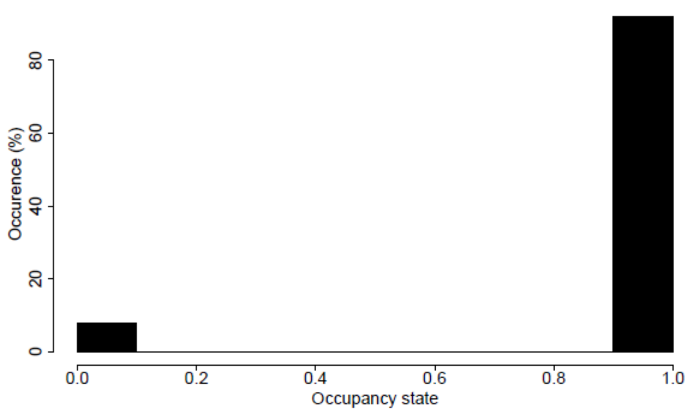

Figure 7. Representation of the descriptive model for the occupancy profile.

5. Conclusions

An experimental investigation of occupancy detection in a university office was conducted by using both human observations and sensor network data. Collected data were analyzed to explore relationships between the occupancy state and the magnitude of indoor parameters, to identify first optimal sensor combinations for accurately detect occupancy.

Seven measured variables were considered, and four demonstrated a good correlation with occupancy: electric power, carbon dioxide, window state, and air conditioning usage. These correlations were determined by using a correlation analysis based on Spearman's correlation coefficient through R software and its corrplot library. The CO_2 and electric power variables were introduced as continuous variables, and window state and air conditioning usage as binary variables.

A simple statistical approach was implemented to determine the optimal combination of these four variables by using histograms. Histograms showed that the occupancy could be accurately detected when using either monitoring the power consumption or the window state. However, higher accuracy was reached (about 91.5%) in the occupancy detection when combining three variables: CO_2 levels, Power, and window state.

In conclusion, this approach shows that a simple sensor-fusion technique can accurately determine the occupancy of the office. These results encourage the development of further studies in order to verify the potential application of the investigated elaboration techniques in diverse office typologies, working schedules, and climatic conditions.

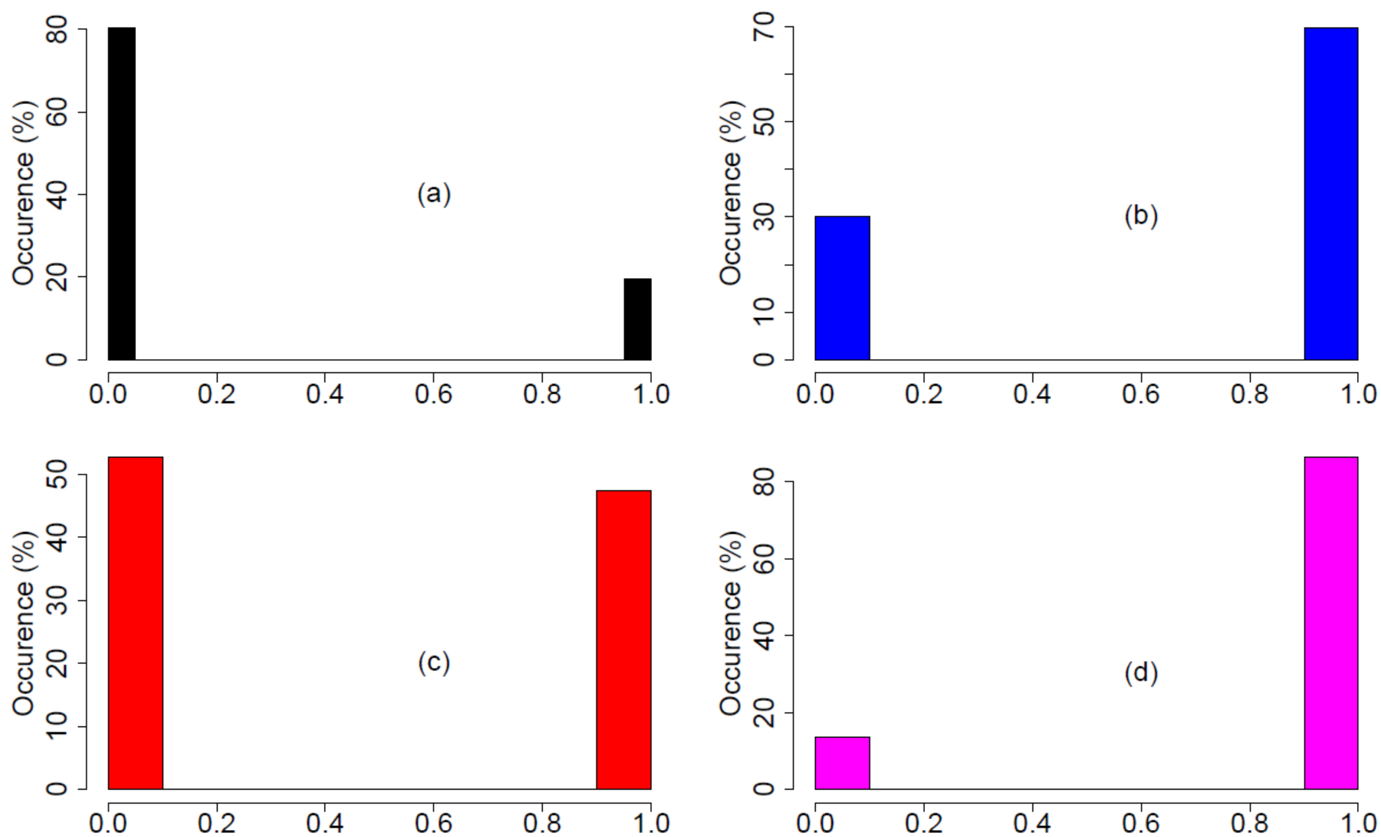

Figure 6. Occupancy state represented using histograms: (a) Real occupancy state, (b) occupancy state when Power > 14.1 W, (c) occupancy state when CO_2 > 368 ppm, and (c) occupancy state when window is opened. Occupancy state at horizontal axis: occupied = 1.

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